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THE ROLE OF PALM OIL PRICE IN INDONESIA'S AGGREGATE DEMAND

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ABSTRACT

This study examines the predictability of Indonesia's aggregate demand using palm oil price. We conduct both in-sample and out-of-sample forecasting evaluations. These evaluations are based on time-series quarterly and monthly data frequencies and cover three different forecasting horizons. Overall, we find that palm oil price predicts real GDP, consumption expenditure, total investment, net spending from overseas, while predictability of government spending is sensitive to the use of forecasting approaches and horizons.

Keywords: Palm oil price; Aggregate demand; Time-series; Predictability.
JEL Classifications: C5; E1.

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I. INTRODUCTION

The aim of this paper is to examine the role of Palm Oil price (*PO*) in Indonesia's aggregate demand. In other words, we test whether *PO* predicts Indonesia's real Gross Domestic Product (*GDP*). In addition, we also test whether *PO* influences all or only some components of *GDP*. Thus, we use *PO* to predict four major components of real GDP, namely household spending (also known as consumption, *Consp*), investment by businesses and households (*Invst*), spending by the government (*GovS*), and the net spending from overseas (exports minus imports, *X-M*).

Our focus on *PO* and application on Indonesia is motivated by the fact that palm oil production plays a vital role in Indonesia's agricultural and economic development. The planted area for palm has increased from 14.67 million hectares to 16.38 million hectares (United States Department of Agriculture, 2020). It is, therefore, expected that this increase in plantation area will lead to 43.5 million tons of oil production in 2020/21. It is also forecasted by the United States Department of Agriculture (2020) that palm oil consumption will slightly increase from 15.30 million tons in 2019/20 to 15.35 in 2020/21. The increase in consumption is due to the stable industrial demand for biodiesel and the increase in consumption in the food sector.

Indonesia is considered as a leading exporter of palm oil. India and China are considered major export markets for Indonesian palm oil, which accounts for 17.4% and 17.3%, respectively, of exports in 2018/19.[1] The other export markets include Pakistan, Malaysia, and the Netherlands (see Indonesia Investments, 2017).[2] Based on the above discussion, it is clear that the palm oil industry plays a vital role in Indonesia's agricultural and economic development. In other words, it can be construed that exports of palm oil are an important source of foreign exchange earnings for Indonesia. The sector also provides employment opportunities to millions of Indonesians. According to the Directorate General of Estate Crops Indonesia (2017), in 2017, the palm oil industry employed 3.8 million people, which is approximately 2.4% of the total Indonesian workforce. The Indonesian government, therefore, increasingly promotes oil palm cultivation in order to alleviate poverty and allow for advance development in remote forested areas (see Potter, 2012; Cooke, 2012, Li, 2016). However, as noted by Obidzinski, Andriani, Komaundin, Andrianto (2012) and Obidzinski, Dermawan, Hadianto (2014), an expansion of the palm oil industry increased income benefits mainly amongst skilled migrants and wealthy farmers while marginalising others. This has led to social disparities.[3] Thus, based on this discussion, we are motivated to investigate whether palm oil industry plays a role in Indonesia's economic performance which is collectively captured by Indonesia's aggregate demand (*GDP*).

1 Kadarusman and Pramudya (2019) provide further insights on the effects of India and China on the sustainability of palm oil production in Indonesia.

2 See https://www.indonesia-investments.com/business/commodities/palm-oil/item166

3 Santika et al. (2019) provide a detailed discussion on the impact of palm oil plantation development on changes in objective and material aspects of well-being across villages in Kalimantan, Indonesia, over the 2000 to 2014 period.

Next, we review the well-established literature which examines the relationship between oil price and economic performance.[4] Two strands of this literature are popular. In the first strand of the literature, studies have examined whether oil price is a significant determinant of economic performance (see for example, Kilian, 2008, Kilian and Vigfusson, 2011). The main findings emanating from this literature are inconclusive. Some studies note that oil price has a negative effect on economic growth (see Kilian, 2008), and some conclude that there exists a non-linear relationship between oil price and economic growth (see Hamilton, 2003).

