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PREDICTABILITY TEST OF COMMODITY FUTURES PRICE INFORMATION ON INDONESIAN COMPOSITE STOCK PRICE INDEX VOLATILITY PERIOD 2007-2023

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Abstract *Indonesia is one of the nations that relies on commodities as the main driver of the economy. Commodities in Indonesia also have a role in the movement of composite stock price in Indonesia (IHSG). Therefore, we conducted research to find out which commodity price information can predict realized volatility (RV) from the IHSG. We use the linear regression model to determine the predictability of the commodity futures RV on the next month's RV of IHSG. We also conduct principal component analysis (PCA) and factor analysis (FA) to extract common factors from each commodity category dan semua komoditas. Our results show that commodities futures RV for Soybeans, Gold, Silver, Wheat and Cotton have a significant effect on the RV of IHSG with their R^2 is explaining the variability of IHSG RV predictions. Extracted common factors using PCA and FA from the types of commodities futures RV of Precious Metals, Grains, and Softs have a significant predictability for the RV of IHSG. All commodity futures extracted using PCA and FA also have the ability to predict the RV of the IHSG significantly. Average method can calculate more R^2 than PCA and FA method, meaning that average methods can predict more information about the types of commodity futures RV variances to the variability of IHSG RV.*

Keyword: *Predictability, Realized Volatilities, Commodities, Stock Price*

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INTRODUCTION

Indonesia has a market that is quite dynamic, the Covid-19 disaster can be an example of this dynamic movement. The movement of the Indonesian Composite Index (IHSG) values suffered a negative trend on a study comparing certain days before and after the emergence of the first Covid-19 case in Indonesia, with the lowest touching the value of 3,937.63 on IHSG (Alghifary et al., 2023). Therefore, IHSG or Indonesian Composite Stock Price Index can also be used as a representative for Indonesian economic because of the IHSG is heavility influenced by macroeconomic events and government surroing the economy (Oktarina, 2015; Astuti et al., 2013; Sunardi & Rabiul Ula, 2017). Despite the stock market's turbulence in Indonesia, commodity prices significantly influence the country's economic health. For example, Parmadi et al. (2018) explain that Indonesia is very dependent on commodity exports, especially the plantation sub-sector. Panjaitan et al. (2020) also explained that commodity export restrictions greatly affect Indonesia's macro-economy. Followed by the data from the Ministry of Trade of the Republic of Indonesia, Indonesian commodity export value has experienced a significant increase in Mining and Oil and Gas, 99.14% and 82.92%, respectively. Followed by Non-Oil and Gas and Agriculture, both respectively has 45.6% and 16.6%, respectively. Moreover, Indonesian commodities export values have increased by 55.95% in total. Also, Based on data from *Badan Pusat Statistic* (BPS), commodities consisting of agriculture, forestry and fisheries, as well as mining and quarrying, contribute 23.62% to GDP on first quarter of 2023 at current prices according to business sector. Because of Indonesia country is very correlated with commodity export-import, commodity also has an effect to the nation economy itself. Study from Adam et al., (2015) discovers that both in the long term and the short term, crude oil (WTI) and Indonesian composite index (IHSG) have a dynamic association. Raharja & Darmansyah, (2019) finds that there is a positive correlation between coal and gold price on IHSG. and Hanitha et al., (2022) discovers that the price of silver has a considerable impact on the SRI KEHATI stock index.

In the context of correlation between commodities and composite stock price, Phoong & Sek (2013) findings exhibit both oil and gold prices have a significant impact on the stock exchanges of these countries in conducting a study exploring the economic relationship between oil prices, gold prices, and their effects on the stock exchanges of Malaysia, Singapore, Thailand, and Indonesia in the context of Southeast Asian commodity and stock prices. Robiyanto (2018) finds there is correlation between world oil price changes and the stock market returns of ASEAN countries (Indonesia, Singapore, Malaysia, the Philippines, and Thailand), that is not static but varies based on the conditions of the stock market and commodity market.

