Financial stress and commodity price volatility

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Abstract

We use a Markov-switching vector autoregressive model to examine the impact of financial stress on the volatility of commodity prices, including energy volatility. An increase in financial stress leads to a persistent increase in the volatility of the commodity index and of individual commodity prices. We confirm the existence of three volatility regimes, with the volatility of the commodity index and of individual commodity prices in the high volatility regime being more than 25 times larger than that in other regimes. A financial stress shock that arrives during a highly volatile period has more destabilizing and persistent effects than when the shock arrives during a low volatility period. The impact on energy volatility in the high volatility regime is over 60% larger than that on the volatility of the commodity index. The high volatility regime is short-lived and reflects major economic events as well as the outbreak of the COVID-19 pandemic.

Keywords: Commodity markets; Realized volatility; Financial stress; COVID-19 pandemic; Markov-switching models

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1. Introduction

The financialization of commodity markets[1] and the outbreak of the COVID-19 pandemic created the "perfect storm" in commodity markets. Dating back two decades, commodity prices exhibited a sharp increase and a subsequent decline in 2008, have since then recovered but experienced a record one-month decline in March 2020, in the midst of the pandemic. Here we analyze how the change in financial market conditions affects commodity price volatility. This is important as understanding commodity price dynamics has significant implications on real economic activity as well as on financial market activity.

Typically, absent financialization, swings in commodity prices are associated with shocks in fundamental supply and demand (see Basak and Pavlova, 2016; Kilian and Murphy, 2014; Irwin and Sanders, 2010). For example, many attribute the changes in commodity prices during the subprime crisis to changes in fundamentals during that period (see Kilian and Murphy, 2014 and Irwin and Sanders, 2010). However, a second set of studies have found sizeable effects of institutional investors on commodity prices (see Basak and Pavlova, 2016; Goldstein and Yang, 2022; Tang and Xiong, 2012; Kilian and Murphy, 2014; and Irwin and Sanders, 2010). During the period after the subprime crisis, leading up to the outbreak of the pandemic, the academic debate on the effect of institutional investors on commodity markets focuses on a possible de-financialization of commodity markets (see Natoil, 2021). Indeed, Adams et al. (2020), Aromi and Clements (2019), and Zhang et al. (2017) show evidence of a potential de-coupling of commodity markets from financial factors.

Several factors point to the direction of a remaining open question - the impact of financial stress on commodity price volatility. First, the correlation between commodity markets and various financial assets is still high and unstable (Natoil, 2021). Second, financialization after the 2008 financial crisis may materialize in other forms. For example, Tang and Zhu (2016) show that another channel via which commodities may be used for financial purposes is as collateral for financing. Third, the integration of commodity markets with the financial markets is not at pre-financial crisis levels. Fourth, the existing studies use small samples and ignore the recent market

[1] This refers to the period after the early 2000s when futures market trading volume rises relative to production (Chari and Christiano, 2017).

turmoil associated with the U.S. Oil Fund, the world's largest oil ETF.

Further, COVID-19 has triggered a spike in uncertainty that had a severe impact on the U.S. real GDP (Baker et al., 2020a) and real GDP growth in more than 210 countries around the world (Ma et al., 2020). Equally, the extreme volatility in the equity market seen during the pandemic is only comparable to those in the 1929 crash and the Black Monday stock market crash (1987), and surpasses those during the 2008 financial crisis (Baker et al., 2020b).

Financial stress can affect the volatility of commodity prices through several channels. First, since commodities are influenced by aggregate demand and supply conditions, their volatilities increase with economic uncertainty (Bakas and Triantafyllou, 2018). Second, increased financial stress causes investors to rebalance their portfolios (Behmiri et al., 2021). Given the prominent role of commodities in portfolio investments (Adams and Glück, 2015), which is at least partially due to the financialization of commodities, portfolio rebalance is expected to affect commodity price volatility.

One measure that successfully captures the interruption caused to financial markets' functioning by high levels of uncertainty is the Kansas City Financial Stress Index (KCFSI). It measures financial stress using eleven financial variables, including yield spreads and actual or market-implied asset prices (Hakkio and Keeton, 2009).

Our objective is twofold. First, we proxy financial stress by using the KCFSI and quantify its impact on commodity price volatility. Second, we employ the Markov-switching vector autoregressive model (MS-VAR) developed by Guidolin et al. (2017) to analyze the time-varying responses of commodity volatilities to financial stress shocks. MS-VAR provides a rich framework to explore how financial stress influences commodity prices and plays a leading role within the models that are used to capture time-varying relationships (Davig et al., 2010; and Hubrich and Tetlow, 2015). While the Markov-switching model has been used in the literature to analyze stock and bond returns (Guidolin and Timmermann, 2006; and Guidolin et al., 2017), its application in commodity markets is rare (Guidolin et al., 2017).

We report a number of findings. First, we show that commodity price volatility is characterized by three volatility regimes. The three-regime model reflects, at least partially, the impact of the financialization of commodity markets and the boom and bust that followed. Each regime mainly reflects differences in commodity price volatility. The volatility of the realized variance of the commodity index in the high volatility regime is more than 25 times larger than that in the transitory regime and more than 45 times larger than that in the low volatility regime. Overall, the low volatility regime covers the period before the subprime crisis, and the transitory regime covers the period that followed the crisis and the months after the outbreak of COVID-19. The high volatility regime captures the 1990 energy crisis caused by the Gulf War, the early 2000s recession triggered by the dot-com bubble, the 2007-2009 subprime crisis, and the COVID-19 pandemic. It also captures the 2011 European debt crisis, the 2015-2016 Chinese stock market turbulence, and the 2018 stock market crash.

Second, we present evidence of regime-switching behavior. The low volatility and transitory regimes are persistent, characterized by stayer probabilities of 93.6% and 86.1%, while the high volatility regime is less persistent, characterized by a stayer probability of 49.7%. Therefore, the probabilities of moving from low to high volatility regimes are lower than that of moving from high to low volatility regimes. That said, markets have a tendency to function towards a steady state by either remaining in low volatility regimes or quickly adjusting from high to low volatility regimes. Indeed, during our sample period, markets spent approximately sixteen months, seven months, and two months in the low volatility, transitory, and high volatility regimes, respectively.

Third, we report a positive and highly significant effect of financial stress on commodity price volatility. This adverse effect is persistent: for the commodity index, it lasts for more than 24 months. Also, the differences across the three regimes are economically meaningful, indicating that a financial stress shock that arrives during a volatile period has potentially more destabilizing and persistent effects that when the shock arrives during a less volatile period. In particular, the impact on commodity price volatility of a shock in financial stress when the market is very volatile is almost 2.8 times as larger as that during a less volatile period.

Fourth, a financial stress shock leads to a rise in the volatility of energy, agriculture, and industrial metals, among which energy price volatility receives the strongest hit. In line with Joëts et al. (2017) that uncertainty is more related to predictability than to volatility, we find that the impact of financial stress on precious metals volatility remains insignificant. We find that the impact of financial stress on precious metals volatility remains insignificant. This is consistent with the literature that precious metals (e.g., gold and silver) have inherent value, and they are traditionally considered as a hedge and safe-haven against financial market turmoil (see, for example, Baur and Lucey, 2010; Baur and McDermott, 2010; and O'Connor et al., 2015). A shock in financial stress during a highly volatile period has an adverse effect on the volatility of individual commodities that is approximately 3.6 times larger than that during a low volatility period for energy and 3.2 times for agriculture. Overall, our results are robust to the alternative volatility measurements and the sample period.

The rest of the paper is proceeded as follows. Section 2 reviews the most relevant literature. Section 3 describes the sample and summary statistics and Section 4 introduces the methodology. Section 5 presents the empirical analysis and Section 6 concludes.

2. Literature review and contribution to the literature

This paper contributes to three strands of the literature. First, there is extensive literature on the effects of financial conditions on commodity prices. Natoli (2021), Cheng and Xiong (2014), and Rouwenhorst and Tang (2012) review the impact of financialization on commodity markets. Despite some notable exceptions (see Kilian and Murphy, 2014; and Irwin and Sanders, 2010), the academic literature generally agrees that financialization has intensified the impact of financial flows from institutional investors on commodity markets (see Henderson et al., 2015; Singleton, 2014; and Tang and Xiong, 2012). We add this literature by empirically investigating the effects of financialization on commodity price volatility.

Second, the literature that employs financial stress indicators is limited, although it is developing rapidly. Existing studies mainly focus on constructing and evaluating the relationship between financial stress indicators and economic activity (see Cardarelli et al., 2011; Chau and Deesomsak, 2014; and Mittnik and Semmler, 2013). In addition, Illing and Liu (2006) construct a financial stress indicator for Canada, while Park and Mercado Jr. (2014), Altınkeski et al. (2022), and Elsayed and Yarovaya (2019) study the propagation of financial stress across countries. Chen et al. (2014) use the KCFSI and show that financial stress triggers a significant adverse response in real oil prices. Nazlioglu and Soytas (2012) use the Cleveland financial stress index (CFSI) and provide evidence of risk transfer from the financial market to the energy market after the subprime financial crisis (see also Nazlioglu et al., 2015). Also, Reboredo and Uddin (2016) use the St. Louis Fed financial stress index (STLFSI) and document the evidence of a negative Granger causality effect in the upper and intermediate quantiles of the commodity return distribution. These papers have provided new insights into the consideration of financial stress as a source of shock amplification in commodity markets, but in most cases the representation of economies is based on a single time-invariant steady-state model. Our study contributes to this literature by analyzing the impact of financial stress on commodity price volatility in a time-varying model.

Third, we contribute to the literature that employs regime-switching models. For the commodity markets, Wan and Kao (2015), Ahmadi et al. (2020), and Behmiri et al. (2021) examine the responses of energy prices to the financial condition in threshold Vector Autoregressive (VAR) models, in which the financial stress serves as the threshold variable. MS-VAR models are better suited to capture the discrete changes in the recent crisis triggered by COVID-19 rather than financial conditions. Among the few MS-VAR models that address financial stress, Davig et al. (2010) and Hubrich and Tetlow (2015), who, like us, include a financial stress index; however, they omit any consideration of the volatility of commodities.

3. Sample selection and variable measurements

3.1 Sample selection

We collect KCFSI data from the Federal Reserve Bank of Kansa City website. Commodity data are retrieved from Thomson Reuters Datastream. To calculate control variables with the exception of the effective exchange rates, we obtain data from Federal Reserve Economic Data, operated by the Federal Reserve Bank of St. Louis. We retrieve the nominal effective exchange rate data from the Bank for International Settlements (BIS). To eliminate the impact of seasonal variation, all series are adjusted using the Autoregressive Integrated Moving Average (ARIMA) methodology. We use the X-13-ARIMA method for seasonal adjustment. This method has been adopted by the U.S. Census Bureau. The final sample consists of 371 monthly observations between February 1990 and December 2020.

3.2 Variable measurement

3.2.1 Financial stress index

The existing literature has developed a number of financial stress measures with the ones developed by the Kansas Federal (KCFSI), the St. Louis Fed (STLFSI), and the Cleveland Fed (CFSI) as the most prominent ones.[2] Whilst it is not easy to reach a consensus on the definition of financial stress, it is generally thought of as a disruption to the normal functioning of financial markets (Hakkio and Keeton, 2009). In this study, we employ the KCFSI because it comprehensively covers the dimensions through which financial stress can arise and because it has the longest coverage from its inception in February 1990 running through several financial market booms and busts.

KCFSI is a more representative measure to capture financial stress than indexes based on a single aspect of the market conditions such as VIX[3], because KCFSI consists of the principal components of eleven financial variables[4] (see, for example, Berger and Pukthuanthong, 2016). Hakkio and Keeton (2009) show that KCFSI captures approximately 61.4% of the total variation in the 11 variables included in the construction of the index. Further, KCSFI is a predictor of economic downturns (Hakkio and Keeton, 2009).[5] Figure 1 shows KCFSI over our sample period. The value of KCFSI ranges from -1.104 to 5.338 with a standard deviation of 1. A negative value represents below-average financial conditions, while a positive value suggests that it is above the long-run mean. KCFSI displays long periods of low readings with modest fluctuations and shorter episodes of high levels and high volatility. The peaks in KCFSI during 2008 and the beginning of 2020 correspond to the subprime crisis and the COVID-19 pandemic, respectively.

Figure 1

3.2.2 Commodity index

We collect the daily excess returns of the S&P GSCI indices in our analysis, including a broad commodity index that covers 24 commodity classes, and commodity indices on certain commodity

[2] The Chicago Fed's National Financial Conditions Index (NFCI) also provides a weekly update on U.S. financial conditions in the "shadow" banking systems, debt and equity markets, and money markets.
[3] VIX is one of the 11 variables included in the index as it captures both the uncertainty about fundamental values of assets as well as uncertainty about the behaviour of other investors
[4] These are the TED spread, 2-year swap spread, off-the-run/on-the-run 10-year Treasury spread, Aaa/10-year Treasury spread, Baa/Aaa spread, high-yield bond/Baa spread, consumer ABS/5-year Treasury spread, the correlation between stock and treasury returns, VIX, idiosyncratic volatility of bank stock prices, and cross-sectional dispersion of bank stock returns.
[5] In this sense, KCSFI is useful for policymakers to detect financial stress and adopt corresponding strategies such as quantitative easing used since early 2020. The main purpose of developing KCFSI is to monitor distress signals in the U.S. financial system. Financial stress can quickly be amplified from one market to the whole financial system, and hence, early detection is crucial for policymakers.

classes such as agriculture, energy, industrial metals, and precious metals.[6] Following Bakas and Triantafyllou (2018, 2019 and 2020), we measure the monthly volatility by using the realized variance of daily returns for each time series. Incorporating the sub-components of the broad index into the analysis enables us to disentangle the asymmetric effects of financial stress on various commodities. We plot the realized variance of four sub-commodity indices in Figure 2.