The second strand of the literature has roots in the work of Hamilton (1983), who examined whether oil price significantly predicts economic growth. The major focus of these studies is on the US economy. One exception is Narayan, Sharma, Poon, and Westerlund (2014), who examine whether oil price predicts economic growth in 45 countries. They find that the predictive power of oil price is country dependent. Overall, they find that oil price significantly predicts economic growth in 70% of the countries in their sample.

In the above-mentioned studies, authors have generally used the world crude oil price series irrespective of the countries in their application. However, for countries such as Indonesia, where palm oil production plays a vital role in their agricultural and economic development, it may be the case that palm oil (rather than crude oil price) is a more relevant price to consider from the economic growth point of view. To the best of our knowledge, there are no studies examining the relationship between *PO* and economic growth. Therefore, considering this research gap, the focus of our study is not on crude oil price but on crude *PO* and how it predicts Indonesia's economic growth. Our hypothesis is that *PO* predicts Indonesia's economic growth. We test this hypothesis by employing a bivariate predictive regression model. More specifically, we regress aggregate demand on the one-period lagged crude *PO*.

Our approach differs from the existing literature in the following ways. Our study is the first to examine the predictability of aggregate demand using *PO* instead of world crude oil price as a predictor variable. Moreover, we not only focus on predictability of Indonesia's economic growth, but we also consider the four other aggregate demand components (namely, *Consp*, *Invst*, *GovS*, and *X-M*). Here, our aim is to understand whether *PO* affects all or only some of the components of aggregate demand. We use the popular Westerlund and Narayan (WN, 2012 and 2015) Flexible Generalized Least Squares (FGLS) estimator to examine the null hypothesis of "no predictability". The literature on the predictability of economic growth does not pay much attention to the different features of time-series data. Narayan et al., (2014) document existence of forecasting related data issues, such as persistency, endogeneity, and heteroskedasticity in their time-series quarterly data and make note that if these issues are ignored, it will have a direct implication

[4] It is worth noting that the literature on oil prices is voluminous and one can classify the literature into multiple strands. The most popular issue which has emerged in the last six months relates to the relationship between pandemic COVID-19 and oil price (see for example, Narayan, 2020; Apergis and Apergis, 2020; Gil-Alana and Monge, 2020; Liu, Wang, and Lee, 2020; Prabheesh et al. 2020; Devpura and Narayan, 2020; Huang and Zheng, 2020; and Salisu and Adediran, 2020). While we do acknowledge different strands of this literature, our focus relates to the literature which examines the relationship between oil prices and economic performance.

on the predictability outcomes. By using the WN estimator, we control for all the commonly known features of data.

We also devote our analysis to ascertaining the robustness of our results. We conduct all analysis by converting quarterly data into monthly frequency. We also use three different forecasting horizons (one-period, three-periods, and six-periods ahead). Finally, in out-of-sample analysis, we increase the estimation window from 50% to 75% of the data sample to generate out-of-sample test statistics.

Our study contributes to the literature which examines the predictability of economic growth using oil prices. Our approaches, as discussed earlier, produce three main findings. First, we uncover strong evidence of in-sample predictability of Indonesia's real GDP using *PO* only when we consider a three-period-ahead (quarterly data) and a six-period-ahead (monthly data) forecasting horizon. Irrespective of the use of data at different frequencies, we do not find evidence of predictability of Indonesia's GDP at the one-period ahead forecasting horizon.

Second, when we consider out-of-sample results, our findings remain inconsistent with respect to the use of two out-of-sample forecasting evaluation measures. Additionally, we note that when we increase the in-sample estimation window from 50% to 75% of the sample to generate recursive forecasts, our results remain unchanged. Another observation worth noting is that our out-of-sample results remain consistent regardless of the use of different data frequencies and different forecasting horizons.