The condition in which the IHSG movement is dominated by foreign and institutional investors affects the nature of the Indonesian capital market (Ree & Wang, 2009; KSEI, 2022). Followed by the futures market in Indonesia is still not mature, with the spot market in Indonesia is not long-term cointegrated with the derivatives market in europe, one of which is commodity futures literacy which is still not enough (Helbawanti et al., 2022). Coupled with financial literacy report from Otoritas Jasa Keuangan, (2022) financial literacy and financial inclusion on capital market contributes the least to other financial literacy in Indonesia. Meanwhile, understanding commodity prices is very useful for knowing the volatility of stock prices. Fernández et al., (2017) suggest that commodity fluctuations play a significant role in output fluctuations. Drechsel & Tenreyro (2018) finds that high commodity prices, noted together, with a lower spread between sovereign borrowing rates and world interest rates, it had a strong positive impact on GDP, consumption, and investment..

RESEARCH METHOD

This research relies on secondary data collected at a daily time frame. The dependent variable, monthly Realized Volatility (RV), is derived from the daily returns of the Indonesian Composite Stock Price index (IHSG). The independent variable, also monthly RV, is obtained from the daily price information of 24 commodity futures. These futures are classified into five energy commodities (crude oil, coal, heating oil, natural gas, and unleaded gasoline), two precious metals (gold and silver), four industrial metals (aluminum, copper, nickel, and zinc), two livestock commodities (live cattle and lean hogs), seven grains (corn, soybeans, soybean oil, crude palm oil, rough rice, and wheat), and four softs (coffee, cotton, sugar, and rubber). The categorization of commodity futures aligns with previous studies conducted by Diebold et al. (2017) and Liang et al. (2020), based on the Bloomberg commodity types. We retrieved 24 commodity futures price data from Investing (Investing, 2023) and SeekingAlpha (Seekingalpha, 2023) then we get the daily price of IHSG from Yahoo! Finance. The sample period that we examined was from 1 January 2007 to 31 May 2023. The data are computed using Microsoft Excel and Stata.

In this research, Principal Component Analysis (PCA) and Factor Analysis (FA) are employed to identify common factors among different types of commodity futures. The purpose is to gain insights into the influence of specific commodity types on predicting the realized volatility of the Indonesian stock market. To begin, monthly Realized Volatility (RV) calculations are performed for all variables considered in the study, including both the commodity RVs and the RV of the IHSG.

$$RV_t = \sum_{j=1}^{M_t} r_{t,j}^{2}$$

RV_t is the RV of month t, Mt shows the total number of trading days in month t, $r_{t,j}$ is the return from the IHSG on day j of month t. As stated by Liang et al. (2020), Realized Volatility (RV) is regarded as a more accurate and less noisy measure compared to squared monthly returns. RV has gained significant popularity in studies focused on predicting stock volatility.

We use standard linear regression model and monthly data of RV to explore the commodity RV predictability for IHSG RV on the next-month. This model is used to predict the IHSG RV against the IHSG RV in the following month (RV_{t+1}). The model can be seen as follows:

$$RV_t = \propto + \beta RV_t + \varepsilon_{t+1},$$

Besides investigating the predictability of 24 commodity futures, we augmented the regression model by including the Realized Volatility (RV) of these futures as an additional predictor. This expansion allowed us to enhance the predictive power of the model.

$$RV_t = \propto + \beta RV_t + \delta RV_{t,i} + \varepsilon_{t+1}, i = 1,2,\dots,24,$$

Where $RV_{t,i}$ is the RV of commodity futures *i* on month *t*. Therefore, *i* represents each of the commodity futures. From that model, we can calculate 22 individual commodities prediction models.

To identify the specific commodity prices that have a significant impact on stock price volatility in Indonesia, we employ the Principal Component Analysis (PCA) and Factor Analysis (FA) techniques to determine the common factors for each individual commodity type as well as for all types of commodity futures. The model is then enhanced by incorporating these common factors as predictors, and its specification can be expressed as follows:

$$RV_t = \propto + \beta RV_t + \delta CF_{t,i}^{M} + \varepsilon_{t+1}, i = 1,2,\dots,7, M = PCA, FA,$$

$\delta CF_{t,i}^{M}$ is the common factor of *i* of the month *t*, *i* represents the 7 types of commodities futures including all of the commodity types. The technique utilized to extract the common factors, denoted as M, involves employing both Principal Component Analysis (PCA) and Factor Analysis (FA). These methods allow for the identification and extraction of the underlying common factors from the dataset and this model will find the respective predictions from PCA and FA analysis persepective. For this reason, this model is calculated twice by extracting the common factor with PCA and also extracting the common factor with FA.

