REALIZED VOLATILITY PREDICTION OF THE US COMMODITY FUTURES DURING THE GLOBAL FINANCIAL CRISIS (GFC) AND COVID-19 PANDEMIC

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Abstract: This research aims to inspect the predictability of the realized volatility (RV) of the US Commodity futures market during the economic crisis period for the last 20 years. The economic crisis period includes the Global Financial Crisis (GFC) and the financial crisis during COVID-19. This study extends its aim to show the forecasting comparison during the financial crisis period and the normal economic period. A standard predictive regression model from the weekly RV data is used to test the certainty of next week's RV of the commodity futures. This study uses data from Q1 of 2000 to Q3 of 2020. It finds that platinum, palladium, gold, and crude oil have significant predictability for the RV forecast during the global financial crisis, whereas sugar, silver, and platinum have high and significant predictability to forecast the RV during the pandemic. In addition, a comparison of RV predictability between normal economic periods and economic crisis periods shows a significant difference in predictability between different economic periods.

Keywords: realized volatility; commodity futures; volatility prediction; global financial crisis; COVID-19

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Introduction

In the recent 20 years (2000 to 2020), we have been witnessed the two most significant economic disruptions, the great recession in 2008 (Gilbert, 2011) and the global financial crisis due to the COVID-19 pandemic. Both these events caused a long-term impact on the worldwide economy. The financial markets have shown the influence of this pandemic from the first quarter of the fiscal year 2020 with an immediate effect on the global commodity market. This pandemic raised concerns

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regarding the damage of the demand system and the global raw material supply chain, directly or indirectly affecting global financial markets (Goodell, 2020; Zhang et al., 2020; Suzuki et al. 2023). High and volatile commodity prices were a serious global issue during 2007 and 2008. The escalating financial crisis in the second half of 2008 and the accompanying commodity prices disrupted it for some time, with some commodity prices returning to mid-2008. However, the causes and consequences of high and volatile commodity prices again attract attention (Gilbert, 2011). While researchers generally find that volatility increases significantly after high negative returns, the behavior of volatility following positive and near-zero returns is less clear (Ederington and Guan, 2010). Also, Ederington and Guan (2010) implied that positive and negative return shocks have differing impacts on US stock volatility. Future volatility is more closely related to the volatility of positive returns than the volatility of negative returns in the past. In addition, the effect of price increases on volatility depends on signs of growth, where negative (positive) growth leads to higher (comparatively lower) future volatility (Patton and Sheppard, 2015). The contribution of this study is also straightforward. Even after answering these research questions, this study shows a clear picture of weekly data predictability of RV of commodity futures. Also, this study extends the contribution by showing the predictability of commodity futures during different economic circumstances, regular economic periods, and economic crisis periods. This study raises several issues that have not been addressed in the literature. According to our best knowledge and belief, no other study showed the RV predictability comparison between the global financial crisis, normal economic period, and COVID-19 financial crisis on weekly data with proper theoretical justification. RV forecasting with weekly data has a strong theoretical foundation; for example, Engle et al. (2013), Fleming et al. (1995), Giot and Laurent (2007), McMillan and Speight (2007), and Schwert (1989) suggested weekly data to predict volatility. In any case, the motivations of this study are very straightforward. The main motive is to investigate the RV predictability of the US commodity futures index during different economic periods. This paper also extends the objective to show the RV predictability comparison during the different economic periods. More clearly, from the weekly data, identifying which commodity futures predict better during the economic crisis compared to the normal economic period. Anyhow, the research based on this specific objective is not so widespread, especially where all commodity futures research was relatively justified compared to the GFC and COVID-19 financial crisis.

This study first uses the RV model to generate RV time series data. After that, the predictive regression model and PRESS statistics are tested to show the predictability of the respective 23 commodity futures models. Therefore, the root means squared forecasting error model is tested to evaluate the forecasting model of this study. Finally, a comparison of RV predictability between regular and economic crisis periods pictures a significant difference in predictability between different economic periods.

Literature Review

Several empirical and theoretical studies have been performed to show how different factors influence commodity futures over the past few decades. In most cases, findings show that financial crises influence the market significantly. However, even in normal economic conditions, several factors work as the reason for market volatility (Kurowska-Pysz, 2021). Based on those concepts, the significant literature of this study is explored in brief.