Third, as mentioned earlier, we further investigate whether *PO* predicts all or only some components of aggregate demand. Overall, we find strong evidence of predictability using *PO* in the case of *Consp*, followed by *Invst*. Again, when in-sample predictability test is considered, the evidence that aggregate demand is predictable from *Consp* and *Invst* is found when $h = 3$ and $h = 6$ for data at quarterly and monthly frequencies, respectively. With respect to out-of-sample evaluations, relative Theil U (RTU) statistics provides favorable evidence in support of *PO*-based predictability model over the constant-only model. This evidence is consistent with the use of two different data frequencies, different in-sample estimation windows, and the use of three different forecasting horizons.

We also embark on robustness checks to ascertain our earlier conclusions. More specifically, we use adjusted-GDP as our dependent variable in predictability models. In other words, we use three variables (Indonesian exchange rate (in terms of the US Dollar, *EXR*), percentage change in consumer price index (*INF*), and foreign direct investment (*FDI*)) from the literature on determinants of economic growth (see for instance, Burdekin et al., 2004; Bittencourt, 2012; Vinayagathasan, 2013; Gunby, Jin, and Reed, 2017; Lee and Yue, 2017; Huang, 2017) to adjust GDP.[5]

Our approach for adjusting *GDP* is very simple and is carried out in two steps. First, we estimate a bivariate regression model, where we regress *GDP* individually on *EXR*, *INF*, and *FDI*. In other words, we estimate three regression

[5] It is important to note that our study does not imply that only these three variables (exchange rate, inflation rate, and foreign direct investments) are statistically significant determinants of GDP. There is a large literature on growth models and many other variables are empirically tested and considered as determinants of GDP for different countries. However, the choice these three variables (namely exchange rate, inflation rate, and foreign direct investments) is entirely based on data availability for Indonesia. We also believe they sufficiently capture the bulk of movements in GDP.

models, one model for each of three variables, *EXR*, *INF*, and *FDI*. Second, we extract the constant and residuals from the estimated model. The sum of the estimated constant and residuals is considered as adjusted-GDP. Given we have estimated altogether three regression models, we have, therefore, constructed three adjusted-GDP series (namely *GDP_EXR*, *GDP_INF*, and *GDP_FDI*). Now, these adjusted-GDP series are considered as dependent variables in our predictability model. Our estimation approach remains same as discussed earlier. Our in-sample predictability results remain the same and consistent with main findings. When we consider out-of-sample evaluations, overall, we find our *PO*-based predictability model outperforms the benchmark constant-only model for *GDP_FDI*. In the case of *GDP_EXR* and *GDP_INF*, we find mix evidence in support of *PO*-based predictability model over the constant only model. It is also worth noting that the evidence in support of *PO*-based predictability model over the benchmark model is based on RTU statistics and not when we consider out-of-sample R-squared (OOSR2). This finding is again consistent with our main findings.

The balance of the paper proceeds as follows. We discuss our data and methodology in Section II. Section III discusses our main findings, followed by a robustness check in Section IV. Section V discusses implications of our findings, and finally, Section VI sets forth our conclusions.

II. DATA AND METHODOLOGY

A. Data set

This study is based on time-series quarterly data for Indonesia. The sample size is dictated by data availability and spans the period 2008Q1 to 2019Q4. The *PO* (measured in USD per metric ton) is sourced from the *Primary Commodity Price System* published by the *International Monetary Fund*. Data on real GDP growth rate and four major components of *GDP*, namely *Consp*, *Invst*, *GovS*, and *X-M* are sourced from *Bank Indonesia*. We have also used three control variables, namely, *INF*, *FDI*, and *EXR*. Again, all control variables are sourced from *Bank Indonesia*, except *INF*, which is sourced from the *International Financial Statistics* (IFS). It is important to note that consumer price index is sourced in monthly frequency and is converted into quarterly series. We have provided full data description in Table 1.