To generate combined forecasts by integrating individual prediction models, we adopt a simple average approach. This method involves taking the average of the separate models' predictions to provide a consolidated forecast. In a comparable manner, seven combination models may be found using Bloomberg's classification from the study of Liang et al., (2020). The basic average model can be estimated statistically as:

$$\widehat{RV}_{ave,t+1} = \sum_{k=1}^{N} \frac{\widehat{RV}_{k,t+1}}{N},$$

$\widehat{RV}_{ave,t+1}$ The average forecast represents the projected volatility of the Indonesian stock market (IHSG) for the following month, denoted as t+1. N is total commodity of the commodity type. $\widehat{RV}_{k,t+1}$ is the prediction of commodities futures on one type of commodity. Therefore, $\widehat{RV}_{k.t+1}$ represents the prediction model for the forecasts of the next month.

This model will later be calculated into an out-of-sample test to determine the predictability of each commodity and also by its types. Therefore, This two model is to generate the quality of the prediction and the significance level for the out-of-sample test.

Following the study of Liang et al., (2020) and Campbell & Thompson, (2008), we use the $adjusted - R^2$ test to judge the regression model ability to forecast data. Followed by Levine et al., (2013), $adjusted - R^2$ is important to compare two or more regression model. $adjusted - R^2$, measures the proportion of variation in Y (RV_{t+1}) that is explained by the independent variable X (RV_t) and ($RV_{t,i}$) in the regression model (Levine et al., 2013).

$$adjusted - R^2 = 1 - \frac{\sum_{k=1}^{q}(RV_t - \widehat{RV}_t)^2}{\sum_{k=1}^{q}(RV_t - \overline{RV}_t)^2}$$

Which RV_t represents the actual RV, $\widehat{RV}_t$ and $\overline{RV}_t$ represent the IHSG RV projections of the model and historical average RV in month t, respectively. $adjusted - R^2$ measures the proportion of variation in dependent variable RV_t that is explained by the independent variable βRV_t and $\delta RV_{t,i}$ in the regression model. Therefore, the bigger R^2, is more of the variation is explained by the variability of independent variable.

RESULTS AND ANALYSIS

As this study incorporates multiple variables, it is essential to provide descriptive statistics to present key characteristics of the data. The descriptive statistics were computed using Stata software. The dataset comprises 197 observations encompassing monthly Realized Volatility (RV) data from January 2007 to May 2023. Analyzing the table below reveals that crude oil exhibits the highest monthly RV at 1143.9270%, representing the maximum volatility, while rough rice displays the lowest monthly RV at 0.0019%, denoting the minimum volatility. These findings highlight that crude oil stands out as the most volatile variable, as evidenced by its highest standard deviation compared to other variables.

Variables	Obs	Mean	Standard Deviation	Minimum	Maximum
IHSG	197	0.3247%	0.5419%	0.0277%	5.2591%
Crude Oil	197	7.1799%	81.4351%	0.1029%	1143.9270%
Natural Gas	197	2.4494%	2.4321%	0.2735%	20.2020%
Unleaded Gasoline	197	1.1639%	2.1188%	0.0945%	23.6047%
Heating Oil	197	1.0607%	1.4972%	0.0659%	13.1349%
Coal	197	1.1448%	3.2711%	0.0099%	34.8514%
Gold	197	0.2650%	0.2787%	0.0336%	2.0457%
Silver	197	0.8833%	0.9287%	0.0727%	6.5294%
Alumunium	197	0.4473%	0.3472%	0.0569%	2.3092%
Copper	197	0.6092%	0.8131%	0.0596%	9.0791%
Nickel	197	1.65%	8.18%	0.14%	100.25%
Zinc	197	0.77%	0.72%	0.08%	6.24%
Live Cattle	197	0.29%	0.38%	0.03%	3.70%
feedercattle	197	0.27%	0.34%	0.01%	2.53%
Corn	197	0.71%	0.62%	0.08%	4.23%
Soybeans	197	0.53%	0.89%	0.06%	11.25%
Soybean Oil	197	0.51%	0.48%	0.07%	3.35%
CrudePalm Oil	197	0.7275%	0.8547%	0.0896%	5.6281%
Rough Rice	197	0.5240%	0.8158%	0.0019%	7.9633%
Wheat	197	1.0986%	1.2867%	0.0823%	10.6897%
Cocoa	197	0.6616%	0.5096%	0.0721%	3.8803%
Coffee	197	0.8563%	0.5854%	0.1610%	4.3260%
Cotton	197	0.9989%	1.3311%	0.0729%	13.8127%
Sugar	197	0.6010%	0.4891%	0.0740%	3.4176%
Rubber	197	12.1693%	23.5335%	0.0471%	154.2544%

We conduct normality tests using Jarque-Bera statistics and stationary test using augmented-Dickey Fuller statistics. From the result, we find that all variables are normally distributed and all the time series are stationary.