There is a relationship between commodity fluctuations and domestic product prices. In addition to production and international price volatility, stock volatility significantly affects the unpredictability of domestic prices. Also, improving market efficiency and reducing transaction costs can stabilize prices. Azar and Chopurian (2018) show that the commodity index of the GCC stock market is an influential diversification factor and is treated as a haven. By including commodity indexes or derivatives, the market can improve the performance of stock portfolios. Comparing to the volatility of prices for agricultural products and fossil fuels, the volatility of woody biomass prices remains low (Kristöfel et al., 2014). Also, the uncertainty associated with the pandemic has a strong negative impact on the instability of the commodity market, especially the crude oil market, while there is a positive impact on the gold market.; However, the impact is not highly significant (Bakas and Triantafyllou, 2020).

When the value of the commodity index is higher, the influence of agents on the commodity market is also more significant. As agricultural income and commodity index income are at a relatively high level, the relationship between agricultural income and stock income becomes particularly important. During periods of extreme volatility, for example, the stock market had a greater impact on the price dynamics of agricultural products during the financial crisis (Aït-Youcef, 2019). Agricultural and industrial markets are highly sensitive to volatility and macroeconomic uncertainty. Since precious metals have a clear hedging effect during periods of economic crisis, the impact on precious metals is relatively simple. In addition, the recent recession of 2007-09 has caused unprecedented uncertainties in the prices of many commodities.

Interestingly, this analysis reveals that price volatility and uncertainty can be separated. It is especially true for the oil market because the major shocks caused price volatility in the 1990s and early 2000s did not produce price uncertainty, which shows that the way we measure uncertainty is to deal with uncertainty and predictability rather than fluctuations (Joëts et al., 2017). Compared with the observable economic uncertainty, the potential uncertainty shock has the greatest impact on commodity price fluctuations. The positive impact on non-obstructive financial and macroeconomic uncertainties increased volatility in commodity market indexes and individual commodity prices, with the most significant impact on the macroeconomy. Bakas and Triantafyllou (2018) showthat the energy commodities' impact is greater than agricultural and metal markets. It finds that structural vulnerabilities are not conducive to economic growth and open policies contribute to resilience (Combes and Guillaumont, 2002). Another study show that the volatility effect of exchange rate and interest rate influences commodities futures volatility. Volatility in fertilizer prices can be transmitted through volatility in sunflower oil. Subsequent analysis reveals that past prices has a significant impact on the current prices for all commodities (except soybean oil, sunflower oil, and cotton) (Ismail et al., 2017). However, surprisingly, good institutions seem to allay the negative effects of volatility compared to less financially sound institutions (Makhlouf et al., 2017).

The stock volume encompasses valuable information to predict market volatility (Monteiro et al., 2022). For example, Marvasti and Lamberte (2016) find that fish commodities prices are consistent and red snapper price volatility is reduced when the volume is high. Expected changes have a greater impact on trading volume than unexpected changes. Since the variance transmission parameter significantly reduces volatility and improves market efficiency against shocks, special considerations have been given to oil spill plugging an individual fishing quota (IFQ) procedures for other species. Siami-Namini et al. (2017) identify that the volatility of agricultural commodity indexes and other commodity indexes exceeds the long-term equilibrium to cope with the impact of monetary policy.

The number of studies discuss the impact of COVID-19 on stock volatility (Bouteska, Hajek, et al., 2023; Bouteska, Sharif, et al., 2023; Chai et al., 2022; Dharani et al., 2022; X. Gao et al., 2022; Hasan, Popp, et al., 2020; Hasan, Yajuan, et al., 2020; Hasan and Khan, 2019; W. Li et al., 2022; Mahmud et al., 2021; Naik et al., 2022; Rahman et al., 2022; Rizvi and Itani, 2022; N. Zhang et al., 2022). With the emergence of a pandemic, the significance of searching for health news can be a good predictor of stock returns. Also, accounting for the "asymmetry" effect, incorporating financial news and adjusting it according to macroeconomic factors can improve the stock market predictability (Salisu and Vo, 2020). During the pandemic, the oil and stock markets themselves, as well as cross shocks, may suffer larger initial and long-term shocks than their previous periods. The likelihood of negative oil and stock market returns throughout the pandemic may also be related to market-related uncertainties (Salisu et al., 2020). The economic impact of the post-pandemic may also be highly significant as the world faces completely new experiences. The financial markets have undergone unprecedented and drastic changes, which is why the global financial market risks are increasing noticeably in response to the pandemic (Zhang et al., 2020). Also, most existing or new financial products have volatility in their prices and predictions (Corbet et al., 2020). The COVID-19 pandemic has also had some contagious effects on the stock market. However, this fractal contagion effect will gradually disappear over time (both medium to long periods) due to stock market returns and volatility (Okorie and Lin, 2020). On average, investors increase brokerage deposits and open comparatively more new accounts. When the number of COVID-19 cases doubled, the average weekly transaction intensity increased by 13.9%. The increase in trading volume is particularly noticeable to men, especially older investors, and directly affects stock