Figure 2

3.2.3 Control variables

We control several macroeconomic factors that are potentially associated with the dynamics of commodities: the growth rate of industrial production (IP), the growth rate of the Consumer Price Index (CPI), the effective federal funds rate (i.e., interest rate, IR), the oil price (OIL), the growth rate of the M2 money supply (M2), and the growth rate of nominal effective exchange rates (EER). Industrial production captures the aggregate demand and enables us to perform monthly analysis. The effective federal funds rate is chosen as the monetary policy instrument (Anzuini et al., 2013; and Hammoudeh et al., 2015). The logarithm of crude oil price is added as the oil price (Ahmadi, et al., 2016; and Van Robays, 2016). The monetary aggregate is included to reflect the official liquidity conditions (Belke et al., 2010, 2013; and Ratti and Vespignani, 2015), while the geometric weighted average of bilateral exchange rates is adopted to measure the strength of the US dollar (Harri et al., 2009; Prokopczuk et al., 2019; and Nazlioglu and Soytas, 2012).

4. Methodology

Our study explores the effects of financial stress on the realized variance of commodities in Markov-switching frameworks. The idea that single-state VAR models cannot reflect the endogenous relations among variables across time has been admitted in previous research (Kapetanios et al., 2012), where the instability of financial stress has recently been recognized and modeled (Ahmadi et al., 2020; Behmiri et al., 2021; and Wan and Kao, 2015). The regime-

[6] The S&P GSCI commodity index includes the following components: Chicago Wheat, Kansas Wheat, Corn, Soybeans, Coffee, Sugar, Cocoa, Cotton, Lean Hogs, Live Cattle, Feeder Cattle, WTI Crude Oil, Heating Oil, RBOB Gasoline, Brent Crude Oil, Gas Oil, Natural Gas, Aluminum, Copper, Nickel, Lead, Zinc, Gold, and Silver.

switching model is appropriate for several reasons. First, since it allows for discrete shifts, it offers a rich framework to examine the existence of nonlinearities. Second, it also distinguishes between coefficient switching and variance switching. The former would suggest either the coefficients switch among different states, or that are the same; while the latter indicates that financial crises are a result of chance. Third, the MS-VAR model can analyze the amplification and feedback effects between financial stress and commodity price volatility. Because financial stress is frequently characterized by structural breaks (i.e., instability), the MS-VAR framework has been adopted in the previous literature (Davig et al., 2010; and Hubrich and Tetlow, 2015). However, the application of the Markov-switching framework in the analysis of financial stress shocks on the commodity market is rather limited. This section lays out the core elements of the model.

Following Hubrich and Tetlow (2015), our focus is on eight-variable MS-VARs identified using Cholesky decomposition. In particular, let $y_t = [RV\ FSI\ IP\ CPI\ IR\ OIL\ M2\ EER]$. We assume it follows a Markov-switching process characterized by regime-dependent intercepts, autoregressive parameters, and heteroskedasticity (MSIAH):

$$y_t = B_{0,S_t} + \sum_{j=1}^{p} B_{j,S_t} y_{t-j} + \Omega_{S_t}^{\frac{1}{2}} u_t \tag{1}$$

$$u_t \backsim IID\ N(0, I_N)$$

where y_t denotes a vector of variables under study, $S_t = 1,2,\ldots,k$, and k is the number of states, B_{0,S_t} is the regime-dependent intercepts, B_{j,S_t} are the autoregressive coefficient matrices, and Ω_{S_t} are the covariance matrices. Hence, $\Omega_{S_t}^{1/2}$ are the lower triangular matrices of the Cholesky decompositions. Moreover, a discrete-state, homogeneous, irreducible, ergodic first order Markov chain generates a state S_t with its transition probabilities,

$$\Pr\left(S_t = j | S_{t-1} = i, S_{t-2} = l, \ldots\right) = p_{i,j} \tag{2}$$

where $p_{i,j}$ satisfies $\sum_{j=1}^{k} p_{i,j} = 1,\ \forall i,j,l \in \{1,\ldots,k\}$ and is an element of the $k \times k$ transition matrix P. Conditional on S_t, the MSIAH (k, p) model degenerates to the standard VAR (p) model, and it requires us to estimate a large number of parameters. As a parsimonious alternative, we also include Markov-switching process specified by regime-dependent intercepts and heteroskedasticity (MSIH),

$$y_t = B_{0,S_t} + \sum_{j=1}^{p} B_j y_{t-j} + \Omega_{S_t}^{\frac{1}{2}} u_t \tag{3}$$

$$u_t \backsim IID\ N(0, I_M)$$

where the autoregressive parameters are regime independent.

We resort to the maximum likelihood method to estimate the Markov-switching models. The estimation is carried out using the expectation-maximization approach developed by Hamilton (1990), who employs an iterative process to estimate parameters and transition matrices. This algorithm consists of the steps of expectation and maximization. In the iteration process, we employ initial parameters to compute the smoothed probabilities Pr $(S_t = j|y_T)$ in each expectation step, conditional on all the information, i.e., all endogenous variables in the regressions, where t=1, 2, …, T. We define the conditional regime probabilities as the smoothed probabilities obtained in the last expectation step. In the maximization step, we estimate parameters by solving the first order conditions of the likelihood functions, which can be used to start again in the next expectation step. We repeat the above iteration process until it converges.

As shown in Guidolin and Pedio (2017), the density of y_t builds on normal distribution given the information set at time $t-1$:

$$\text{p}\ (y_t|S_t = i, Y_{t-1}) = \sum_{j=1}^{k} \sum_{i=1}^{k} p_{ij} [\ln\ (2\pi)^{-\frac{1}{2}} \ln\ |\Omega|^{-\frac{1}{2}} \exp\ \{(y_t - \overline{y_{k,t}})' \Omega_k^{-1} (y_t - \overline{y_{k,t}})\}] \tag{4}$$

We utilize the information criterion to determine the best-fitted MS-VAR models. [7]

We use impulse response function (IRF) analysis to measure the impact of financial stress shocks on commodity markets. The h-step-ahead IRF is as follows:

$$IRF_{\Delta u}(h) = E[y_{t+h}|y_t(u_t + \Delta u)] - E[y_{t+h}|y_t(u_t)], \tag{5}$$

that is, it shows the difference between the conditional expectation of y_{t+h} in case y_t is under a

[7]Note that the expectation-maximization algorithm is used to conduct an iterating process to determine the parameters and the probabilities jointly. The details can be found in Guidolin and Pedio (2017).

financial stress shock and that of y_{t+h} without any shock. We then extend it to a Markov-switching framework,

$$IRF_{\Delta u}(h) = E[y_{t+h}|\eta_t, u_t + \Delta u, y_{t-1}] - E[y_{t+h}|\eta_t, u_t, y_{t-1}] \quad (6)$$

where η_t indicates the latent vector of the regime. Thus, the behavior of the IRF depends to a large extent on the regime that prevails at time t when the shock occurs. To identify the shock, we use a standard Cholesky decomposition to covariance matrices that depend on the regime. We then calculate the 90% confidence interval for each IRF using Monte Carlo simulations with ten thousand draws.

5. Empirical results

5.1 Summary statistics

In Table 1, Panel A, we report the descriptive statistics of the KCFSI and the commodity volatilities. KCFSI ranges between -1.104 and 5.338, with a mean of 0.008. The average realized volatility is highest for energy commodity index returns and lowest for precious metals returns. The mean values of the commodity volatilities range from 0.025 to 0.094. For both the KCFSI and the commodity realized volatilities, the Jarque-Bera test suggests that their time series are not normally distributed, therefore exhibiting excess skewness and kurtosis. Panel B presents the summary statistics of the control variables, including IP, CPI, the growth rate of M2, oil price, and the USD nominal effective exchange rates index.

*** Table 1 ***

In Table 2, we present the correlation matrix between the commodity volatilities. As expected, all volatilities are positively correlated. In particular, the correlation coefficient between the commodity and the energy indices is approximately 85%. It is consistent with the findings of Christoffersen et al. (2018), who document that the correlation of volatility across commodity classes has increased since financialization. Further, in Table 3, we report the results of the augmented Dickey-Fuller (ADF) and Phillips-Perron for stationarity. In all cases, we reject the unit root null hypothesis, thereby confirming that the realized variances of commodities and the KCFSI series are stationary. [8]

*** Table 2, Table 3***

5.2 Evidence of regime-switching

As mentioned in the previous section, we explore if the commodity price volatility and the financial stress index exhibit regime-switching behavior. In doing so, we fit a Markov-switching model with k from one up to three regimes, and with p up to two lags. The best-fitted model is decided based on the information criteria such as the Schwarz (SIC), Akaike (AIC), and Hannan-Quinn (HQ). We consider three types of models: MSIA, MSIH, and MSIAH. Here, MSIA stands for Markov-switching model specified by regime-dependent intercepts and autoregressive coefficients.

The results presented in Table 4 uniformly suggest that a three-regime model is superior to one- and two-regime models. Further, in order to check the existence of more than one regime, we carry out a likelihood ratio (LR) test. In this test, Davies' (1987) values are associated with the null hypothesis of a single state against the alternative of multiple states. We uniformly reject the null hypothesis. Regarding the number of lags, we select MSIH (3,1) as the best-fitted model according to the values of SIC, and this model is more parsimonious than MSIH (3,2) model, which contains 64 additional parameters.

Table 4

The three-regime model - MSIH (3,1) - suggests that the bout of turbulence caused by the financialization of commodity markets and the boom and bust that followed did not cause a direct switch from the low volatility to the high volatility regime. Instead, the turbulence caused a shift to the medium volatility regime but also raised the odds of extreme volatility. Importantly, this sheds doubt on the validity of previous research that fits two possible regimes. For example, Scarcioffolo and Etienne (2021) find a two-regime MS-GARCH model in the volatility of natural

[8] In unreported results, we also confirm that all control variables are stationary. They are available upon request.

gas and crude oil. Equally, Choi and Hammoudeh (2010) find a two-regime model in the volatility of oil, industrial commodity and equity markets. In Fong and See (2002), the volatility of crude oil futures prices is only allowed to shift between two regimes. More recently, Liu and Lee (2021) specify a two-regime MS model in the modelling of China crude oil futures. Alizadeh et al. (2021) specify a two-regime MS Heterogeneous Autoregressive model in modelling the volatility of the Tokyo Commodity Exchange futures. An important difference between our findings and these papers is that we do not impose a two-state MS model, instead, we find that a three-state volatility regime is supported by the data.

5.3 A three-regime MSIH model

This section reports the results of the three-regime MSIH(3,1) model. To investigate the identification of the regimes, we present the transition probability matrix for each regime in Table 5. The low volatility and transitory regimes are persistent, characterized by stayer probabilities (i.e., the probability of staying in the same state in the next month) of 93.6% and 86.1%, respectively. The high volatility regime is less persistent, characterized by a stayer probability of 49.7%. This finding indicates that the probability of shifting from a higher volatility regime to a lower volatility regime is higher than that of shifting from a low volatility regime to a high volatility regime. Stability and persistence are therefore lower in the high volatility regime, and markets spend more time in the low volatility regime. This is consistent with the results of Alizadeh et al. (2021) for the TOCOM energy futures. However, as mentioned, we identify a three-state MS model instead of exogenously fitting a two-state volatility regime. In our sample, the duration of the low volatility regime is approximately sixteen months, compared to approximately seven months for the transitory regime and two months for the high volatility regime.

Table 5

Table 6 reports the results of the MSIH(3,1) for the commodity index. The impact of financial stress on commodity volatility is positive and highly significant (KCFSI = 0.551), indicating that increases in KCFSI result in increases in commodity volatility. At the bottom of Table 6, we estimate the volatility of realized variance, confirming that each regime effectively captures changes in commodity volatility, with regime 1 being the low volatility regime, regime 2 being the transitory regime, and regime 3 being the high volatility regime. This finding is important because fluctuations in commodity volatility are not predicted by market variables (such as inventories or convenience yields) and can be considered exogenous (see Pindyck, 2004). Being therefore able to distinguish between different volatility levels has implications in the demand for hedging and the pricing of commodity-based contingent claims (Pindyck, 2001 and Kang et al., 2020). In our sample, the volatility of the realized variance of the commodity index in the high volatility regime is more than 25 times greater than that in other regimes, while the volatility of KCFSI in the high volatility regime is more than 16 times higher than that in other regimes.

Table 6

Figure 3 plots the smoothed probabilities of each regime. The low volatility regime covers much of the period before the subprime crisis, except for some isolated slumps. It also peaks in the months just before the COVID-19 pandemic. The transitory regime instead characterizes the periods following the subprime crisis and the months after the outbreak of COVID-19. The high volatility regime effectively identifies the 1990 energy crisis caused by the Gulf War, the early 2000s recession triggered by the dot-com bubble, the 2007-2009 subprime crisis, and the COVID-19 pandemic. It also captures the 2011 European debt crisis, the 2015-2016 Chinese stock market turbulence, and the 2018 stock market crash.

*** Figure 3***

The results for the four commodity index classes are quantitatively and qualitatively similar for energy, agriculture, and industrial metals. For precious metals, the coefficient for the financial stress index is positive but not significant (KCFSI = 0.095). The findings for the precious metals are consistent with the results of Joëts et al. (2017) who show that for precious metals, uncertainty is more related to predictability than to volatility. The results for each specific commodity type are available in Tables A.1 - A.4 in the appendix.

5.4 Impulse response analysis

This section presents the IRF analysis as described in equation (6). Figure 4 plots the impulse responses of the realized variance of the commodity index to a one-standard-deviation shock of the KCFSI. Across all the three regimes, a positive shock of the KCFSI leads to an increase in the commodity price volatility lasting over a period of 24 months before retrieving back to zero. The differences in the effects across regimes are economically meaningful. A positive shock to the KCFSI increases commodity volatility in the subsequent month by 8.5 basis points and 23.5 basis points in the low and high volatility regimes, respectively. This suggests that the impact of a financial stress shock during the periods when the market is very volatile is almost 2.8 times as larger as that during a less volatile period.

In addition, three months after the financial stress shock, the difference in the impulse responses between the high and low volatility regimes is even larger, when the value of the impulse response reaches the highest of 27.7 basis points. In the transitory regime, after three months, the impulse response declines to 8.0 basis points. It implies that a financial stress shock that arrives during a volatile period has potentially more destabilizing and persistent effects that when the shock arrives during a less volatile period.