Variables	Jbstat	p-value	ADFstat	p-value
IHSG	12972.8700	0	-7.734	0.0000

Crude Oil	314381.1000	0	-9.801	0.0000
Natural Gas	1459.4580	0	-6.176	0.0000
Unleaded Gasoline	40354.3400	0	-7.652	0.0000
Heating Oil	5765.7150	0	-6.774	0.0000
Coal	34988.9600	0	-7.386	0.0000
Gold	1244.3120	6.30E-271	-5.917	0.0000
Silver	1044.7400	1.40E-227	-6.271	0.0000
Alumunium	462.7140	3.30E-101	-6.917	0.0000
Copper	29769.1500	0	-5.739	0.0000
Nickel	114417.2000	0	-9.963	0.0000
Zinc	1937.2490	0	-5.657	0.0000
Live Cattle	13846.7400	0	-7.909	0.0000
feedercattle	2580.4450	0	-7.734	0.0000
Corn	395.3283	1.43E-86	-6.047	0.0000
Soybeans	91754.0700	0	-7.729	0.0000
Soybean Oil	1084.7490	2.80E-236	-4.359	0.0025
Crude Palm Oil	617.5387	8.00E-135	-4.62	0.0010
Rough Rice	31247.8100	0	-7.979	0.0000
Wheat	4990.6330	0	-7.92	0.0000
Cocoa	759.8812	9.90E-166	-6.82	0.0000
Coffee	837.0829	1.70E-182	-6.886	0.0000
Cotton	16277.2000	0	-6.834	0.0000
Sugar	674.0188	4.40E-147	-6.497	0.0000
Rubber	1107.9030	2.60E-241	-7.046	0.0000

We report the spearman correlation coefficient to test the significance of correlation between the RV of IHSG and commodities futures. The correlation indicates gold, silver, copper, nickel, and zinc have a correlation exceeding 0.4, meaning that it is strongly correlated with IHSG. However, the realized volatility of other commodity futures exhibits a weak correlation with the realized volatility of IHSG, as indicated by the relatively small correlation coefficient. Additionally, the analysis reveals that there is a relatively high correlation between the realized volatilities of commodity futures within the same category (e.g., gold and silver in precious metals, copper, nickel, and zinc in industrial metals). However, the correlation between the realized volatilities of other types of commodity futures is low.

The forecasts of the twenty-four individual models are obtained through regression analysis, where a set of predictors is used to generate the forecasts to predict RV_{t+1} from the RV_t of IHSG and RV_t of twenty four commodities futures respectively. We regress each of the 24 variable based on the study of Liang et al., (2020) so that we can see each of the R^2 that explains the variability of IHSG RV prediction. The table below report the R^2 of the twenty four commodities futures RV_t and its p-value.

Commodity types	**Commodities**	**R Square**	***p*-value**
	Crude Oil	0.1178	0.508
	Natural Gas	0.1190	0.401
	Unleaded Gasoline	0.1166	0.674
	Heating Oil	0.1161	0.792
Energy	Coal	0.1161	0.774
	Gold	0.3230	0.001
Precious Metals	Silver	0.2027	0.000
	Alumunium	0.1163	0.733
	Copper	0.1163	0.732
	Nickel	0.1159	0.871
Industrial Metals	Zinc	0.1318	0.060
	Live Cattle	0.1218	0.248
Livestock	Lean Hogs	0.1220	0.243
	Corn	0.1295	0.081
	Soybeans	0.4277	0.000
	Soybean Oil	0.1227	0.216
	Crude Palm Oil	0.1271	0.114
	Rough Rice	0.1158	0.928
Grains	Wheat	0.1554	0.003
	Cocoa	0.1263	0.128
	Coffee	0.1197	0.371
	Cotton	0.1411	0.018
	Sugar	0.1364	0.033
Softs	Rubber	0.1172	0.572

From the table above, we find that there are six commodities realized value that calculated using regression model to investigate which have ability to significanty predict the RV of IHSG. The results of six significant commodity futures to the benchmark model are:

1. The biggest R^2 are Soybeans, with 42.77% of the variation is explaining the IHSG RV_{t+1} variability predictions.
2. Followed by Gold with 32.30% of the variation is explaining the IHSG RV_{t+1} variability predictions.