and index trading (Ortmann et al., 2020). (Bakas and Triantafyllou, 2020) found that it has a strong negative impact on the volatility of the commodity market, particularly the crude oil market. However, the effect on the gold market is somewhat positive but not highly significant.
Based on the significant background of this research issue, we address the following research questions: (1) How does RV fluctuate during the global crisis due to COVID-19 and the great recession of 2008 compared to the normal time? (2) Which types of commodity futures do predict better in the economic crisis period?

Research Methodology

This study is mainly based on the Commodity Index of the US stock market and focuses on 23 commodities which are extracted from Yahoo Finance. It mainly uses the weekly data of selected commodities from the first quarter of 2000 to the third quarter of 2020. Some studies have attempted to show stock volatility during the global economic crisis (Adämmer and Schüssler, 2020; Fernandez, 2019; He et al., 2020; Ismail et al., 2017; Khan et al., 2020; Liang et al., 2020a; Mahmud et al., 2021; Popp et al., 2018; Schwert, 2011). Many studies use monthly data to show which types of commodity prices are more useful to predict stock market volatility during an economic crisis. However, the importance of monthly data provides longer-term information and is not a reasonable consideration. For example, Schwert (1989), a well-known study in this field, aggregates daily data into monthly RVto examine the relationship between economic activity and stock market volatility. However, if several components influence the volatility, monthly RV is not an appropriate measure to consider (Engle et al., 2013). In addition, Fleming et al. (1995) investigate the volatility-timing portfolio. They indicate that the volatilities prediction tends to fall, and mean returns forecasting tends to rise as the measurement horizon gets longer. However, timing affects the relative performance, but it is not very significant. Giot and Laurent (2007) also point out that in addition to the daily data, both the weekly and continuous monthly components are also significant. McMillan and Speight (2007) prove the significance of weekly data to forecast future RV. Based on the above justification, weekly data has the acceptability to predict the realized volatility.
From this perspective, this study assumes that weekly data can predict better with more helpful information. Therefore, we predict commodity futures information from weekly data. First, the definition of RV is adopted, and the method of calculating RV is consistent with the study done by (Andersen et al., 2001). This study has followed the methods of some other related studies, such as Wang et al. (2018), Patton and Sheppard (2015), and a few others.
We first show equation (1) to calculate the process of weekly RV.

$$RV_t = \sum_{j=1}^{W_t} r_{t,j}^2 \quad \text{(Equation 1)}$$

Here, RVt denotes the RV of the tth week, Wt denotes the total number of trading days in the tth week, and $r_{t,j}$ represents the return of the respective commodity in the jth trading day of the tth week. Usually, RV comparatively measures better than squared weekly return as well (Liang et al., 2020).
We use the weekly RV data and the predictive regression framework to predict the RV of the selected commodities for the next week's RV. From a statistical point of view, the benchmark model can be written as following equation 2:

$$RV_{t+1} = \alpha_i + \beta_{it} RV_{it} + \varepsilon_{t+1} \quad \text{(Equation 2)}$$

Among them, RV_{t+1} represents the RV of the next week, ε_{t+1} represents the error term of the model, and i represents the number of commodities.
The predicted R-squared value designates how well a regression model forecasts a response for the new observations. The value of the predicted R-squared helps determines when any model fits the original data at the time; however, it is not sufficient to provide valid forecasts for new observations (Osborne, 2001). Similar to the adjusted R-squared, the predicted R-squared can be negative, as well as it always shows a lower value than the R-squared. The predicted R-squared has a principal advantage, which prevents the model from overfitting (Frost, 2013).
After that, one step ahead, to predict more statistics, the prediction error sum of squares (PRESS) statistics, which is similar to the sum of squares of the residual error (SSE), is also tested here to show the deviation between the observed values and the fitted values. The PRESS statistics model can be written as following equation 3. The model of PRESS statistics has been taken from (Tarpey, 2000).