*** Figure 4***

Further, Figure 5 presents the IRFs of the realized variance of energy and agriculture under a shock to the KCFSI in the three regimes. A positive shock to the KCFSI increases agriculture volatility by 5.8 basis points in the low volatility regime, which is close to 2.1% of the mean of agriculture volatility. On the other hand, the initial level of the IRFs is 18.8 basis points in the high volatility regime, which is close to 7.0% of the mean of agriculture volatility. The impact of the KCFSI in the high volatility regime is about 3.2 times as larger as that in the low volatility regime. In the transitory regime, the impulse response declines again to 3.4 basis points, which is close to 1.3% of the mean of agriculture volatility. Equally, a positive shock to the KCFSI increases energy volatility by 10.6 basis points in the low volatility regime, which is about 1.1% of the mean of energy volatility, but a similar shock increases energy volatility by 37.7 basis points in the high volatility regime, which is about 4.0% of the mean of energy volatility. The impact of a financial stress shock on energy volatility is therefore about 3.6 times larger during a more volatile period than during a more stable period.

*** Figure 5***

Figure 6 plots the IRFs of the realized variance of industrial metals and precious metals to a shock of the KCFSI, respectively. A positive shock in the KCFSI has a strongly adverse and persistent effect during the transitory and high volatility regimes. During the low volatility regime, a shock in financial stress increases industrial metals volatility by 1.7 basis points, which is close to 0.5% of the mean of industrial metals volatility. The equivalent figures for transitory and high volatility regimes are 0.7% and 2.0% of the mean of industrial metals volatility, respectively. Relating to precious metals, a positive shock in the KCFSI is associated with an increase of approximately 1.4% of the mean of precious metals volatility in the high volatility regime. This figure compares to 0.4% for the low volatility regime and 0.6% for the transitory regime, however, as indicated in Table 4, there is no evidence that shocks in the KCFSI have a significant impact on the volatility of precious metals.

*** Figure 6***

In summary, we identify three volatility regimes. Each regime reflects differences in commodity price volatility. The impact of a financial stress shock is much more pronounced and persistent when it occurs in the high volatility regime than in the low and transitory regimes. Also, the probability of switching from a high to a lower volatility regime is higher than that of shifting from a low to a high volatility regime. The high volatility regime is short-lived and effectively reflects the major economic and financial crisis as well as the outbreak of the COVID-19 pandemic. Our results are also robust for specific commodities, including energy, agriculture, and industrial metals. However, we don't find similar evidence for the volatility of precious metals. Our results indicate that the impact of financial stress is stronger on the volatility of energy futures compared to other futures contracts.

5.5 Robustness

We conduct three robustness tests. The first robustness test is to use two alternative measures of commodity volatility, and the second robustness test is to use a sub-sample that excludes the COVID-19 pandemic period. Finally, we employ STLFSI and VIX as alternative measures of financial stress.

For the first robustness test, we follow Hannan and Pagliari (2017) and calculate the first alternative volatility measure by using the residuals of a GARCH (1,1) model. Specifically, we consider the following process:

$$
\begin{aligned}
r_t &= \mu + \varepsilon_t \sigma_t, \text{ and} \\
\sigma_t^2 &= \alpha_0 + \alpha_1 r_{t-1}^2 + \alpha_2 \sigma_{t-1}^2
\end{aligned} \tag{7}
$$

where r_t is the S&P GSCI commodity index monthly return, ε_t is a white noise, and σ_t^2 is the corresponding conditional variance. We estimate the conditional variance based on a maximum likelihood estimation approach, and designate this measure as GARCH RV.

The second alternative volatility measure is constructed by the Principal Component Analysis (PCA). We first calculate the realized volatility of the 24 constituent commodity indices of the S&P GSCI. Then, we aggregate the 24 realized volatility measures by using their first principal component factor loading.[9] We designate this measure as PCA RV. Panel C of Table 1 reports the descriptive statistics of the two alternative volatility measures, and Panel B of Table 2 presents the correlations between the two volatility measures. GARCH RV is highly correlated with the Commodity RV. Equally, the PCA RV is approximately 82.9% correlated with the Commodity RV.

Table 7 presents the results of the MSIH (3,1) by using the volatility measure of GARCH RV. For the autoregression where GARCH RV is the dependent variable, the coefficient of the financial stress index (KCFSI) is 0.107 at the 5% significance level. Similarly, Table 8 shows the results of the MSIH (3,1) by using the volatility measure of PCA RV. For the autoregression where GARCH RV is the dependent variable, the coefficient of the financial stress index (KCFSI) is 0.368 at the

[9] Principal Component Analysis (PCA) is a dimension reduction method that is often used in the volatility literature. See Guo et al. (2022) and He et al. (2021) for two recent examples.

10% significance level. The findings of the two alternative volatility measures of the commodity index are consistent with those using realized volatility of the commodity index as shown in Table 6.

*** Table 7 and Table 8***

Figure 7 plots the IRFs of the GARCH RV and PCA RV to the shock of KCFSI. A shock of financial stress increases GARCH RV by 1.3 basis points in the low volatility regime, but it is 5.9 basis points in the high volatility regime, and is relatively mild at 2.6 basis points in the transitory regime. This pattern is much more obvious when employing the PCA RV, where the impact of a shock of financial stress under the high volatility regime is close to three times greater than that in the low volatility regime. Overall, our results are robust across all three measures of commodity volatility.

For the second robustness test, we repeat the analysis as shown in sections 5.3 and 5.4 by excluding the period of the COVID-19 pandemic. To this end, we use a sample that ends in December 2019. We present the results in Table A.5 and Figure A.1 in the appendix. Interestingly, when we exclude the period of the COVID-19 pandemic from the sample, the effect of financial stress on commodity price volatility becomes weaker (KCFSI = 0.336). The volatility of realized variance of commodity index in the high volatility regime is reduced by approximately 55% (29.808 in Table A.5 as compared to 64.403 in Table 6) when the COVID-19 pandemic period is excluded from the sample, while there are no big changes in the low volatility and transitory regimes. This confirms that the high volatility regime captures the period of the COVID-19 pandemic in our estimation. This finding clearly demonstrates the impact of the pandemic on commodity price volatility. Nevertheless, the impulse response of commodity price volatility to a shock in financial stress remains long-lived and persistent.

For the third robustness test, we employ the Federal Reserve Bank of St. Louis Financial Stress Index (STLFSI) and VIX as alternative measures of financial stress. Data for STLFSI start in 1994. STLFSI and VIX are 87.6% and 80.9% correlated with KCFSI, respectively (results not reported to conserve space). To compare with the financial stress measures, we standardize VIX to have zero mean and unit standard deviation. For STLFSI (VIX), we present the results in Table A.6

(Table A.7) and Figure A.2 (Figure A.3) in the appendix. The coefficient of STLFSI (VIX) is 0.696 (0.546) at the 1% significant level in Table A.6 (Table A.7). The findings of the two alternative measures of financial stress are consistent with those using KCFSI as shown in Table 6. Moreover, Figure A.2 (Figure A.3) plots the IRFs of the commodity RV to the shocks of STLFSI (VIX). A shock of the STLFSI (VIX) increases commodity RV by 15.8 (15.3) basis points and 45.0 (37.6) basis points in the low and high volatility regimes, respectively. This suggests that the impact of a shock of the STLFSI (VIX) during the periods when the market is volatile is almost 2.8 (2.5) times as larger as that during a less volatile period. These results remain consistent with the main findings of our paper.

6. Conclusions

This paper explores the impact of financial stress on commodity price volatility. We employ a MS-VAR that allows for a more formal investigation in the presence of nonlinearities and structural breaks embedded in the data.

We find that commodity price volatility can be better explained by three volatility regimes rather than two volatility regimes as found in the existing literature. We show that each regime mainly reflects the differences in commodity price volatility. The volatility of the commodity index during the highly volatile period is approximately 25 times larger than that during the transitionary period and is 45 times larger than that in the low volatility period. The probability of switching from a low to a higher-volatility regime is lower than the probability of switching from a high to a low-volatility regime.

We then analyze the effect of financial stress on commodity price volatility across the three volatility regimes. We show that a shock in financial stress has an adverse and highly significant effect on commodity price volatility. We report the significant differences in the effect of financial stress across volatility regimes. Quantitatively, we found that the impact of a shock of financial stress on commodity price volatility when the market is very volatile is almost 2.8 times larger than that during a less volatile period. Finally, we confirm that the impact of financial stress on commodity price volatility holds for the commodity index and for the sub-index of energy, agriculture and industrial metals, but not for precious metals.

Our study offers several contributions. First, by empirically investigating the effects of financialization on commodity price volatility, we contribute to the literature on the effects of financial conditions on commodity prices. Second, by analyzing the impact of financial stress on commodity price volatility in a time-varying model, we contribute to the nascent literature that employs financial stress indicators. Third, by employing a MS-VAR model in the volatility of commodities, we contribute to the established literature that uses regime-switching models in finance.

Volatility dynamics in commodity markets have important implications for investors, speculators, and policymakers. Importantly, we show substantial evidence that a two-regime model is inadequate in capturing the volatility dynamics in commodity markets, therefore policy responses that rely on single- or two-regime models are possibly not appropriate. In that respect, trade-policy makers should be more proactive in quantitatively monitoring the role of financial stress in commodity price volatility. Given the evidence we present in this paper that financial stress shocks have substantially more destabilizing effects in commodity markets during periods of high volatility, being able to identify regimes in advance is crucial for the effectiveness of investment strategies and policies that aim to stabilize commodity markets.

This paper serves as a first step toward understanding the impact of financial stress on commodity price volatility in a MS-VAR framework. It opens up several avenues for future research. One natural extension would be an in-depth examination of the impact of financial stress on futures volatility, such as crude oil and gasoline futures volatility. This is crucial as the unprecedented inflow of institutional funds into commodity futures markets has changed the nature of commodity price fluctuations, that we know attribute to the financialization of commodities (see Singleton 2014; Basak and Pavlova, 2016). Finally, further research should investigate the determinants of the three volatility regimes, therefore improving the effectiveness of policies that aim to stabilize commodity markets.

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Table 1. Summary statistics of the variables

Panel A	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
KCFSI	0.008	-0.315	5.338	-1.104	0.993	2.611	12.698	1875.298***
Commodity RV	0.042	0.028	0.460	0.004	0.050	4.220	27.598	10454.390***
Agriculture RV	0.027	0.019	0.192	0.004	0.026	3.489	18.456	4445.523***
Energy RV	0.094	0.062	2.402	0.006	0.159	10.300	137.026	284237.500***
Industrial Metals RV	0.036	0.023	0.354	0.001	0.041	3.455	19.608	5002.096***
Precious Metals RV	0.025	0.017	0.246	0.002	0.028	3.450	19.239	4812.447***
Panel B								
IP	1.479	2.456	8.477	-16.636	4.248	-1.704	6.990	425.666***
CPI	2.382	2.211	5.653	0.583	0.885	1.522	5.996	281.959***
IR	2.883	2.393	9.598	0.004	2.445	0.342	1.833	28.311***
OIL	3.673	3.705	4.850	2.469	0.625	0.041	1.705	26.019***
M2	5.874	5.791	25.442	0.197	3.485	2.624	14.847	2595.394***
EER	0.180	0.134	19.948	-13.294	6.525	0.299	2.964	66.699***
Panel C								
GARCH RV	0.054	0.039	0.484	0.013	0.057	4.468	28.292	11122.540***
PCA RV	0.000	-0.200	11.031	-0.705	1.000	8.132	83.011	103050.900***

The table presents the summary statistics of the variables in a monthly series over the sample period from 1990:02 to 2020:12. KCFSI is the Kansas City Financial Stress Index (http://fred.stlouisfed.org/). Commodity RV, Agricultural RV, Energy RV, Industrial Metals RV and Precious Metals RV are the realized volatility of the associated commodity index that is calculated as the monthly variance of the daily commodity index returns. IP is the growth rate of industrial production expressed in percentage. CPI is the growth rate of the Consumer Price Index expressed in percentage, i.e., inflation, IR is the nominal federal funds rate. OIL is the WTI crude oil price, M2 is the growth rate of M2 money supply expressed in percentage. EER is the return of the USD nominal effective exchange rate expressed in percentage. GARCH RV is the volatility of the commodity index estimated as the average daily residual within a month generated by a fitted GARCH(1,1) model. PCA RV is the volatility of the commodity index estimated as the first principal component of the 24 constituent commodity indices. *** denote statistical significance at 1% level of significance.

Table 2. Correlation matrix

	Commodity RV	Energy RV	Agriculture RV	Industrial Metals RV	Precious Metals RV	GARCH RV
Energy RV	0.847					
Agriculture RV	0.446	0.15				
Industrial Metals RV	0.453	0.164	0.604			
Precious Metals RV	0.514	0.314	0.524	0.561		
GARCH RV	0.66	0.578	0.369	0.405	0.35	
PCA RV	0.829	0.894	0.088	0.089	0.276	0.529

The table presents the correlation matrix for the monthly realized variance of the commodity index (Commodity RV) and its two alternative realized variance measures (GARCH RV and PCA RV), and the monthly realized variance of four sub-indices, including Energy RV, Agriculture RV, Industrial Metals RV and Precious Metals RV. All variables are defined in Table 1.