3. Silver with 20.27% of the variation is explaining the IHSG RV_{t+1} variability predictions.
4. Wheat with 15.54% of the variation is explaining the IHSG RV_{t+1} variability predictions.
5. Cotton with 14.11% of the variation is explaining the IHSG RV_{t+1} variability predictions.
6. Sugar with 13.64% of the variation is explaining the IHSG RV_{t+1} variability predictions.

Obviously, apart from the six commodities above, the results were not significant. Therefore, we aligned the other commodities from which is close to significant to the least significant:

1. Zinc with 13.28% of the variation is explaining the IHSG RV_{t+1} variability predictions.
2. Corn with 12.95% of the variation is explaining the IHSG RV_{t+1} variability predictions.
3. Crude Palm Oil with 12.71% of the variation is explaining the IHSG RV_{t+1} variability predictions.
4. Cocoa with 12.63% of the variation is explaining the IHSG RV_{t+1} variability predictions.
5. Soybean Oil with 12.27% of the variation is explaining the IHSG RV_{t+1} variability predictions.
6. Feeder Cattle with 12.2% of the variation is explaining the IHSG RV_{t+1} variability predictions.
7. Live Cattle with 12.18% of the variation is explaining the IHSG RV_{t+1} variability predictions.
8. Coffee with 11.97% of the variation is explaining the IHSG RV_{t+1} variability predictions.
9. Natural Gas with 11.9% of the variation is explaining the IHSG RV_{t+1} variability predictions.
10. Crude Oil with 11.78% of the variation is explaining the IHSG RV_{t+1} variability predictions.
11. Rubber with 11.72% of the variation is explaining the IHSG RV_{t+1} variability predictions.
12. Unleaded Gasoline with 11.66% of the variation is explaining the IHSG RV_{t+1} variability predictions.
13. Copper and alumunium with 11.63% of the variation is explaining the IHSG RV_{t+1} variability predictions.
14. Coal and Heating Oil with 11.61% of the variation is explaining the IHSG RV_{t+1} variability predictions.
15. Nickel with 11.59% of the variation is explaining the IHSG RV_{t+1} variability predictions.
16. Rough Rice with 11.58% of the variation is explaining the IHSG RV_{t+1} variability predictions.

We utilize the PCA and FA methods to extract common factors for each specific type of commodity futures as well as for all types of commodity futures. This is done to examine the predictive value of different types of commodity price information for the RV of the IHSG. Additionally, we combine the individual prediction models for each type and all types of commodity futures using a simple average approach. This results in the creation of seven PCA models, seven FA models, and seven average models. The table below reports the R^2 results of the forecasting models.

Forecasting models	R^2	***p*-value**	**Forecasting models**	R^2	***p*-value**	**Forecasting models**	R^2	***p*-value**
PCA METHOD			**FA METHOD**			**AVERAGE METHOD**		
PCA-energy	0.1176	0.5260	FA-energy	0.1165	0.6910	AVE-energy	0.1195	0.3620
PCA-Precious	0.2830	0.0000	FA-Precious	0.2830	0.0000	AVE-Precious	0.3110	0.0000
PCA-IndMet	0.1206	0.3040	FA-IndMet	0.1228	0.2130	AVE-IndMet	0.1283	0.0970

PCA-Live	0.1243	0.1710	FA-Live	0.1243	0.1710	AVE-Live	0.1243	0.1710
PCA-Grains	0.2011	0.0000	FA-Grains	0.1816	0.0000	AVE-Grains	0.3484	0.0000
PCA-Softs	0.1500	0.0060	FA-Softs	0.1510	0.0050	AVE-Softs	0.1554	0.0030
PCA-ALL	0.1821	0.0000	FA-ALL	0.1812	0.0000	AVE-ALL	0.3962	0.0000

We find that the following results have the p-value below 0.05, the commodity types is significant for each method (PCA, FA, and Average Method). The results of using PCA, FA, and Average method to know wether the types of price information are more useful in predicting the RV of the IHSG are:

1. Both method of Precious Metals commodities (PCA and FA) are contributed the R^2 with 28.30% and 31.1% for the Average method to the variability of IHSG RV_{t+1}.
2. Grains commodity types (Corn, Soybeans, Soybean Oil, Crude Palm Oil, Rough Rice, Wheat, and Cocoa) are contributed for the R^2 of 20.11% for PCA method, 18.16% for FA method, and 34.84% for Average method to the variability of IHSG RV_{t+1}.
3. Softs commodity types (Coffee, Cotton, Sugar, Rubber) are contributed the R^2 of 15% for PCA, 15.10% for FA and 15.54% for Average method to the variability of IHSG RV_{t+1}.