$$\text{PRESS} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \text{ [Here, i represent 1 to 23]} \quad \text{(Equation 3)}$$

Here, the PRESS statistics are also carried out for the entire 23 kinds of commodities. Generally, a lower PRESS value defines a better predictive ability of the model. Both the PRESS statistics and predictive R^2-squared value help predict the RV of the selected commodities. In addition, these statistics together can prevent the model from overfitting. In addition, the out-of-sample forecast of the RV of the entire commodity lists from the below model has been experimented with here. The concept of this model has been taken from (Campbell and Thompson, 2008). The out-of-sample forecast model is written as follows equation 4.

$$R^2_{oos} = 1 - \frac{\sum_{i=1}^{t} (RV_{t+1} - \widehat{RV}_{t+1})^2}{\sum_{i=1}^{t} (RV_{t+1} - \overline{RV}_{t+1})^2} \quad \text{(Equation 4)}$$

Here, the first part $\widehat{RV}_t$ is the fitted value of the RV predictive regression model in the one-week ahead (RVt+1) of the model, and $\overline{RV}_{t+1}$ is the historical average RV forecasting model. Using this weekly time series data, this study forecasts out-of-sample RV here. This model measures the reduction of the mean squared prediction error of the forecasting strategy in this study relative to the historical mean forecast. Also, if regressions is stable over time, in-sample estimation is more effective in econometrics (Gao et al., 2018).

If the value of the out-of-sample forecast is greater than 0, the strategy forecast is better than the historical average forecast in the sense of mean squared error (Adämmer and Schüssler, 2020). Usually, there are several models used to measure the forecasting model. Based on the literature, here, the Root Mean Square Error (RMSE) is used to measure the error of the model in predicting the RV data of commodity futures.

Equation 5 represents the formula to calculate RMSE:

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}-y)^2}{n}} \qquad \text{(Equation 5)}$$

If the R^2_{oos} shows a positive value, the predictive regression has a lower average mean-squared prediction error than the historical average return (Campbell and Thompson, 2008).

Research Results and Analysis

Table 1 presents the descriptive statistics of weekly RV for the 23 commodity futures that are used in this research. In total around 1045 observations have been used to predict and forecast the RV on one commodity. In some cases, there are some missing values in the variables. The minimum RV value starts from 0, and the maximum RV value is below 1. The value of standard deviation is also good to accept, not more than 1% for all commodity futures.

Table 1. Descriptive Statistics.

RV	N	Min	Max	Mean	Std. Deviation	ADF stat
Cocoa	1035	0.000	0.101	0.014	0.012	-3.862***
Sugar	1045	0.000	0.106	0.015	0.013	-4.289***
Soybeans	1045	0.000	0.130	0.012	0.011	-5.702***
Soybeans oil	1045	0.000	0.062	0.011	0.009	-4.379***
Soybeans meal	1045	0.000	0.137	0.013	0.012	-5.622***
Silver	1045	0.000	0.139	0.013	0.013	-3.524***
Rough rice	1040	0.000	1.992	0.014	0.062	-5.567***
Platinum	901	0.000	0.096	0.010	0.010	-3.705***
Palladium	953	0.000	0.169	0.015	0.015	-5.857***
Oats	1045	0.000	0.126	0.017	0.016	-6.730***
Natural gas	1045	0.000	0.124	0.023	0.020	-7.265***
Lumber	1045	0.000	0.091	0.016	0.014	-4.504***
Live cattle	1045	0.000	0.095	0.009	0.008	-8.228***
Lean hogs	1045	0.000	0.162	0.016	0.018	-3.284***
Wheat	1045	0.000	0.072	0.013	0.011	-6.126***