Table 1.
Data Description

This table provides detail data description of all variables considered in this study.

Variables	Description	Frequency	Source
GDP	Percentage change in total gross domestic product (2000p; Billion USD)	Quarterly [2008Q1 – 2019Q4]	CEIC
Consp	Percentage change in Household Consumption Expenditure (GDP Constant 2010 Prices)	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia
Invst	Percentage change in Gross Fixed Capital Formation (GDP Constant 2010 Prices)	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia

Table 1.
Data Description (Continued)

Variables	Description	Frequency	Source
X	Total exports of goods and services (billion USD)	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia
M	Total imports of goods and services (billion USD)	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia
X-M	Percentage change in net spending from overseas (*X - M*)	Quarterly [2008Q1 – 2019Q4]	Authors calculation
GovS	Percentage change in government spending [*government spending* = *GDP*– (*consumption*+*investment*+ (*exports-imports*))]	Quarterly [2008Q1 – 2019Q4]	Authors calculation
PO	Palm Oil Price (USD per metric ton)	Quarterly [2008Q1 – 2019Q4]	International Monetary Fund e-library
Control variables			
CPI	Consumer price index (CPI) measure of prices paid by consumers for a market basket of consumer goods and services	Data is sourced in monthly frequency and has been converted into quarterly frequency Quarterly [2008Q1 – 2019Q4]	International Monetary Fund e-library
INF	Percentage change in CPI	Quarterly [2008Q1 – 2019Q4]	Authors computation
FDI	Percentage change in foreign direct investment.	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia
EXR	Percentage change in Indonesia's exchange rate in terms of USD.	Quarterly [2008Q1 – 2019Q4]	Bank Indonesia

B. Methodology

In order to examine the predictability of Indonesia's aggregate demand, we use the following time-series predictive regression model:

$$GDP_t = \alpha + \beta PO_{t-1} + \varepsilon_t \qquad (1)$$

Here, GDP_t denotes economic growth in quarter t proxied by the growth rate in real GDP, PO_{t-1} is the one-period lag palm oil price (predictor) variable, and ε_t is the disturbance term. The null hypothesis of no predictability is $Ho : \beta - 0$. In addition, we use *PO* to predict the four major components of aggregate demand (*Consp*, *Invst*, *GovS*, and *X-M*). Therefore, we estimate Equation (1) five times, one model in which *GDP* is the dependent variable and one model for each of the four aggregate demand components. It is important to note that all our dependent variables are taken in percentage growth form.

We use a newly developed estimator proposed by WN (2012, 2015), namely a flexible-generalised-least-squares (WN-FGLS) estimator, to examine the null hypothesis of no predictability. Several studies note the estimator's importance particularly in how it handles data issues such as persistency, endogeneity and heteroscedasticity.[6] These features of data matter because the literature shows that financial time-series data (even at the quarterly frequency) suffer from persistency, endogeneity and heteroscedasticity.[7]

III. MAIN FINDINGS

A. Preliminary results

We begin by considering the descriptive statistics We read selected results from Table 2, where we report statistical features of data. We note that the mean of aggregate demand components, except *GovS*, is positive. The mean value of *PO* is \$735.29 (per metric ton), and its standard deviation is \$194.87 (per metric ton). For all aggregate demand components (except for *X-M*), the skewness statistic has a negative sign, implying a left-tailed distribution. Two aggregate demand components (*GovS* and *X-M*) have a relatively higher kurtosis statistic compared to *GDP*, *Consp*, and *Invst*. However, for all aggregate demand variables, the kurtosis statistic is greater than 3, implying a leptokurtic distribution. On the other hand, in the case of *PO*, the skewness and kurtosis statistics are 0.72 and 2.61, respectively. The main implication of these descriptive statistics is that the distribution of all variables is non-normal.