And ALL commodity types RV are contributed for the R^2 of 18.21% for PCA, 18.12% for FA, and 39.62% for Average method to the variability of IHSG RV_{t+1}.

CONCLUSION

Knowing commodity prices is also important to know the volatility of the composite stock price index (IHSG) amidst the lack of financial literacy in the capital market in Indonesia. We use data from commodity futures prices and the IHSG from January 1 2007 to May 31 2023. Then we calculate commodity futures prices and the IHSG to obtain monthly Realized Volatility data for each variable. Then we carry out multiple linear regression with the dependent variable, namely the RV of the next month's IHSG against the independent variables, namely the RV of the IHSG and the RV of Commodity futures. Then we carry out PCA and FA analysis to extract common factors from the RV of each type of futures commodity and all futures commodities so that we can possibly known of what RV of commodity types that are significantly affect the predictability of IHSG RV. The results of individual regression model for all of commodities realized volatility were as follows:

In summary, our findings indicate that Soybeans, Gold, Silver, Wheat, Cotton, and Sugar exhibit significant predictability for the RV of the IHSG. Each of the variables discussion that have a significant predictability description are as follows:

1. Soybeans is one of the most consuming agricultural commodities in Indonesia. Many Indonesian people use soybeans to produce many foods such as tofu, *tempe*, *tauco*, *oncom*, and soysauces. Majority of the soybeans production are come from import. A study of soybeans is conducted and income per kapita of Indonesian people is significant effect on soybean imports. (Setyawan & Huda, 2022)

2. Gold has been commonly used for alternative asset and hedge. Gold also used as to make jewellery, accessories, and even computer parts. This study is also aligned with Raharja & Darmansyah, (2019) that gold has an significant effect to return of IHSG.

3. Like Gold, silver has been known to use for investing. Other than that, silver are used for health and treatment, electronic, jewellery and accessories (Ministry of Trade of Indonesia, 2012). This study also extended Hanitha et al., (2022) about the silver have a positive return on SRI KEHATI index.

4. Wheat is used for the fulfillment of the manufacture for bread and flour. The Indonesian public's need for wheat still depends on imports. Data gathered from Ministry of Trade of Indonesia, (2023), import of wheat is increasing from the period of 2020-2023.

5. Indonesia has a large population so that the need for textiles is also affected. In research from Iwan Hermawan & Adam, (2010) explained that most of the cotton in Indonesia is imported cotton. Factors that affect the demand for cotton include the amount of production, exports, imports. The need for cotton imports is influenced by Indonesia's population, time trends, and the amount of imports in the previous year.

6. Sugar is also a staple commodity consumed by Indonesians. The price of sugar is determined by the price of imports because sugar is registered as a sensitive list in the AFTA (ASEAN Free Trade Agreement) which increases import tariffs by up to 40%, because the fulfillment of sugar in Indonesia is heavily influenced by the price of sugar, it has an economic effect on the sugar itself (Pudjiastuti et al., 2013). Followed by the data from Ministry of Trade of Indonesia, the prices of sugar is increased from 2018-2022.

7. The use of average method is also to knowing the predictability of the commodities futures without extracting common factors using PCA and FA method.

The price information of 4 types of commodities forecasting models containing Precious Metal, Grains, Softs, and All types of commodities contributes significantly to the performance of R^2. Meaning that they thave better performance of R^2 to predict the RV of IHSG by looking at its common factors extracted with PCA and FA method.