Heating oil	1045	0.000	0.148	0.015	0.014	-4.050***
Gold	1045	0.000	0.054	0.008	0.007	-4.440***
Feeder cattle	1045	0.000	0.061	0.008	0.007	-6.009***
Crude oil	1045	0.000	0.155	0.017	0.017	-6.209***
Cotton	1035	0.000	0.141	0.013	0.012	-4.292***
Corn	1045	0.000	0.110	0.013	0.012	-5.821***
Copper	1045	0.000	0.115	0.012	0.011	-5.004***
Coffee	1035	0.000	0.081	0.014	0.011	-5.749***

Here, we use the Augmented Dickey-Fuller test (ADF) to test the unit roots. According to Table 1, all null hypotheses have a unit root. Usually, this test is used here to check the normal distribution and stationarity levels of all variables. The entire sample contains the weekly data from 2000 to 2020 first half. In some cases, data is missing, so the number of observations from descriptive statistics is considered here. Here, *** denotes significance at the 1% confidence interval level. The empirical findings of this study are divided into two parts: the normal economic period and the crisis period.. Also, the economic crisis period refers to the 2007 to 2009 GFC and the COVID-19 period (January 2020 – June 2020). A pictorial display of commodity futures forecasting using the PRESS statistics is presented in Figure 1. Figure 1 present when and which types of commodity futures predict RV better. Also, the details of PRESS statistics result are given in Table 2.

Table 2. Commodity futures forecasting using PRESS statistics

Forecasting Model	Jan 2000 to Dec 2006	Jan 2010 to Dec 2019	Jan 2007 to Dec 2009	Jan 2020 to June 2020
Cocoa	0.061	0.052	0.028	0.003
Sugar	0.053	0.075	0.039	0.003
Soybeans	0.042	0.036	0.048	0.001
Soybeans oil	0.029	0.025	0.025	0.002
Soybeans meal	0.049	0.060	0.043	0.002
Silver	0.038	0.082	0.040	0.012
Rough rice	0.069	0.042	0.024	0.103
Platinum	0.021	0.031	0.015	0.017
Palladium	0.072	0.066	0.037	0.050
Oats	0.113	0.117	0.033	0.003
Natural gas	0.181	0.138	0.066	0.009
Lumber	0.070	0.082	0.035	0.014
Live cattle	0.023	0.033	0.008	0.012
Lean hogs	0.096	0.163	0.043	0.049
Wheat	0.031	0.059	0.031	0.002
Heating oil	0.078	0.062	0.035	0.029
Gold	0.014	0.019	0.012	0.005
Feeder cattle	0.014	0.025	0.007	0.007
Crude oil	0.070	0.074	0.062	0.067
Cotton	0.047	0.081	0.027	0.001

Corn	0.037	0.066	0.041	0.001
Copper	0.029	0.040	0.042	0.005
Coffee	0.048	0.065	0.019	0.004

Also, it can make a prediction from the PRESS statistics, usually, the smaller the PRESS value, the better the predictive ability of the model. From this aspect, this study found that most of the commodity futures that have significant predictive ability also have a lower value of PRESS statistics. It can be seen from Table 2, the GFC period and the COVID-19 crisis period shows comparatively lower PRESS value, however, it's not so significant during the period from 2007 to 2009. But the commodity futures predictive model shows that it has a better predictive ability during the COVID-19 global crisis.

Stock prices movement is deeply related to financial stability and economic policy in both the short and long run (Blot et al., 2015; Chen et al., 2020; He et al., 2020; Kirikkaleli, 2020; G. Li and Wang, 2020; Razmi et al., 2020). Stock price volatility always increases the uncertainty of financial and economic policies (Chen et al., 2020). At the same time, stock price information helps allocate market resource efficiency, enhance expected economic growth, and promote real economic development. On the other hand, the excessively fast price can cause crowding out of savings, increase market risk exposure, and endanger financial stability (Li and Wang, 2020). In addition, stock price information significantly influences global economic policy uncertainty (EPU) on financial conditions (He et al., 2020; Z. Li and Zhong, 2019). An excellent connection between stock prices and financial stability fluctuates over time and economic cycles. In this aspect of this study, it is clear that the forecast of commodity futures during a normal economic period can be better during economic crises. As shown in Table 3, the first two columns show the commodity futures' predictability during normal economic periods, indicating that most commodity futures have the predictive ability during the normal economic period. The following two columns show the commodity futures' predictability during the economic crisis period, indicating that a few numbers of particular commodity futures have predictive ability. There are highly significant R^2_{pred} values in the global economic crisis during 2007-2008 and the global pandemic during the COVID-19 period. More specifically, it can be seen from the second part of Table 3 that the values of R^2_{pred} are higher than the other two economic period segments. For example, the R^2_{pred} value of sugar is only 2.14% during the 2010 to 2019 economic period; however, it was shown at 33.83% during the COVID-19 crisis period. This scenario is the same for silver, platinum, palladium, gold, and crude oil. The value is higher during the economic crisis period than during the normal economic period.