Table 2.
Descriptive Statistics

This table reports selected descriptive statistics of aggregate demand components and palm oil price. The detailed definition of variables is provided in Table 1.

	GDP	Consp	Invst	GovS	X-M	PO
Mean	0.5516	0.4623	0.8791	-76.6623	1110.3970	735.2957
Median	1.0898	0.8420	1.7753	2.0962	-47.7226	687.7028
Maximum	12.8744	15.3988	15.0501	58.1262	55622.8300	1209.7850
Minimum	-19.3974	-14.7921	-15.5679	-2090.9240	-737.9636	454.0657
Std. Dev.	5.1181	4.7188	5.7920	375.3110	8126.2570	194.8730
Skewness	-1.1004	-0.2145	-0.3701	-4.6594	6.6299	0.7190
Kurtosis	6.8208	5.9019	3.8690	23.4164	44.9787	2.6097

In unreported (un-tabulated) results, we note that for all aggregate demand components the first order autoregressive coefficient is less than 0.5; however, in the case of predictor variable (*PO*), the coefficient is 0.84. This implies that the predictor variable is highly persistent. The ADF unit root test suggests that the null hypothesis of unit root is comfortably rejected at 1% level for all aggregate

[6] The discussion on the derivation of the WN-FGLS estimator is not provided in detail because the model has been extensively explained in the original paper of Westerlund and Narayan (2012, 2015). Furthermore, several studies (see for instance, Devpura et al., 2018; Sharma, 2016; Sharma, 2019; Phan, Sharma, Tran, 2018) have adopted the WN-FGLS estimator and have provided a summary of the model derivations. We refer interested readers to these papers.

[7] Sharma, Tobing, and Azwar (2018) provide an extensive discussion on the features of time-series macroeconomics data for Indonesia.

demand variables, but the same is not true in the case of *PO*, which follows a non-stationary process. We also test the null hypothesis of no autoregressive conditional heteroskedasticity. The null hypothesis is rejected at the 1% significance level only in the case of *GovS*. This implies that all aggregate demand (except *GovS*) components and the predator variable, *PO*, are heteroskedastic.

We conclude with a test of predictor endogeneity using the test of Westerlund and Narayan (2015). We find that *PO* is endogenous when the it is used to predict *GDP* and *Consp*. In the remaining three models, that is, when *Invst*, *GovS*, and *X-M* are predicted, we find that *PO* is not endogenous. Overall, this analysis confirms that the commonly statistical issues faced by predictive regression models are active in our data sample and it is important to model persistency, endogeneity and heteroskedasticity in test for predictability of aggregate demand.

B. Main results

Now we turn to our main findings obtained by estimating Equation (1). Results reported in Table 3 are obtained using two criteria. First, we obtain results using quarterly (Panel A) and month data (Panel B). Note our data series are sourced at quarterly frequency. However, due to a smaller number of observations, we convert quarterly series to monthly series using the linear frequency conversion method.[8] This is done to see if our results hold if we use more observations for empirical analysis. Second, we report the WN-FGLS coefficient and its corresponding *p*-values at the one-period-ahead (h = 1) three-periods-ahead (h = 3), and six-periods-ahead (h = 6) for all predictability models using data at both quarterly and monthly frequencies.

Table 3.
In-sample Predictability Test Results

Here, we report in-sample predictability test results obtained using WN (2012, 2015) time-series predictability model. More specifically, we report the WN-FGLS estimator with its corresponding *p*-values which determines the null hypothesis of "no predictability". The results are reported for a one-period (h = 1), three-period (h = 3) and six-period (h = 6) forecasting horizons for quarterly (Panel A) and monthly (Panel B) datasets. Finally, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quarterly			Panel B: Monthly		
	h = 1			**h = 1**	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP	0.1349	0.2571	*GDP*	0.0603	0.5224
Consp	-0.0126	0.8903	*Consp*	-0.1120	0.2294
Invst	0.0577	0.5619	*Invst*	0.0176	0.8381
GovS	-0.0304	0.8017	*GovS*	0.0283	0.8222
X-M	-0.0764	0.3585	*X-M*	-0.0535*	0.0951

8 Data are converted from low (quarterly) to high (monthly) frequency using the linear frequency method programmed in the EVIEWS software.