1. Precious metals are consisted of Gold and Silver that both have a higher R^2 result on individual regressing model, assuming that both commodities are parallel with the PCA and FA method for the precious metals ability to predict the RV of IHSG.
2. Grains type is consisted of Soybeans and Wheat that have significant level below 0.05. Soybeans is considered as the highest R^2 results among other commodities. But, Wheat have a very different results of R^2 with 15.54% of the variation is explaining the IHSG RV_{t+1} variability predictions. Therefore, we assume that the R^2 of Soybeans plus the R^2 of Wheat can offset the insignificant predictability of other commodities. Besides, this study is using PCA and FA method to extract the common factor of each variable so that the type of grains commodity that contains other commodities of Soybeans and Wheat also influences the predictability of the grain itself to predict the RV of the IHSG.

3. Softs is contains of Cotton and Sugar, which that variable is significantly have effect to the predictability of IHSG RV. Assuming that PCA and FA method extracted the common factors of all softs commodity types common factors, the performance for $R^2$to ability for predicting IHSG RV is significant.

4. We also extract the common factors of all commodities futures RV using PCA and FA method to know the predictability of using all commodities futures common factors for IHSG Realized Value. The results using average method are all average commodity RV is significantly effect the predictability of IHSG RV. The R^2 result is also the highest amongst other commodity types, followed by Grains, Precious Metals, and Softs. Most of the average method R^2 are higher than the PCA and FA method. Although, average method is different from PCA and FA method because average method only calculating the mean of the variables while PCA and FA are extracting the common factors of each variable. But, average method can generate more R^2 compared to other methods, it is also explains that average methods can predict more information about the variability of IHSG RV.

We conclude that Soybeans, Gold, Silver, Wheat, and Cotton are significantly can predict the RV of IHSG by the R^2 explaining the variability of the predictions. While the category of Precious Metals, Grains, Softs, and ALL commodity types are significantly influence to predict the realized volatility of IHSG. In this case, average method can calculate more R^2 than PCA and FA method, meaning that average methods can predict more information about the types of commodity futures RV variances to the variability of IHSG RV.

Since this research studying the long-term based data, further research can conduct study of different time series data and short-term based data. Further research can also be conducted by searching the predictability of commodities price during certain period of time, such as in the low-volatility and high-volatility regime. Adjusted data can also be used to see more about commodities that affecting the Realized Volatility of IHSG or other types of composite stock price index.

REFERENCES

Adam, P., Rianse, U., Cahyono, E., & Rahim, M. (2015). Modeling of the Dynamics Relationship between World Crude Oil Prices and the Stock Market in Indonesia. *International Journal of Energy Economics and Policy*, *5*(20), 550-557. https://dergipark.org.tr/en/pub/ijeeep/issue/31913/350911

Alghifary, M. S., Kadji, D., & Hafizah, I. (2023, January). Indonesian Stocks' Volatility during COVID-19 Waves: Comparison between IHSG and ISSI. *International Journal of Islamic Economics and Finance (IJIEF)*, *6*(1), 105-132. https://doi.org/10.18196/ijief.v6i1.14838

Astuti, R., Prihatini, A. E., & Susanta, H. (2013, September). Analisis Pengaruh Tingkat Suku Bunga (SBI), Nilai Tukar (Kurs) Rupiah, dan Indeks Bursa Internasional terhadap IHSG (Studi pada IHSG di BEI Periode 2008-2012). *Jurnal Ilmu Administrasi Bisnis*, *2*(4), 136-145.

Campbell, J. Y., & Thompson, S. B. (2008). "Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, *21*(4), 1509-1531.

Diebold, F. X., Liu, L., & Yilmaz, K. (2017, August). Commodity connectedness. *National Bureau of Economic Researc*. https://www.doi.org/10.3386/w23685

Drechsel, T., & Tenreyro, S. (2018, May). Commodity booms and busts in emerging economies. *Journal of International Economics*, *112*, 200-218. https://doi.org/10.1016/j.jinteco.2017.12.009

Fernández, A., Schmitt-Grohé, S., & Uribe, M. (2017, May). World shocks, world prices, and business cycles: An empirical investigation. *Journal of International Economics*, *108*(Supplement 1), S2-S14. https://doi.org/10.1016/j.jinteco.2017.01.001

Hanitha, V., Purnama, M., & Purna,a, O. (2022). The Effect of World Oil Prices, Silver Prices, Exchange Rates, Dow Jones Industrial Average, on the SRI Kehati Index on the Indonesia Stock Exchange for the period January 2021–December 2021. *eCo-Buss*, *5*(2), 429-440. https://garuda.kemdikbud.go.id/documents/detail/3080324