Table 3. Unit root test

	ADF		Phillips-Perron	
	t-Stat.	Lag	t-Stat.	Bandwidth
Commodity RV	-9.622***	0	-9.987***	7
Agriculture RV	-4.543***	2	-8.278***	10
Energy RV	-11.087***	1	-10.765***	8
Industrial Metals RV	-5.682***	1	-8.167***	8
Precious Metals RV	-7.367***	1	-11.911***	12
GARCH RV	-6.398***	0	-6.411***	7
PCA RV	-10.289***	1	-10.617***	4
KCFSI	-3.511**	3	-3.259*	5

The table presents the results of unit root tests for the variables in our analysis using the ADF and Phillips-Perron methods. The bandwidth for the Phillips-Perron test is determined using the Bartlett kernel and Newey-West bandwidth selection algorithm (Newey and West, 1994). All variables are defined in Table 1. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table 4. The result of the Markov-switching VAR models selection

	Model (k,p)	Log Likelihood	Number of parameters	Saturation ratio	SIC	AIC	HQ	LR test for Linearity	Davies	Iterations
1 Regime	Linear(1,1)	-2145.00	108	27.41	11.17	9.54	10.19	NA	NA	NA
	Linear(1,2)	-1959.37	172	17.16	13.38	11.55	12.28	NA	NA	NA
2 Regimes	MSIA(2,1)	-1698.57	182	16.26	12.09	10.17	10.93	892.84	0.000	60
	MSIA(2,2)	-1600.02	310	9.52	13.64	10.35	11.66	718.71	0.000	62
	MSIH(2,1)	-1610.72	154	19.22	11.17	9.54	10.19	1068.55	0.000	38
	MSIH(2,2)	-1493.12	218	13.54	11.58	9.27	10.19	932.50	0.000	15
	MSIAH(2,1)	-1543.55	218	13.58	11.83	9.52	10.44	1202.89	0.000	24
	MSIAH(2,2)	-1357.34	346	8.53	12.90	9.23	10.69	1204.07	0.000	29
3 Regimes	MSIA(3,1)	-1556.92	258	11.47	12.54	9.81	10.89	1176.15	0.000	16
	MSIA(3,2)	-1284.21	450	6.56	14.17	9.40	11.29	1350.33	0.000	14
	MSIH(3,1)	-1454.62	202	14.65	**11.09**	8.95	**9.80**	1380.75	0.000	55
	MSIH(3,2)	-1268.25	266	11.10	**11.13**	**8.32**	**9.44**	1382.25	0.000	38
	MSIAH(3,1)	-1391.33	330	8.97	12.79	**9.30**	10.69	1507.33	0.000	29
	MSIAH(3,2)	-1140.94	522	5.66	14.55	9.01	11.21	1636.86	0.000	16

The table shows the statistics used to select the best-fitted multivariate MS-VAR models for the Commodity RV. The models selected by each criterion are in bold. The column "LR test for Linearity" reports Davies' (1987) corrected likelihood ratio test statistics for the null hypothesis of a single regime. The column of "Davies" consists of the p-values of the upper bound for the LR test statistic under nuisance parameters. The tests reject the null hypothesis of a single regime at any conventional significance level. MSIA stands for Markov-switching models with regime-dependent intercepts and autoregressive coefficients, MSIH stands for Markov-switching models with regime-dependent intercepts and heteroscedasticity, while MSIAH stands for Markov-switching models with regime-dependent intercepts, autoregressive parameters, and heteroscedasticity.

Table 5: Transition matrix of the MSIH(3,1) model

Transition	Regime 1	Regime 2	Regime 3
Regime 1	0.936	0.000	0.064
Regime 2	0.042	0.861	0.097
Regime 3	0.121	0.381	0.497

The table presents the estimated transition matrix of the MSIH(3,1) model for Commodity RV as expressed in equation (3). The stayer probability denotes the probability of remaining in the same regime for an additional period.

Table 6: Estimates of the MSIH (3,1) model based on Commodity RV

Panel A	Commodity RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	2.230**	1.483***	-0.009	0.314**	0.155***	0.415	-2.681**	-0.218**
	(0.855)	(0.456)	(0.069)	(0.135)	(0.039)	(0.268)	(1.201)	(0.099)
Regime 2	0.767	1.536***	-0.016	0.253**	0.169***	0.432	-3.219**	-0.224**
	(0.930)	(0.495)	(0.073)	(0.105)	(0.042)	(0.307)	(1.292)	(0.104)
Regime 3	8.923***	0.783	-0.017	0.172	0.070	0.689**	-3.005**	0.074
	(1.500)	(0.556)	(0.081)	(0.168)	(0.050)	(0.341)	(1.419)	(0.145)
VAR(1) Matrix								
KCFSI (t-1)	0.551***	-0.201***	-0.007	-0.026**	0.001	-0.092**	0.049	0.919***
	(0.139)	(0.069)	(0.010)	(0.012)	(0.006)	(0.040)	(0.181)	(0.016)
Commodity RV (t-1)	0.193***	-0.040**	-0.003	0.000	0.003**	0.022**	0.054	0.001
	(0.030)	(0.015)	(0.002)	(0.002)	(0.001)	(0.010)	(0.035)	(0.003)
IP (t-1)	-0.120***	0.883***	-0.005**	0.000	-0.004***	-0.022*	0.136***	0.006*
	(0.038)	(0.019)	(0.002)	(0.002)	(0.002)	(0.013)	(0.044)	(0.004)
CPI (t-1)	-0.754***	-0.132*	0.952***	0.009	-0.023***	-0.117**	0.489**	-0.009
	(0.153)	(0.080)	(0.012)	(0.014)	(0.007)	(0.048)	(0.209)	(0.016)
IR (t-1)	0.034	0.022	0.015***	0.965***	0.004	0.042**	-0.150	0.017**
	(0.070)	(0.039)	(0.006)	(0.015)	(0.003)	(0.021)	(0.098)	(0.008)
OIL (t-1)	0.719***	-0.234**	0.026*	-0.054**	0.973***	-0.074	0.362	0.028
	(0.164)	(0.091)	(0.015)	(0.024)	(0.008)	(0.052)	(0.254)	(0.020)
M2 (t-1)	-0.004	0.006	-0.001	-0.004**	-0.001	0.994***	0.072*	0.007**
	(0.036)	(0.019)	(0.002)	(0.002)	(0.002)	(0.012)	(0.042)	(0.003)
EER (t-1)	0.018	-0.019***	-0.001	-0.002*	-0.003***	0.000	0.957***	0.000
	(0.013)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.018)	(0.001)
Panel B								
Volatilities								
Regime 1	1.416	0.452	0.016	0.223	0.004	0.111	4.395	0.025
Regime 2	2.527	0.862	0.011	0.003	0.006	0.475	3.323	0.025
Regime 3	64.403	3.280	0.034	0.474	0.032	1.271	10.091	0.421

In this table, Panel A shows the estimates of the MS-VAR where the Commodity RV is used. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) model for each dependent variable. Standard errors are in parentheses. All variables are defined in Table 1. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. Standard errors are presented in parentheses. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table 7: Estimates of the MSIH (3,1) model based on the GARCH RV

Panel A	GARCH RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	2.550***	1.382***	0.027	0.072	0.081**	0.192	-1.646	-0.242**
	(0.354)	(0.451)	(0.068)	(0.126)	(0.037)	(0.279)	(1.214)	(0.098)
Regime 2	0.779**	1.541***	0.011	0.096	0.095**	0.153	-1.841	-0.300***
	(0.303)	(0.453)	(0.068)	(0.118)	(0.037)	(0.279)	(1.214)	(0.096)
Regime 3	8.633***	1.068	0.001	0.215	0.048	1.511***	-1.282	0.056
	(2.841)	(0.938)	(0.099)	(0.254)	(0.082)	(0.512)	(1.618)	(0.251)
VAR(1) Matrix								
KCFSI (t-1)	0.107**	-0.170**	-0.008	-0.091***	0.005	-0.097**	0.139	0.926
	(0.051)	(0.066)	(0.010)	(0.019)	(0.006)	(0.040)	(0.173)	(0.015)
GARCH RV (t-1)	0.669***	-0.043***	-0.002	0.012***	0.000	0.012	0.015	0.002
	(0.012)	(0.014)	(0.002)	(0.004)	(0.001)	(0.008)	(0.036)	(0.003)
IP (t-1)	0.016	0.907***	-0.004*	0.008*	-0.001	-0.002	0.081*	0.003
	(0.011)	(0.018)	(0.003)	(0.004)	(0.001)	(0.011)	(0.046)	(0.003)
CPI (t-1)	-0.078	-0.131*	0.953***	-0.009	-0.019***	-0.086*	0.330	-0.002
	(0.051)	(0.078)	(0.012)	(0.020)	(0.006)	(0.047)	(0.208)	(0.016)
IR (t-1)	0.000	0.014	0.013***	0.984***	0.001	0.029	-0.047	0.019***
	(0.020)	(0.030)	(0.005)	(0.008)	(0.002)	(0.018)	(0.081)	(0.006)
OIL (t-1)	0.008	-0.232***	0.018	-0.029	0.988***	-0.040	0.239	0.043**
	(0.059)	(0.087)	(0.013)	(0.023)	(0.007)	(0.054)	(0.237)	(0.019)
M2 (t-1)	0.014	0.006	0.000	-0.003	0.000	1.004***	0.000	0.006*
	(0.010)	(0.016)	(0.002)	(0.004)	(0.001)	(0.010)	(0.042)	(0.003)
EER (t-1)	-0.003	-0.017***	0.000	-0.004**	-0.002***	0.000	0.950***	0.001
	(0.005)	(0.006)	(0.001)	(0.002)	(0.001)	(0.004)	(0.017)	(0.001)
Panel B								
Volatilities								
Regime 1	3.971	0.509	0.013	0.335	0.007	0.174	4.565	0.063
Regime 2	0.124	0.618	0.014	0.018	0.003	0.241	3.903	0.017
Regime 3	144.074	11.836	0.082	0.843	0.093	3.093	16.496	0.940

In this table, Panel A shows the estimates of the MS-VAR where the GARCH RV is used. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) model for each dependent variable. Standard errors are in parentheses. All variables are defined in Table 1. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. Standard errors are presented in parentheses. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table 8: Estimates of the MSIH (3,1) model based on the PCA RV

Panel A	PCA RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	5.917***	1.654***	0.014	0.043	0.100**	-0.086	-1.835	-0.186
	(1.527)	(0.485)	(0.077)	(0.088)	(0.042)	(0.345)	(1.489)	(0.114)
Regime 2	6.524***	1.867***	0.021	0.128	0.108**	-0.091	-1.480	-0.214
	(1.847)	(0.526)	(0.092)	(0.095)	(0.047)	(0.340)	(1.941)	(0.133)
Regime 3	20.478***	0.785	-0.003	-0.116	-0.003	0.158	-2.174	-0.030
	(4.735)	(0.634)	(0.096)	(0.175)	(0.064)	(0.414)	(1.841)	(0.189)
VAR(1) Matrix								
KCFSI (t-1)	0.368*	-0.248***	-0.008	-0.008*	0.000	-0.043	0.332**	0.970 ***
	(0.194)	(0.062)	(0.008)	(0.005)	(0.006)	(0.041)	(0.159)	(0.015)
PCA RV (t-1)	0.202***	-0.022**	-0.001	0.000	0.003***	0.029***	0.005	-0.002
	(0.033)	(0.008)	(0.001)	(0.001)	(0.001)	(0.006)	(0.020)	(0.002)
IP (t-1)	-0.201***	0.891***	-0.005**	0.000	-0.002	0.001	0.101**	0.004
	(0.062)	(0.020)	(0.003)	(0.002)	(0.002)	(0.014)	(0.051)	(0.004)
CPI (t-1)	-1.081***	-0.091	0.949***	0.015	-0.013*	-0.081	0.261	-0.021
	(0.275)	(0.089)	(0.012)	(0.014)	(0.008)	(0.059)	(0.223)	(0.019)
IR (t-1)	0.101	0.020	0.016***	1.002***	0.002	0.035	-0.006	0.016*
	(0.117)	(0.034)	(0.005)	(0.005)	(0.003)	(0.022)	(0.103)	(0.009)
OIL (t-1)	-1.294***	-0.395***	0.017	-0.029	0.982***	0.067	0.238	0.046*
	(0.313)	(0.098)	(0.018)	(0.024)	(0.009)	(0.061)	(0.384)	(0.025)
M2 (t-1)	-0.024	0.019	0.000	-0.003**	0.000	0.993***	0.016	0.002
	(0.072)	(0.022)	(0.002)	(0.001)	(0.002)	(0.012)	(0.051)	(0.005)
EER (t-1)	0.041**	-0.015**	0.000	-0.001**	-0.003***	0.000	0.944***	0.001
	(0.021)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.025)	(0.002)
Panel B								
Volatilities								
Regime 1	3.421	0.406	0.016	0.223	0.004	0.163	4.480	0.026
Regime 2	8.587	1.036	0.011	0.002	0.006	0.361	4.233	0.038
Regime 3	644.664	3.485	0.043	0.734	0.060	1.044	8.666	0.599

In this table, Panel A shows the estimates of the MS-VAR where the PCA RV is used. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) model for each dependent variable. Standard errors are in parentheses. All variables are defined in Table 1. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

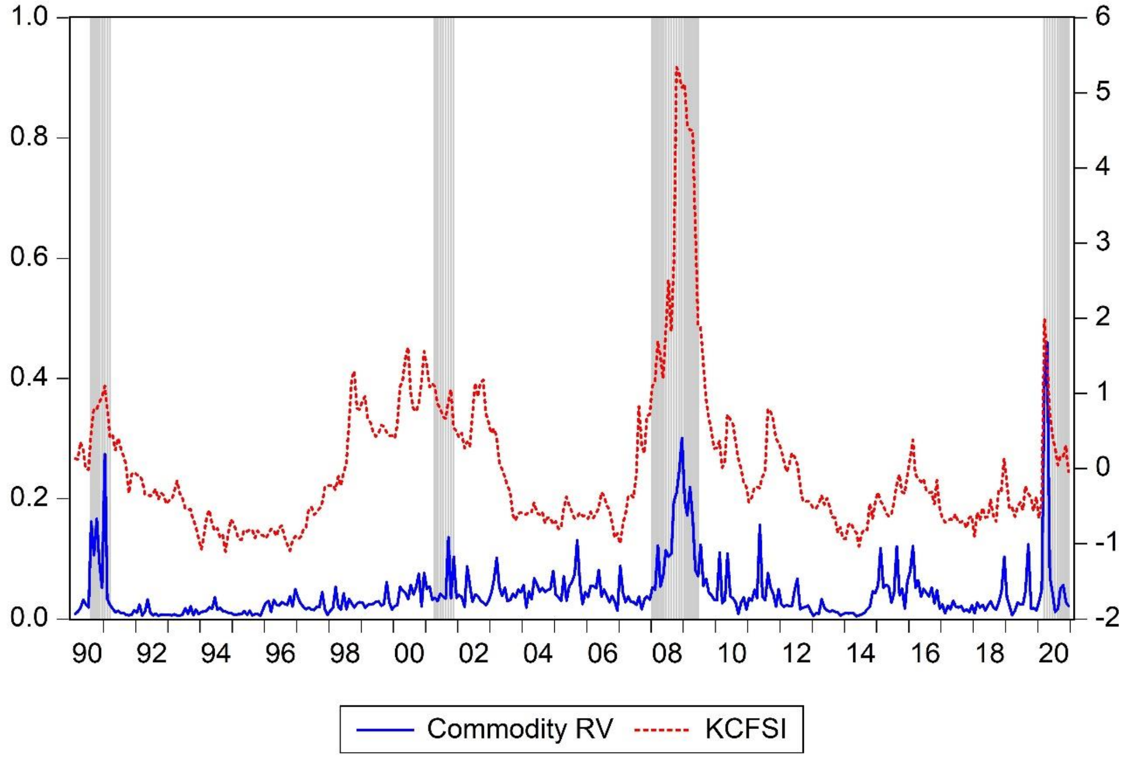


Figure 1: Kansas City Financial Stress Index (KCFSI) and commodity index volatility (Commodity RV). The figure plots the time series of the KCFSI and the realized variance of the commodity price index (Commodity RV) from 1990:02 to 2020:12. The variables are defined in Table 1. The NBER-dated recessions are marked in gray.