Table 3. RV predictability through predictive regression framework

Forecasting Model	Normal Economic Period		Crisis Economic Period	
	Jan 2000 to Dec 2006	Jan 2010 to Dec 2019	Jan 2007 to Dec 2009	Jan 2020 to June 2020
	R^2_{pred}	R^2_{pred}	R^2_{pred}	R^2_{pred}
Cocoa	0.00%	0.00%	0.00%	0.00%
Sugar	0.00%	2.14%	0.00%	33.83%
Soybeans	0.00%	2.11%	0.00%	0.00%
Soybeans oil	0.88%	0.00%	0.00%	0.00%
Soybeans meal	1.96%	0.88%	0.00%	0.00%
Silver	0.34%	0.00%	0.00%	8.64%
Rough rice	0.00%	0.00%	4.86%	0.00%
Platinum	0.79%	0.00%	15.18%	2.11%
Palladium	1.59%	0.32%	12.33%	0.00%
Oats	0.40%	0.00%	0.00%	0.95%
Natural gas	0.00%	0.00%	0.00%	0.00%
Lumber	0.00%	0.00%	0.00%	0.00%
Live cattle	0.00%	0.53%	0.00%	0.00%
Lean hogs	0.00%	0.00%	0.00%	0.00%
Wheat	0.00%	0.00%	0.00%	0.00%
Heating oil	0.00%	0.39%	0.00%	0.00%
Gold	0.09%	0.00%	3.84%	0.00%
Feeder cattle	1.00%	1.08%	0.00%	0.00%
Crude oil	0.31%	0.00%	14.42%	0.00%
Cotton	0.00%	2.79%	0.00%	0.00%
Corn	0.00%	2.56%	0.00%	0.00%
Copper	2.11%	0.74%	0.00%	0.00%
Coffee	0.00%	0.00%	0.00%	0.00%

** present 95% confidence interval level of significance

Table 4 presents the R^2_{oos} value. By looking at the out-of-the-sample tests, this study evaluates the volatility predictability in more detail. By using a volatility forecaster, the goal is to predict the weekly realized volatility. This paper considers one-week rolling fixed window forecast that include 80 observations starting from Q1 2018. This period is selected to reduce Covid-19 bias effects. According to the R^2_{oos} value of Table 4, sugar, soybeans, soybeans oil, silver, platinum, palladium, and cotton are 5% significant R^2_{oos} value. And heating oil, gold, corn, copper, and coffee are significant at a 10% confidence interval. These results indicate that these commodities have positive forecasting ability. It means that these commodity futures can usually be predicted based on the weekly RV value of the respective commodity futures.

We also experiments with the root mean square error (RMSE) in Table 4. The RMSE measures the error between the dependent and independent variables. It compares the predicted value with the observed value, where the smaller RMSE value represents how closely the predicted value is to the observed values.

Table 4. Commodity futures forecasting using R^2_{oos} statistics and forecast evaluation.

Forecasting Model	R^2_{oos}	RMSE
Cocoa	-4.32	0.013
Sugar	5.34**	0.012
Soybeans	6.21*	0.017
Soybeans oil	1.65*	0.010
Soybeans meal	-2.51	0.011
Silver	2.05**	0.09
Rough rice	-2.41	0.013
Platinum	3.25**	0.004
Palladium	1.03**	0.024
Oats	-0.98	0.018
Natural gas	-1.25	0.016
Lumber	-16.23	0.015
Live cattle	-0.05	0.008
Lean hogs	-5.712	0.018
Wheat	-0.86	0.011
Heating oil	0.12*	0.011
Gold	1.05*	0.006
Feeder cattle	-0.68	0.007
Crude oil	-11.52	0.012
Cotton	2.98%**	0.012
Corn	1.18*	0.011
Copper	0.26*	0.009
Coffee	2.65*	0.011