Helbawanti, O., Permata Bunda, C. A., & Faqihuddin. (2022). Integrasi Pasar Berjangka Komoditi Crude Palm Oil (CPO) Indonesia Di Masa Pandemi Covid-19. *Jurnal Agrica*, *15*(1), 61-74. 10.31289/agrica.v15i1.5401

Iwan Hermawan, & Adam, L. (2010). Analisis faktor-faktor yang mempengaruhi penawaran dan permintaan serat kapas di Indonesia. *Jurnal Ekonomi dan Kebijakan Publik*, *1*(1), 101-128. https://jurnal.dpr.go.id/index.php/ekp/article/view/77/44

KSEI. (2022, November 21). Investor Pasar Modal Tembus 10 Juta. *Berita Pers*, 1-3.

Levine, D. M., Berenson, M. L., & Krehbiel, T. C. (2013). *Business Statistics: A First Course*. Prentice Hall/Pearson.

Liang, C., Ma, F., Li, Z., & Li, Y. (2020, December). Which types of commodity price information are more useful for predicting US stock market volatility? *Economic Modelling*, *93*, 642-650. https://doi.org/10.1016/j.econmod.2020.03.022

Ministry of Trade of Indonesia. (2012, April). *Membedah potensi industri perak di Indonesia*.

Kementerian Perdagangan Republik Indonesia
Ministry of Trade of Indonesia. (2023). *Perkembangan Impor Non Migas (Komoditi)*. Kementerian Perdagangan Republik Indonesia.
Otoritas Jasa Keuangan. (2022, July 28). *2021-2025 National Strategies on Indonesian Financial Literacy*. Otoritas Jasa Keuangan.
Panjaitan, D. V., Ingot, S. R., Mardiansyah, A., & Christoffel, L. M. (2020, Juni). Analisis Dampak Export Restriction Komoditi Pertanian terhadap Indonesia. *Jurnal Agribisnis Indonesia*, *8*(21), 1-16. https://doi.org/10/29244/jai.2020.8.1.1-16
Parmadi, Emilia, & Zulgani. (2018). Daya Saing Produk Unggulan Sektor Pertanian Indonesia dalam Hubungannya dengan Pertumbuhan Ekonomi. *Jurnal Paradigma Ekonomika*, *13*(2), 77-86. https://online-journal.unja.ac.id/paradigma/article/view/6677/9427
Phoong, S. W., & Sek, S. K. (2013). A markov switching vector error correction model on oil price and gold price effect on stock market returns. *Information Management and Business Review*, *5*(7), 331-336. https://doi.org/10.22610/imbr.v5i7.1059
Pudjiastuti, A. Q., Anindita, R., Hanani, N., & Kaluge, D. (2013). Effects of Sugar Price Increase in Indonesia. *Studia Universitatis Babes-Bolyai*, *58*(1), 28.
Raharja, R. T., & Darmansyah, A. (2019). The effect of the returns of global stock indexes and global commodities toward IHSG returns period 2009-2018. *International journal of business and economy*, *1*(2), 31-41. https://myjms.mohe.gov.my/index.php/ijbec/article/download/7023/2821
Ree, S. G., & Wang, J. (2009). Foreign institutional ownership and stock market liquidity: Evidence from Indonesia. *Journal of Banking & Finance*, *33*(7), 1312-1324. https://doi.org/10.1016/j.jbankfin.2009.01.008
Robiyanto, R. (2018). The Dynamic Correlation between ASEAN-5 Stock Markets and World Oil Prices. *Jurnal Keuangan dan Perbankan*, *22*(2), 198-210. https://jurnal.unmer.ac.id/index.php/jkdp
Setyawan, G., & Huda, S. (2022). Analysis of the influence of soybean production, soybean consumption, per capita income, and exchange rate on soybean imports in Indonesia. *Jurnal Ekonomi dan Manajemen*, *19*(2), 215-225. 10.29264/jkin.v19i2.10949
Sunardi, N., & Rabiul Ula, L. N. (2017, December). Pengaruh BI RATE, Inflasi dan Kurs terhadap. *Jurnal Sekuritas*, *1*(2), 27-41.
Wang, J., Huang, Y., Ma, F., & Chevalier, J. (2020). Does high-frequency crude oil futures data contain useful information for predicting volatility in the US stock market? New evidence. *Energy Economics*, *91*, 104897. https://doi.org/10.1016/j.eneco.2020.104897