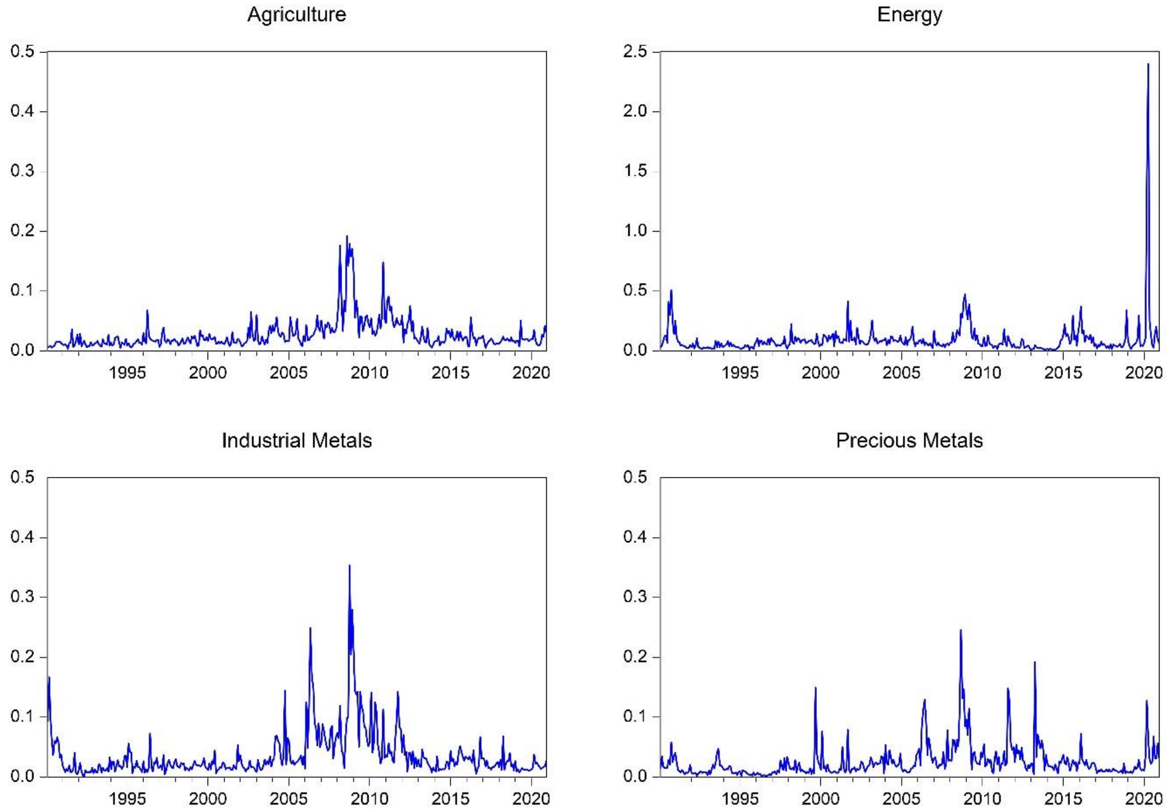


Figure 2: The realized variance of agriculture, energy, industrial metals, and precious metals commodities. The figure plots the realized variance of four sub-commodity indices from 1990:02 to 2020:12, including agriculture, energy, industrial metals, and precious metals commodities. The variables are defined in Table 1.

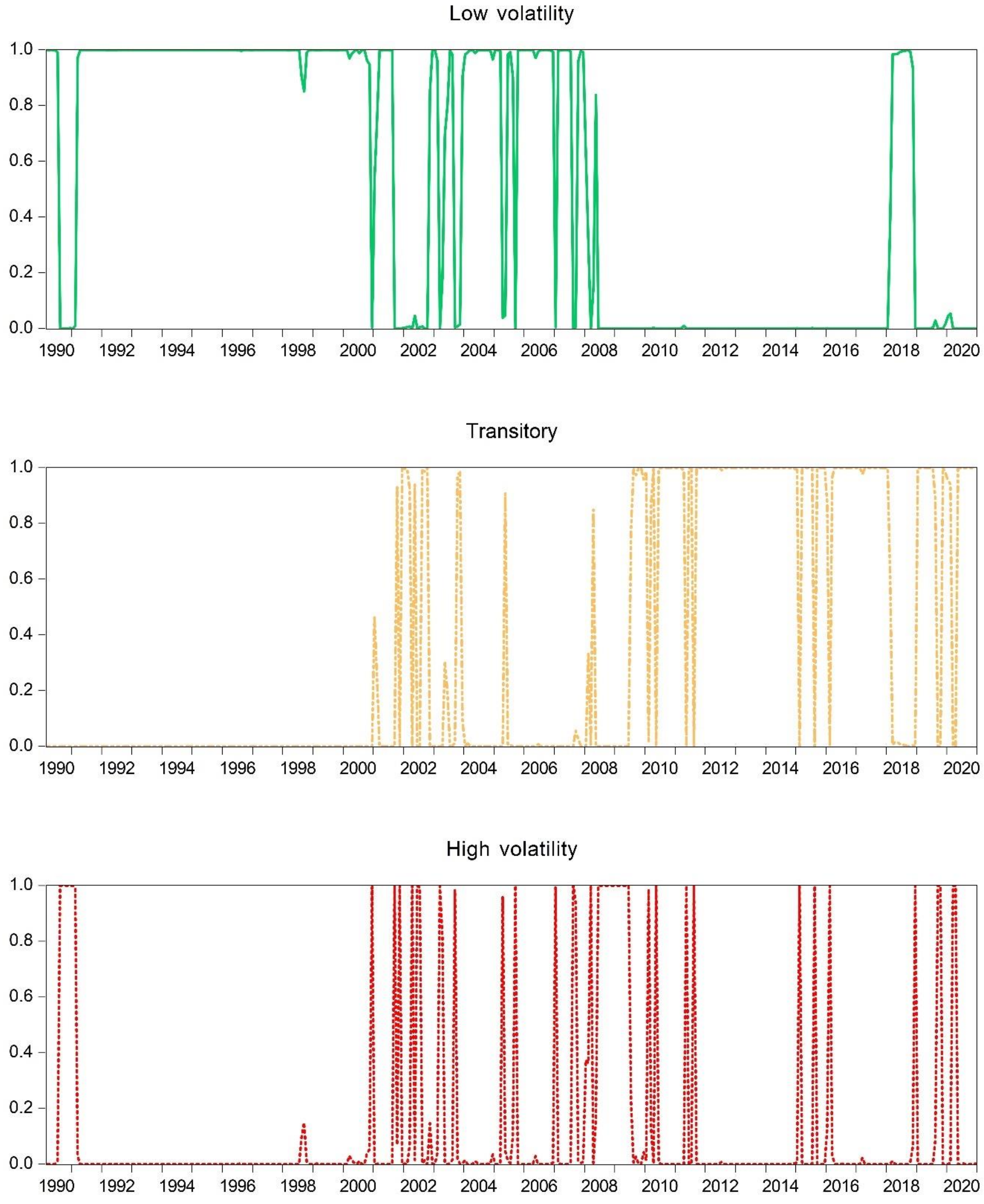
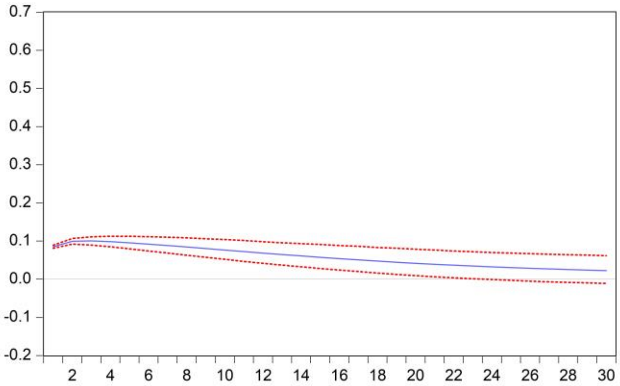


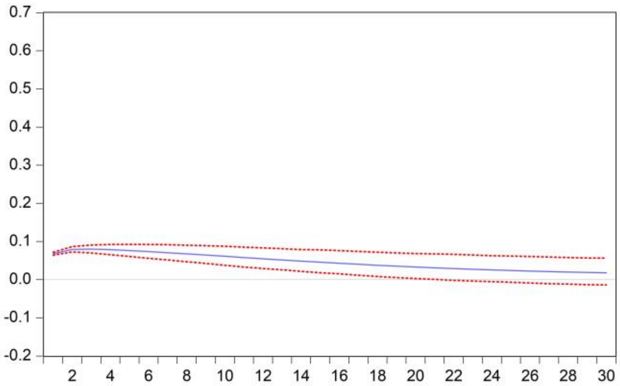
Figure 3: Smoothed probabilities of the MSIH(3,1) model.

This figure plots the smoothed probabilities of Commodity RV in three volatility regimes during 1990 – 2020, that is estimated by the MSIH (3,1) model as expressed in equation (3).

IRFs in low volatility regime



IRFs in transitory regime



IRFs in high volatility regime

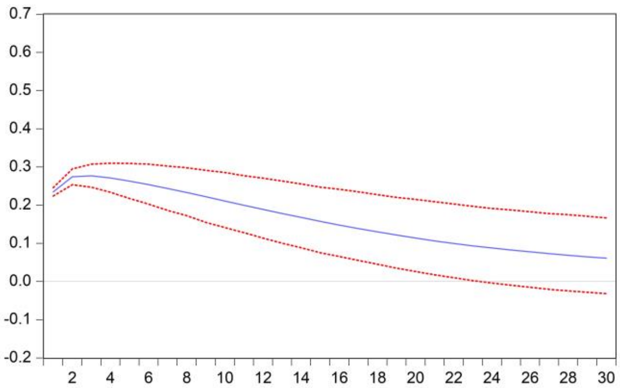
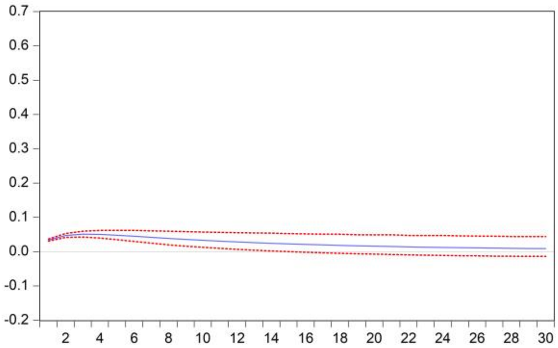


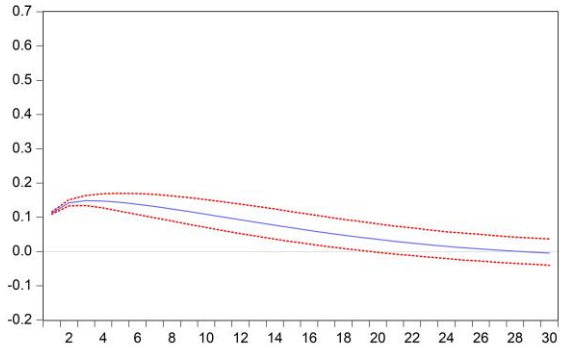
Figure 4: Impulse response functions (IRFs) of the realized variance of the commodity to a shock of the financial stress.