** and * denotes significant at the 5% and 10% level, respectively

Discussion

The results are reasonable; Gilbert (2011) finds that the commodity index shows significant price fluctuations during different periods. Therefore, the inefficient combination of demand and supply for many products refers to unexpected changes in demand or supply that may cause significant price fluctuations in the short term. This paper also presents concludes that weekly data show different results and better predictability than monthly data. For example, Liang et al. (2020) find that gold, corn, soybeans, soybean oil, and cotton, respectively, show positive R^2_{oos} values. This result is consistent with the findings of this study. In addition, we find that sugar, silver, platinum, palladium, and heating oil also show positive and significant R^2_{oos} values.

There are significant differences in outcome for the weekly data experiment rather than monthly data. In most cases, this study has found that weekly data predict better compared to monthly data. For example, monthly data has nearly no predictability during the normal economic period referred to as economic expansion. However, from 2000 to 2006, weekly data shows positive predictability of soybean oil, soybean meal, silver, platinum, palladium, oats, gold, feeder cattle, and crude oil. Thus, this study concludes that weekly data predicts better during the expansion period. Also, aluminum, soybeans, soybean oil, and cotton have good predictability with monthly data during the economic crisis period. However, weekly data shows different results. Rough rice, platinum, palladium, gold, and crude oil have very high predictability with weekly data during the global financial crisis period. In addition, sugar, silver, platinum, and oats have high predictability during the COVID-19 crisis. To conclude, this study finds that weekly data has better RV predictability in most cases. Therefore, the justification for using weekly data is also very specific.

In any case, the results of the study also satisfy the research questions. To answer the first research question, most commodity futures do not predict significantly during COVID-19, but some do predict. RV predictability is very high for that predictable RV of commodity futures. Also, the results show that weekly data use useful to predict RV during all economic periods. Finally, regarding the second research question, rough rice platinum, palladium, gold, and crude oil have predictability during the global financial crisis. In addition, sugar, silver, platinum, and oats can be predicted during the COVID-19 financial period. Some other studies, Zhang and Wang (2022) also support the result of this study. They reveal that while the daily COVID-19 infection rate has mixed effects on short-term volatilities, the pandemic event significantly boosted long-run volatilities for all future returns. Qiao and Han (2023) also found that pandemic significantly affects agriculture commodities, metals commodities, and energy commodity volatility. However, metals and energy commodities were more volatile relative to agriculture commodities during the pandemic.

This study aims to present more precise results, which will support making decisions for the investor, decision-makers, financial analysts, economists, etc. Group-wise predictability may sometimes use for inductive reasoning for financial and investment decisions. However, this study emphasizes the individual predictability that will be helpful for the investment decision.

The continuation of the coronavirus pandemic for a long period may cause financial volatility, challenging the risk-management activity. Even after the pandemic hit the United States, relatively safe commodities suffered losses and also had abnormal returns (Goodell and Huynh, 2020). The economic uncertainty related to global pandemics has also substantial impact on the volatility of the broad commodity price index and the sub-indexes such as crude oil and gold. The US commodity futures market still lacks RV volatility forecasts during COVID-19. Since the COVID-19 scenario is new and lengthy, it is completely unpredictable. However, due to the lack of extensive literature on RV volatility in US commodity futures markets during COVID-19, this study cannot justify predictability for some commodities. This is considered a limitation of the study. Therefore, this study will have a significant impact on future research on commodity futures of the US market. There is a huge opportunity to work on this issue in future. For example, as the commodity futures predictive model shows better predictive ability in the COVID-19 global crisis, this study suggests high future research prospects based on commodity futures and the COVID-19 crisis.