This figure plots the IRFs of the realized variance of the commodity (Commodity RV) to a shock of the KCFSI as estimated by equation (6). The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

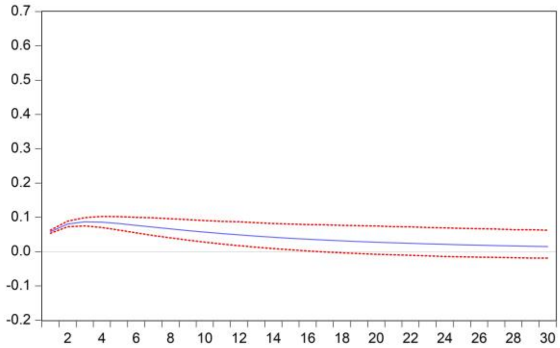
Agriculture RV IRFs in low volatility regime



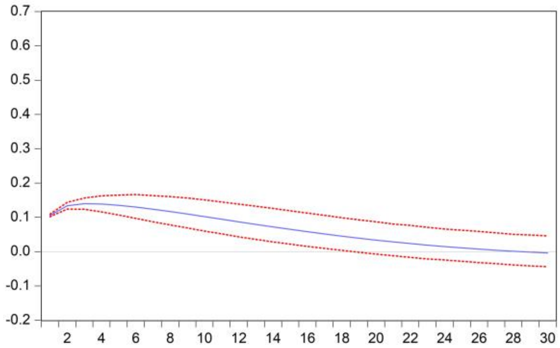
Energy RV IRFs in low volatility regime



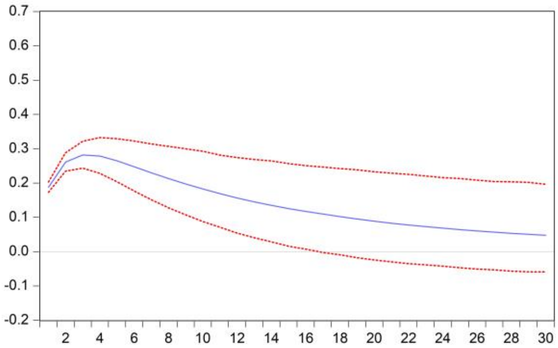
Agriculture RV IRFs in transitory regime



Energy RV IRFs in transitory regime



Agriculture RV IRFs in high volatility regime



Energy RV IRFs in high volatility regime

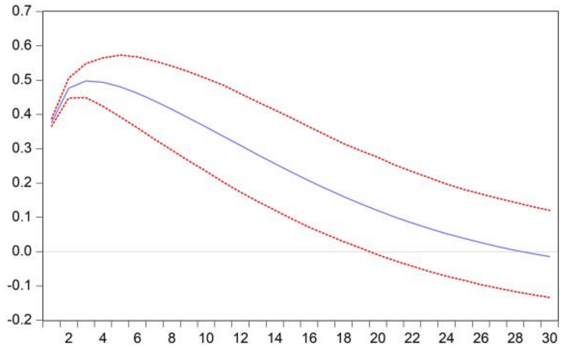


Figure 5: Impulse response functions (IRFs) of the realized variance of the agriculture commodity index and energy commodity index to a shock of the financial stress.

This figure plots the IRFs of the realized variance of the agriculture commodity index and energy commodity index to a shock of the KCFSI as estimated by equation (6). The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

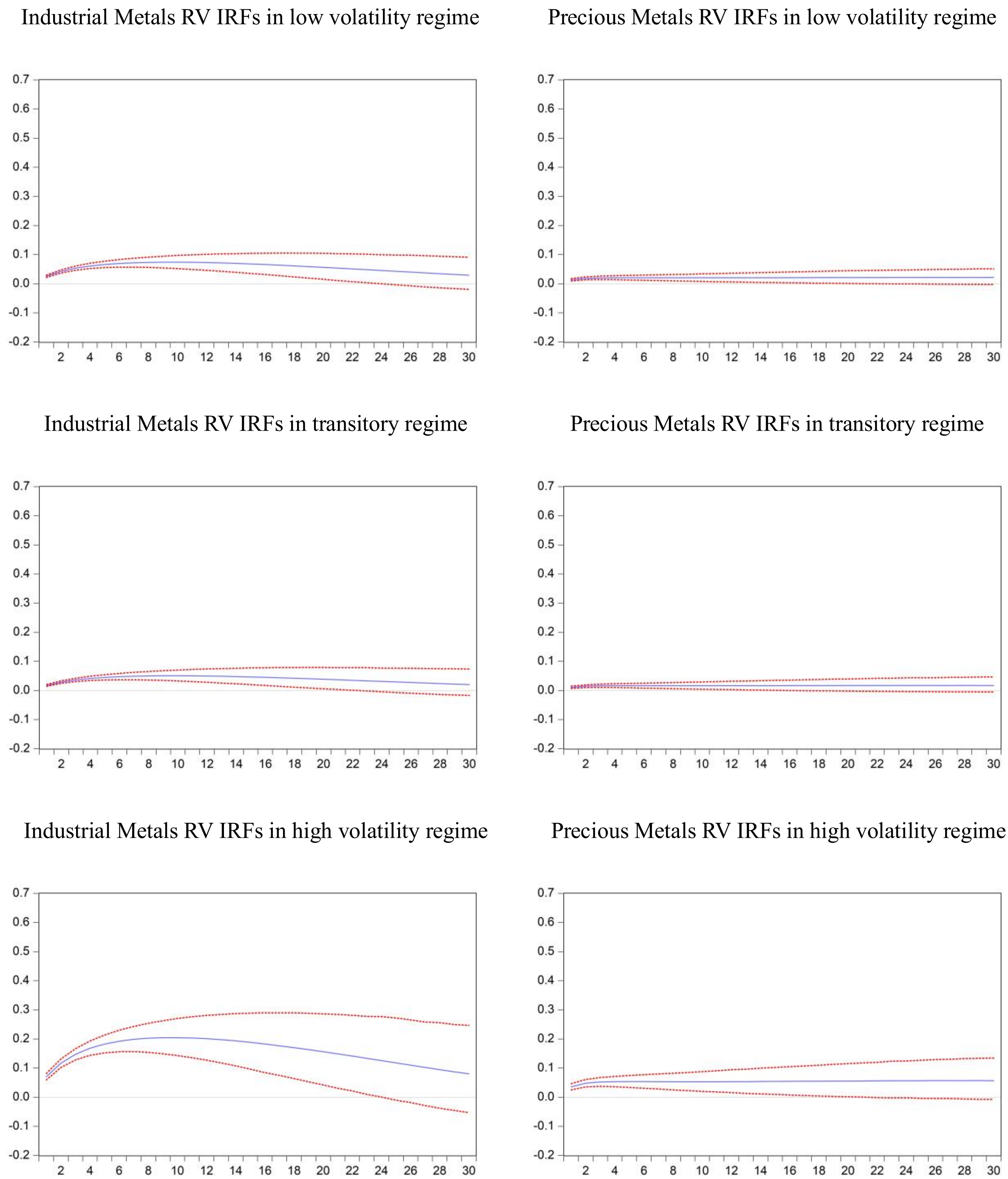


Figure 6: Impulse response functions (IRFs) of the realized variance of the industrial metals commodity index and precious metals commodity index to a shock of the financial stress.

This figure plots the IRFs of the realized variance of the industrial metals index and precious metals commodity index to a shock of the KCFSI as estimated by equation (6). The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

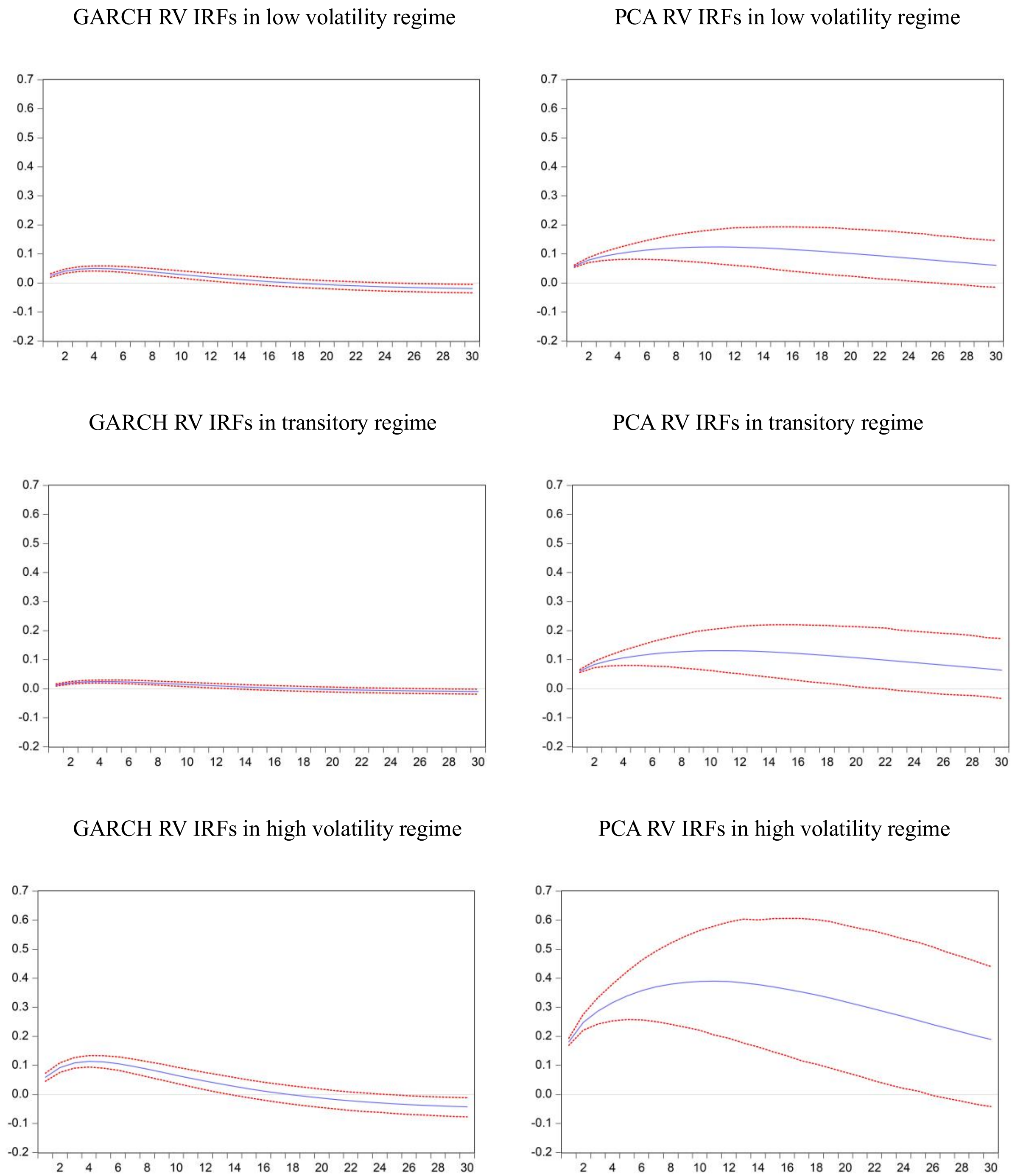


Figure 7: Impulse response functions (IRFs) of GARCH RV and PCA RV to a shock of the financial stress. This figure plots the IRFs of the alternative measures of the realized variance of the commodity index – GARCH RV and PCA RV - to a shock of the KCFSI as estimated by equation (6). The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

APPENDIX

Table A1: Estimates of the MSIH (3,1) based on Agriculture RV

Panel A	Agriculture RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	-0.056	0.874**	-0.018	0.182*	0.119***	0.233	-1.557***	-0.153***
	(0.667)	(0.432)	(0.068)	(0.094)	(0.041)	(0.242)	(1.195)	(0.096)
Regime 2	-0.398	1.722*	-0.107	0.190*	0.106	0.239	-3.316***	-0.354***
	(0.707)	(0.896)	(0.081)	(0.097)	(0.068)	(0.537)	(1.249)	(0.103)
Regime 3	0.803	0.938**	0.010	0.102	0.111**	0.271	-1.614	0.038
	(0.802)	(0.472)	(0.075)	(0.137)	(0.046)	(0.271)	(1.310)	(0.122)
VAR(1) Matrix								
KCFSI (t-1)	0.433***	-0.252***	-0.015	-0.068***	0.001	-0.018	0.147	0.908***
	(0.117)	(0.068)	(0.011)	(0.015)	(0.007)	(0.040)	(0.196)	(0.021)
Agriculture RV (t-1)	0.478***	-0.030	-0.003	0.014**	0.000	0.012	0.026	0.010
	(0.058)	(0.024)	(0.004)	(0.006)	(0.002)	(0.015)	(0.067)	(0.007)
IP (t-1)	-0.007	0.959***	-0.004	-0.005**	-0.001	-0.019*	0.027	-0.002
	(0.025)	(0.017)	(0.003)	(0.002)	(0.002)	(0.010)	(0.046)	(0.004)
CPI (t-1)	-0.251**	0.013	0.956***	-0.029	-0.020***	-0.128***	0.162	-0.008
	(0.125)	(0.075)	(0.012)	(0.019)	(0.007)	(0.043)	(0.208)	(0.017)
IR (t-1)	0.030	-0.035	0.012**	0.999***	0.002	0.043***	0.003	0.013*
	(0.044)	(0.030)	(0.005)	(0.006)	(0.003)	(0.016)	(0.083)	(0.007)
OIL (t-1)	0.567***	-0.234**	0.024	-0.030	0.981***	0.000	0.329	0.016*
	(0.146)	(0.091)	(0.014)	(0.023)	(0.009)	(0.051)	(0.255)	(0.021)
M2 (t-1)	-0.042	0.023	0.001	-0.006**	0.000	0.998***	-0.011	0.004
	(0.026)	(0.015)	(0.002)	(0.002)	(0.001)	(0.009)	(0.043)	(0.003)
EER (t-1)	-0.026***	-0.019	-0.001	-0.002**	-0.002	0.001	0.943***	0.002
	(0.010)	(0.006)	(0.001)	(0.001)	(0.001)	(0.004)	(0.018)	(0.001)
Panel B								
Volatilities								
Regime 1	1.065	0.455	0.012	0.035	0.004	0.141	3.894	0.021
Regime 2	1.395	11.460	0.039	0.004	0.057	4.354	4.618	0.033
Regime 3	8.659	0.911	0.024	0.751	0.013	0.542	7.279	0.284

The table presents the results of the MS-VAR where the endogenous variables include the realized variance of the agriculture (Agriculture RV). Standard errors are in parentheses. All variables are defined in Table 1. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) for each dependent variable. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A2: Estimates of the MSIH (3,1) based on Energy RV

Panel A	Energy RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	8.195***	1.608***	0.025	0.266***	0.136***	-0.105	-2.417**	-0.217**
	(1.789)	(0.435)	(0.069)	(0.096)	(0.039)	(0.264)	(1.215)	(0.093)
Regime 2	6.957***	1.883***	0.034	0.307***	0.139***	0.020	-2.895**	-0.223**
	(1.932)	(0.490)	(0.075)	(0.085)	(0.042)	(0.297)	(1.328)	(0.100)
Regime 3	22.837***	1.116**	0.042	0.227*	0.073	0.232	-2.918**	0.127
	(5.202)	(0.527)	(0.080)	(0.137)	(0.050)	(0.323)	(1.376)	(0.137)
VAR(1) Matrix								
KCFSI (t-1)	0.818***	-0.299***	-0.008	-0.010	0.001	-0.083**	0.194	0.917***
	(0.279)	(0.061)	(0.009)	(0.008)	(0.006)	(0.040)	(0.165)	(0.015)
Energy RV (t-1)	0.273***	-0.015***	-0.001*	-0.001*	0.001**	0.018***	0.010	-0.002
	(0.037)	(0.004)	(0.001)	(0.001)	(0.000)	(0.003)	(0.010)	(0.001)
IP (t-1)	-0.194**	0.884***	-0.005**	0.001	-0.003*	-0.003	0.133***	0.005
	(0.075)	(0.018)	(0.002)	(0.001)	(0.001)	(0.011)	(0.045)	(0.003)
CPI (t-1)	-0.923***	-0.112	0.950***	0.014	-0.021***	-0.078*	0.433**	-0.006
	(0.297)	(0.075)	(0.012)	(0.012)	(0.006)	(0.045)	(0.205)	(0.015)
IR (t-1)	0.083	0.037	0.016***	0.982***	0.002	0.048**	-0.147	0.013*
	(0.136)	(0.035)	(0.006)	(0.008)	(0.003)	(0.021)	(0.098)	(0.007)
OIL (t-1)	-0.347	-0.345***	0.016	-0.069***	0.977***	0.000	0.371	0.033*
	(0.347)	(0.088)	(0.015)	(0.018)	(0.008)	(0.054)	(0.260)	(0.019)
M2 (t-1)	0.092	0.018	-0.001	-0.003**	-0.001	0.991***	0.063	0.006
	(0.074)	(0.019)	(0.002)	(0.001)	(0.001)	(0.012)	(0.044)	(0.003)
EER (t-1)	0.027	-0.016**	-0.001	-0.001	-0.002***	-0.001	0.963***	-0.001
	(0.030)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.019)	(0.001)
Panel B								
Volatilities								
Regime 1	5.992	0.426	0.015	0.223	0.004	0.140	4.400	0.020
Regime 2	12.844	0.996	0.012	0.002	0.005	0.347	4.063	0.026
Regime 3	1148.371	2.942	0.034	0.468	0.035	0.977	8.052	0.402

The table presents the results of the MS-VAR where the endogenous variables include the realized variance of the energy (Energy RV). Standard errors are in parentheses. All variables are defined in Table 1. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) for each dependent variable. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A3: Estimates of the MSIH (3,1) based on Industrial Metals RV

Panel A	Industrial Metals RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	0.851	1.115**	0.028	0.171	0.123***	0.437*	-1.140	-0.238**
	(0.772)	(0.437)	(0.069)	(0.121)	(0.042)	(0.260)	(1.247)	(0.111)
Regime 2	0.769	1.394	-0.009	0.185	0.085	0.782	-2.998**	-0.380***
	(0.787)	(0.893)	(0.082)	(0.119)	(0.069)	(0.541)	(1.281)	(0.118)
Regime 3	2.958***	1.157**	0.082	0.146	0.116**	0.528*	-1.016	-0.123
	(0.980)	(0.470)	(0.074)	(0.152)	(0.046)	(0.281)	(1.342)	(0.130)
VAR(1) Matrix								
KCFSI (t-1)	0.183	-0.323***	-0.024**	-0.089***	0.002	-0.015	0.091	0.944***
	(0.117)	(0.062)	(0.010)	(0.019)	(0.006)	(0.037)	(0.170)	(0.018)
Industrial Metals RV (t-1)	0.582***	0.016	0.001	0.015***	0.000	-0.002	-0.012	-0.002
	(0.027)	(0.013)	(0.002)	(0.005)	(0.001)	(0.008)	(0.037)	(0.004)
IP (t-1)	-0.064**	0.961***	-0.004	0.003	0.000	-0.025**	0.000	-0.002
	(0.027)	(0.017)	(0.003)	(0.004)	(0.002)	(0.010)	(0.047)	(0.004)
CPI (t-1)	-0.395***	0.028	0.957***	0.006	-0.017**	-0.151***	0.087	-0.008
	(0.131)	(0.075)	(0.012)	(0.022)	(0.007)	(0.044)	(0.208)	(0.018)
IR (t-1)	0.089*	-0.051	0.009*	0.977***	0.000	0.042**	0.007	0.019**
	(0.051)	(0.031)	(0.005)	(0.009)	(0.003)	(0.019)	(0.090)	(0.007)
OIL (t-1)	0.330**	-0.351***	0.008	-0.055**	0.977***	-0.014	0.265	0.050**
	(0.160)	(0.094)	(0.015)	(0.025)	(0.009)	(0.057)	(0.268)	(0.024)
M2 (t-1)	-0.053**	0.039**	0.000	0.002	0.002	0.984***	0.007	0.001
	(0.021)	(0.017)	(0.003)	(0.003)	(0.002)	(0.011)	(0.041)	(0.004)
EER (t-1)	-0.004	-0.019***	0.000	-0.004*	-0.003***	0.002	0.941***	0.000
	(0.011)	(0.006)	(0.001)	(0.002)	(0.001)	(0.004)	(0.019)	(0.002)
Panel B								
Volatilities								
Regime 1	0.984	0.453	0.011	0.032	0.004	0.181	3.997	0.023
Regime 2	0.802	11.400	0.040	0.005	0.057	4.321	4.163	0.038
Regime 3	23.986	0.914	0.025	0.616	0.012	0.345	6.635	0.254

The table displays the results of the MS-VAR where the endogenous variables include the realized variance of the industrial metals (Industrial Metals RV). Standard errors are in parentheses. All variables are defined in Table 1. Panel B reports the volatility of the residuals that are estimated from the MSIH (3,1) for each dependent variable. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A4: Estimates of the MSIH (3,1) based on Precious Metals RV

Panel A	Precious Metals RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	-0.582	0.815*	0.051	0.228	0.118***	0.418	-0.989	-0.186*
	(0.635)	(0.416)	(0.071)	(0.139)	(0.043)	(0.255)	(1.220)	(0.105)
Regime 2	-0.367	1.603*	-0.059	0.228*	0.089	0.621	-2.505**	-0.335***
	(0.634)	(0.914)	(0.081)	(0.124)	(0.069)	(0.561)	(1.225)	(0.108)
Regime 3	2.059**	0.717	0.096	0.197	0.107**	0.459*	-1.189	-0.025
	(0.835)	(0.455)	(0.079)	(0.176)	(0.046)	(0.277)	(1.306)	(0.128)
VAR(1) Matrix								
KCFSI (t-1)	0.095	-0.273***	-0.014	-0.065***	0.005	-0.006	0.039	0.939***
	(0.092)	(0.058)	(0.010)	(0.019)	(0.006)	(0.034)	(0.165)	(0.017)
Precious Metals RV (t-1)	0.361***	0.002	0.000	0.002	-0.002	-0.003	0.102*	-0.002
	(0.042)	(0.020)	(0.003)	(0.006)	(0.002)	(0.011)	(0.054)	(0.006)
IP (t-1)	0.003	0.957***	-0.005*	-0.005	-0.001	-0.025**	0.029	-0.003
	(0.024)	(0.017)	(0.003)	(0.004)	(0.002)	(0.010)	(0.047)	(0.004)
CPI (t-1)	-0.004	0.033	0.952***	-0.036	-0.020***	-0.151***	0.213	-0.015
	(0.108)	(0.072)	(0.012)	(0.023)	(0.007)	(0.043)	(0.205)	(0.018)
IR (t-1)	-0.050	-0.036	0.009*	0.992***	0.001	0.046**	-0.021	0.018**
	(0.041)	(0.029)	(0.005)	(0.009)	(0.003)	(0.018)	(0.085)	(0.007)
OIL (t-1)	0.469***	-0.262***	0.012	-0.025	0.983***	-0.017	0.067	0.044**
	(0.126)	(0.086)	(0.014)	(0.026)	(0.009)	(0.053)	(0.252)	(0.021)
M2 (t-1)	0.014	0.036**	-0.002	-0.007**	0.001	0.991***	0.017	-0.002
	(0.024)	(0.016)	(0.003)	(0.003)	(0.002)	(0.009)	(0.042)	(0.004)
EER (t-1)	0.002	-0.016**	-0.001	-0.002	-0.003***	-0.001	0.944***	0.001
	(0.009)	(0.006)	(0.001)	(0.002)	(0.001)	(0.004)	(0.018)	(0.002)
Panel B								
Volatilities								
Regime 1	0.739	0.438	0.011	0.040	0.004	0.184	4.003	0.024
Regime 2	0.904	11.941	0.041	0.003	0.057	4.616	4.033	0.037
Regime 3	17.754	1.022	0.027	0.749	0.013	0.381	7.080	0.300

The table displays the results of the MS-VAR where the endogenous variables include the realized variance of the precious metals (Precious Metals RV). Standard errors are in parentheses. All variables are defined in Table 1. Panel B reports the volatility of the residuals that are estimated from the MSIH (3,1) for each dependent variable. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A5: Estimates of the MSIH (3,1) based on Commodity RV (excluding 2020)

Panel A	Commodity RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	KCFSI(t)
Intercept terms								
Regime 1	0.606	1.423***	-0.003	0.209**	0.146***	0.176	-3.035**	-0.208**
	(0.897)	(0.459)	(0.074)	(0.097)	(0.042)	(0.278)	(1.291)	(0.092)
Regime 2	-0.847	1.590***	-0.021	0.257***	0.161***	0.207	-3.769**	-0.200*
	(1.056)	(0.537)	(0.085)	(0.098)	(0.051)	(0.326)	(1.486)	(0.107)
Regime 3	4.292***	1.223**	0.010	0.167	0.106**	0.341	-3.512**	0.074
	(1.212)	(0.517)	(0.085)	(0.136)	(0.047)	(0.321)	(1.468)	(0.118)
VAR(1) Matrix								
KCFSI (t-1)	0.336**	-0.212***	-0.016	-0.015	0.011	0.024	0.117	0.893***
	(0.147)	(0.073)	(0.011)	(0.014)	(0.007)	(0.043)	(0.202)	(0.016)
Commodity RV (t-1)	0.261***	-0.036**	-0.001	-0.003	-0.001	-0.004	0.027	0.002
	(0.039)	(0.016)	(0.002)	(0.002)	(0.002)	(0.009)	(0.044)	(0.004)
IP (t-1)	-0.111***	0.905***	-0.004	0.000	-0.003*	-0.004	0.149***	0.007*
	(0.034)	(0.018)	(0.003)	(0.002)	(0.002)	(0.011)	(0.047)	(0.004)
CPI (t-1)	-0.608***	-0.067	0.953***	0.003	-0.021***	-0.123***	0.487**	0.011
	(0.144)	(0.076)	(0.012)	(0.020)	(0.007)	(0.045)	(0.216)	(0.015)
IR (t-1)	0.080	0.005	0.013**	0.991***	0.003	0.050**	-0.160*	0.007
	(0.059)	(0.033)	(0.005)	(0.005)	(0.003)	(0.020)	(0.090)	(0.006)
OIL (t-1)	0.897***	-0.295***	0.022	-0.054**	0.976***	0.053	0.506	0.003
	(0.237)	(0.108)	(0.018)	(0.022)	(0.011)	(0.066)	(0.319)	(0.023)
M2 (t-1)	0.046	0.016	0.001	-0.001	0.000	0.955***	0.086	0.013***
	(0.043)	(0.023)	(0.004)	(0.004)	(0.002)	(0.014)	(0.063)	(0.004)
EER (t-1)	0.004	-0.017**	-0.001	-0.002*	-0.003***	0.005	0.951***	-0.001
	(0.013)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.019)	(0.001)
Panel B								
Volatilities								
Regime 1	1.291	0.394	0.015	0.241	0.003	0.131	4.621	0.013
Regime 2	1.752	0.812	0.011	0.002	0.004	0.316	3.387	0.021
Regime 3	29.808	0.907	0.026	0.372	0.014	0.370	8.211	0.260

The table displays the results of the MS-VAR where the endogenous variables include the realized variance of the commodity index (Commodity RV). Standard errors are in parentheses. All variables are defined in Table 1. Panel B reports the volatility of the residuals that are estimated from the MSIH (3,1) for each dependent variable. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A6: Estimates of the MSIH (3,1) model using STLFSI as a financial stress measure

Panel A	Commodity RV(t)	IP(t)	CPI(t)	IR(t)	OIL(t)	M2(t)	EER(t)	STLFSI(t)
Intercept terms								
Regime 1	1.923*	1.008**	0.109	0.150	0.147***	0.052	-3.918***	-0.091
	(1.101)	(0.475)	(0.073)	(0.098)	(0.047)	(0.298)	(1.381)	(0.179)
Regime 2	3.520*	1.463*	0.050	0.151	0.086	0.577	-5.194***	-0.223
	(1.937)	(0.766)	(0.081)	(0.100)	(0.063)	(0.496)	(1.387)	(0.206)
Regime 3	5.661***	0.937*	0.131*	0.137	0.114**	0.148	-2.634*	0.331
	(1.449)	(0.511)	(0.076)	(0.155)	(0.052)	(0.318)	(1.462)	(0.224)
VAR(1) Matrix								
STLFSI (t-1)	0.696***	-0.200***	-0.010	-0.085***	-0.003	0.024	0.112	0.840***
	(0.185)	(0.073)	(0.010)	(0.016)	(0.007)	(0.040)	(0.195)	(0.028)
Commodity RV (t-1)	0.271***	-0.029	-0.005*	0.002*	0.000	-0.001	0.046	-0.019***
	(0.047)	(0.018)	(0.003)	(0.001)	(0.002)	(0.011)	(0.040)	(0.007)
IP (t-1)	-0.192***	0.955***	-0.009***	0.000	-0.005***	-0.004	0.120**	-0.013*
	(0.041)	(0.018)	(0.003)	(0.002)	(0.002)	(0.011)	(0.048)	(0.007)
CPI (t-1)	-0.742**	0.089	0.925***	0.069***	-0.033***	-0.074	0.897*	0.004
	(0.287)	(0.126)	(0.020)	(0.023)	(0.012)	(0.080)	(0.360)	(0.047)
IR (t-1)	0.232***	-0.057*	0.013**	0.971***	0.004	0.043**	-0.141	0.018
	(0.078)	(0.034)	(0.005)	(0.006)	(0.003)	(0.021)	(0.093)	(0.013)
OIL (t-1)	0.541**	-0.268***	0.016	-0.060***	0.983***	0.018	0.367	0.016
	(0.213)	(0.089)	(0.013)	(0.017)	(0.009)	(0.054)	(0.248)	(0.033)
M2 (t-1)	-0.041	0.019	-0.002	-0.002	0.000	0.993***	0.081*	0.003
	(0.039)	(0.017)	(0.003)	(0.002)	(0.002)	(0.014)	(0.046)	(0.007)
EER (t-1)	-0.008	-0.022**	-0.001	-0.002*	-0.003***	0.003	0.928***	-0.003
	(0.016)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.019)	(0.003)
Panel B								
Volatilities								
Regime 1	2.211	0.437	0.012	0.027	0.004	0.198	3.800	0.057
Regime 2	57.604	8.143	0.033	0.005	0.043	3.580	3.227	0.245
Regime 3	37.433	1.235	0.011	0.700	0.013	0.432	8.052	0.800