Conclusion

Investors pay close attention to the two prices of their stocks. The current and future prices help fix the right choice of their investment. Hence, it is highly important to know the real market situation. However, investors are always conscious of the historical prices of the stocks and analysis to proceed with the right investment decision despite these two prices. That is why they constantly review historical prices to influence their investment decisions in the future. This study uses a large dataset to investigate which type of commodity futures have better RV predictability during the economic crisis. A standard predictive regression model is used here for all commodity futures from the weekly RV data. First, the weekly RV of the 23 commodity variables is experimented with; we then use the extended benchmark model for all commodity futures. From the specified model, the PRESS statistics are also used here to measure RV predictability. However, the R^2_{oos}, the root mean squared error (RMSE), the PRESS statistics, and finally, the R^2_{pred} are used here to explore the predictive ability of the commodity futures. The finding of this study is highly connected to the objectives and research questions of this study. First, this paper finds that different commodity futures have different predictability in different economic periods. For example, it finds that cocoa, natural gas, lumber, wheat, and coffee cannot predict RV. Besides, rough rice has no predictability during a normal economic period. Except for the above-stated commodities, other commodity futures have significant predictability during the normal economic period. In some cases, a specific commodity may have significant predictability during a one-time segment, while others may not. For instance, sugar and soybeans were significantly predictable after the GFC period; however, not before the GFC period. Secondly, we show the predictability comparison between time segments, normal economic periods, and economic crisis periods. For example, according to the findings of this study, it can be concluded that during general economic periods, most commodity futures have RV predictability except for some commodity futures. For example, cocoa, rough rice, natural gas, lumber, wheat, and coffee have no significant predictive ability from January 2006 to December 2006 and from January 2010 to December 2019. However, the scenario is different during the economic crisis period. Only a few commodity futures have predictability during the COVID-19 and GFC period specified in this study. In particular, rough rice, platinum, palladium, gold, and crude oil have RV predictability during the GFC period. Only sugar, silver, platinum, and oats can predict RV during the COVID-19 period. Also, the predictability is comparatively much higher during the COVID-19 period. The predictive values during normal economic periods are relatively lower than the economic crisis periods.

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PROGNOZA ZREALIZOWANEJ ZMIENNOŚCI KONTRAKTÓW TERMINOWYCH NA TOWARY W USA PODCZAS GLOBALNEGO KRYZYSU FINANSOWEGO (GFC) I PANDEMII COVID-19

Streszczenie: Niniejsze badanie ma na celu zbadanie przewidywalności zrealizowanej zmienności (RV) na amerykańskim rynku kontraktów terminowych na towary w okresie kryzysu gospodarczego w ciągu ostatnich 20 lat. Okres kryzysu gospodarczego obejmuje globalny kryzys finansowy (GFC) i kryzys finansowy podczas COVID-19. Niniejsze badanie rozszerza swój cel, aby pokazać porównanie prognoz w okresie kryzysu finansowego i normalnego okresu gospodarczego. Standardowy model regresji predykcyjnej z tygodniowych danych RV jest wykorzystywany do testowania pewności przyszłotygodniowej RV kontraktów terminowych na towary. W badaniu wykorzystano dane z okresu od 1. kwartału 2000 r. do 3. kwartału 2020 r. Stwierdzono, że platyna, pallad, złoto i ropa naftowa mają znaczną przewidywalność prognozy RV podczas globalnego kryzysu finansowego, podczas gdy cukier, srebro i platyna mają wysoką i znaczącą przewidywalność w prognozowaniu RV podczas pandemii. Ponadto porównanie przewidywalności RV między normalnymi okresami gospodarczymi a okresami kryzysu gospodarczego pokazuje znaczną różnicę w przewidywalności między różnymi okresami gospodarczymi.

Słowa kluczowe: zmienność zrealizowana; kontrakty terminowe na towary; przewidywanie zmienności; Światowy kryzys finansowy; COVID 19

全球金融危机 (GFC) 和 COVID-19 大流行期间美国商品期货的实际波动率预测

摘要：**本研究旨在**检验过去 20 年经济危机期间美国商品期货市场已实现波动率 (RV) **的可**预测性。 经济危机时期包括全球金融危机（GFC）**和**COVID-19**期**间的金融危机。**本研究**扩展了其目的，以显示金融危机时期和正常经济时期的预测比较。 **来自每周** RV **数据的**标准预测回归模型用于测试下周商品期货 RV **的确定性**。 **本研究使用**2000**年第一季度至**2020**年第三季度的数据**，发现铂金、钯金、黄金和原油对全球金融危机期间的RV预测具有显着的可预测性，而白糖、白银和铂金具有高且显着的可预测性 预测大流行期间的 RV。 **此外**，**比较**正常经济时期和经济危机时期的RV**可**预测性，可以看出不同经济时期之间的可预测性存在显着差异。

关键词：已实现波动率；**商品期货**；波动率预测；**全球金融危机**；**新冠肺炎**