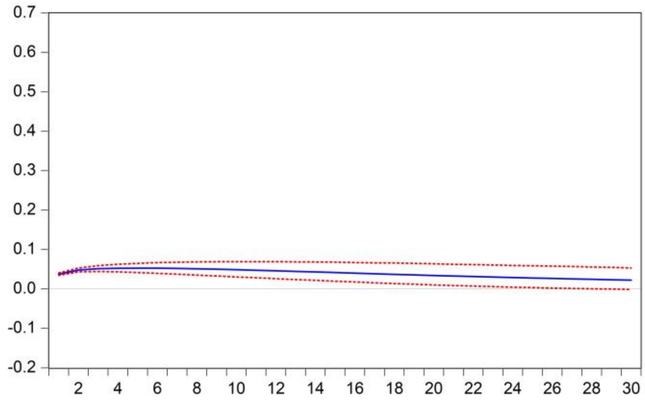
In this table, Panel A shows the estimates of the MS-VAR where the STLFSI is used. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) model for each dependent variable. Standard errors are in parentheses. All variables are defined in Table 1. The sample data is in a monthly basis and covers from 1994:01 to 2020:12. Standard errors are presented in parentheses. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

Table A7: Estimates of the MSIH (3,1) model using VIX as a financial stress measure

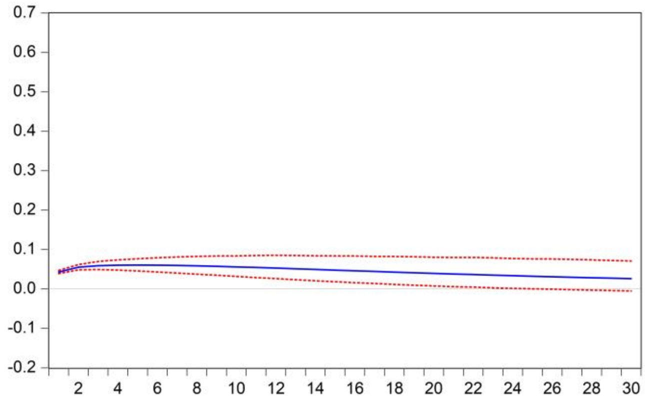
Panel A	Commodity RV	IP	CPI	IR	OIL	M2	EER	VIX
Intercept terms								
Regime 1	1.694*	1.258***	0.005	0.083	0.120***	0.139	-3.523***	-0.066
	(0.991)	(0.452)	(0.069)	(0.056)	(0.039)	(0.289)	(1.234)	(0.232)
Regime 2	1.837*	1.287***	0.010	0.174***	0.113***	0.213	-3.774***	0.090
	(1.082)	(0.491)	(0.073)	(0.047)	(0.042)	(0.311)	(1.430)	(0.251)
Regime 3	9.013***	0.504	-0.021	-0.120	0.074	1.004**	-4.638***	0.209
	(2.362)	(0.699)	(0.091)	(0.189)	(0.067)	(0.466)	(1.569)	(0.329)
VAR(1) Matrix								
VIX (t-1)	0.546***	-0.018	-0.016*	-0.008*	-0.001	-0.010	0.231	0.781***
	(0.167)	(0.066)	(0.009)	(0.004)	(0.006)	(0.040)	(0.164)	(0.035)
Commodity RV (t-1)	0.340***	-0.067***	0.000	-0.002	0.000	0.005	0.045	0.000
	(0.044)	(0.017)	(0.002)	(0.001)	(0.001)	(0.011)	(0.040)	(0.009)
IP (t-1)	-0.217***	0.916***	-0.003	0.001	-0.003**	-0.008	0.124***	-0.011
	(0.045)	(0.019)	(0.002)	(0.001)	(0.002)	(0.012)	(0.044)	(0.010)
CPI (t-1)	-0.802***	-0.089	0.951***	-0.002	-0.023***	-0.107**	0.520**	-0.052
	(0.180)	(0.080)	(0.012)	(0.010)	(0.007)	(0.050)	(0.214)	(0.041)
IR (t-1)	0.253***	0.000	0.015***	1.008***	0.003	0.050**	-0.084	0.045***
	(0.085)	(0.034)	(0.005)	(0.003)	(0.003)	(0.020)	(0.099)	(0.017)
OIL (t-1)	0.723***	-0.170*	0.013	-0.039***	0.984***	0.011	0.564**	-0.044
	(0.211)	(0.095)	(0.015)	(0.010)	(0.008)	(0.058)	(0.281)	(0.047)
M2 (t-1)	-0.115**	0.002	0.002	0.001	-0.001	0.980***	0.044	0.027**
	(0.052)	(0.021)	(0.003)	(0.001)	(0.002)	(0.013)	(0.049)	(0.012)
EER (t-1)	-0.003	-0.017**	0.001	0.000	-0.002***	-0.001	0.942***	-0.003
	(0.016)	(0.007)	(0.001)	(0.001)	(0.001)	(0.004)	(0.018)	(0.004)
Panel B								
Volatilities								
Regime 1	1.573	0.418	0.015	0.228	0.003	0.117	4.278	0.089
Regime 2	6.718	0.918	0.012	0.002	0.006	0.388	4.359	0.383
Regime 3	109.988	5.667	0.057	0.865	0.061	2.627	10.503	1.026

In this table, Panel A shows the estimates of the MS-VAR where the VIX is used. Panel B reports the volatility of the residuals that are estimated from the MSIH(3,1) model for each dependent variable. Standard errors are in parentheses. All variables are defined in Table 1. The sample data is in a monthly basis and covers from 1990:02 to 2020:12. Standard errors are presented in parentheses. ***, **, and * denote at 1%, 5%, and 10% levels of significance, respectively.

IRFs in low volatility regime (excluding 2020)



IRFs in transitory regime (excluding 2020)



IRFs in high volatility regime (excluding 2020)

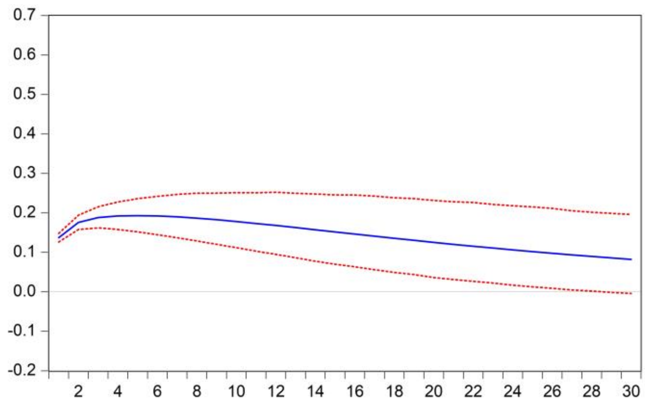
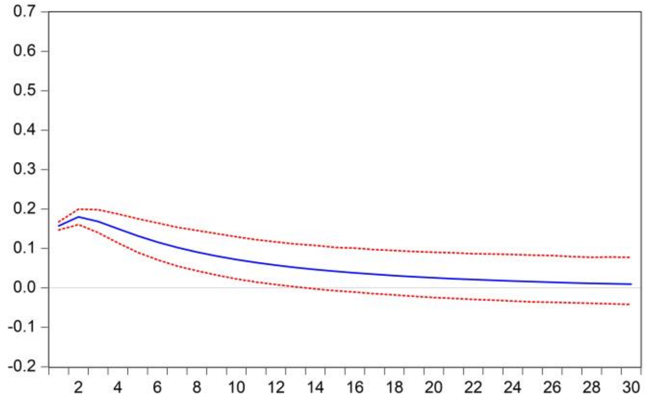


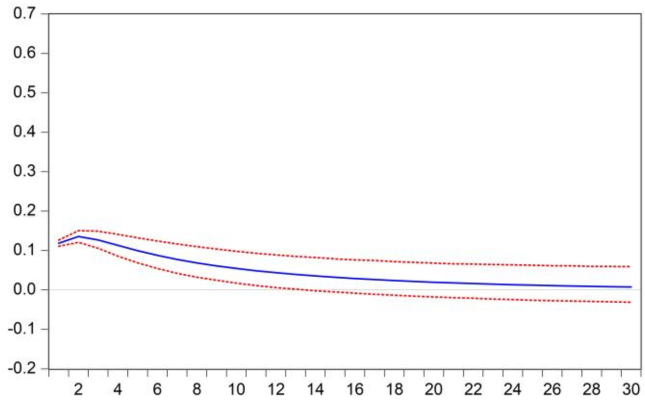
Figure A1: Impulse response functions (IRFs) of the realized variance of the commodity to a shock of the financial stress.

This figure plots the IRFs of the Commodity RV to a shock of the KCFSI as estimated by equation (6) using a sub-period sample from 1990 to 2019. The solid lines are the estimated responses, and the dashed lines are the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

IRFs in low volatility regime



IRFs in transitory regime



IRFs in high volatility regime

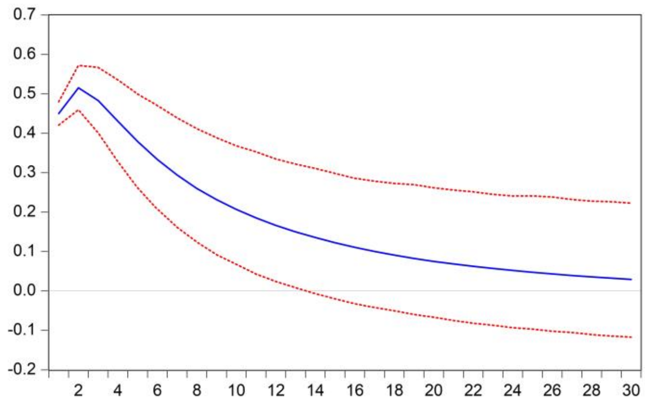
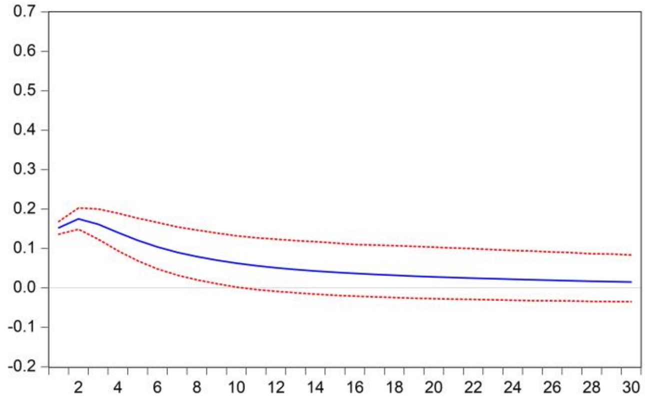
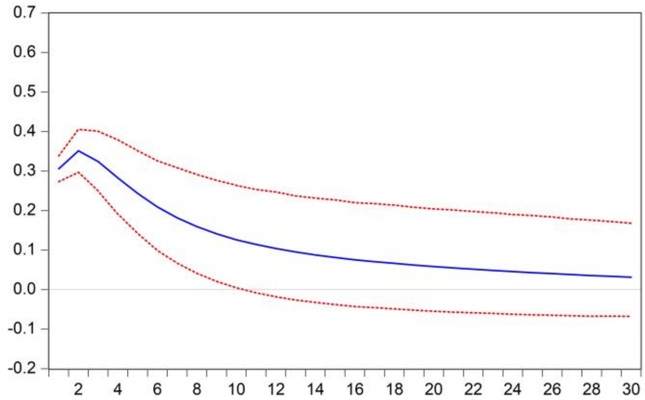


Figure A2: Impulse response functions (IRFs) of the realized variance of the commodity to a shock of the STLFSI. This figure plots the IRFs of the realized variance of the commodity (Commodity RV) to a shock of the STLFSI as estimated by equation (6) using a sample from 1994 to 2020. The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.

IRFs in low volatility regime



IRFs in transitory regime



IRFs in high volatility regime

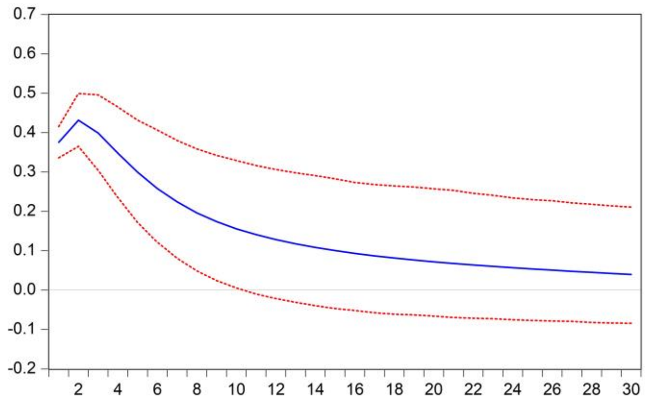


Figure A3: Impulse response functions (IRFs) of the realized variance of the commodity to a shock of the VIX.
This figure plots the IRFs of the realized variance of the commodity (Commodity RV) to a shock of the VIX as estimated by equation (6) using a sample from 1990 to 2020. The solid lines represent the estimated response functions, and the dashed lines represent the 10% confidence intervals. The x-axis denotes the 30-month interval, while the y-axis denotes the IRFs value expressed as a percentage.