Table 3.
In-sample Predictability Test Results (Continued)

Panel A: Quarterly			Panel B: Monthly		
	h = 3			*h* = 3	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP	-0.2955**	0.0148	*GDP*	-0.1294	0.3141
Consp	-0.2353***	0.0087	*Consp*	-0.2725**	0.0314
Invst	-0.2907**	0.0233	*Invst*	-0.1735	0.1397
GovS	-0.1451	0.2546	*GovS*	0.0352	0.7951
X-M	0.0292	0.6227	*X-M*	-0.0613*	0.0983
	h = 6			*h* = 6	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP	-0.1665	0.3449	*GDP*	-0.3299***	0.0049
Consp	-0.1132	0.5066	*Consp*	-0.3368***	0.0009
Invst	-0.1359	0.3989	*Invst*	-0.3146**	0.0171
GovS	-0.0035	0.5940	*GovS*	-0.1028	0.2323
X-M	-0.0602	0.4123	*X-M*	-0.0051	0.8646

Our findings are as follows. We begin with results in Panel A, which shows that *PO* is a statistically significant predictor of *GDP* only when we consider the three-periods-ahead forecasting horizon. In the case of $h = 1$ and $h = 6$, we note that *PO* is an insignificant predictor of *GDP*. Next, we examine whether *PO* predicts the four components of aggregate demand. Overall, we find that *PO* significantly predicts *Consp* and *Invst* in the case of $h = 3$. Moreover, we do not find any statistically significant evidence of *PO* as a predictor of the components of aggregate demand.

Additionally, we consider results using monthly data as reported in Panel B. We do not see much difference in our findings. More specifically, we report *PO* as a statistically significant predictor of *GDP* at $h = 6$. This is expected as we have now moved from a low to a high data frequency, and therefore, the significance observed using data at the two frequencies will differ for different forecasting horizons. In fact, any significant results observed at lower forecasting horizons using quarterly data should be collaborated with higher forecasting horizon in the case of monthly data. This is exactly what we observe from the results. More specifically, when we consider quarterly data, most of the significant results are obtained at $h = 3$, whereas, in the case of monthly data, the significant results are obtained at $h = 6$. We make the same observation when predicting *Consp* and *Invst*. In other words, *PO* significantly predicts *Consp* and *Invst* at $h - 6$ when using monthly data. Additionally, we note that *PO* is found to be a statistically significant predictor of *X-M* at $h = 1$ and $h = 3$. Overall, we conclude that, irrespective of data frequency and forecasting horizons, *PO* is found to be a statistically insignificant predictor of *GovS*, whereas, in other cases (such as when predicting *GDP*, *Consp*, *Invst*, and *X-M*), we find some evidence of significant predictability.

Next, we report out-of-sample evaluation results. More specifically, here we examine the importance of *PO* in forecasting aggregate demand components vis-à-vis the constant model. Our approach is as follows. We use 50% and 25% in-sample periods to generate recursive forecasts of aggregate demand components for the remaining 50% and 75% of the sample, respectively. We use two out-of-sample forecasting statistics, namely the OOSR2 and the RTU, such that they allow us to compare the *PO*-based predictability model with a constant-only model. The difference in the mean squared errors resulting from the *PO*-based forecasting model and the constant model is captured by OOSR2. While RTU is simply a ratio of Theil U statistics from *PO*-based predictability model relative to Theil U statistics from constant model. The construction of these statistics is further explained in Sharma (2019). The OOSR2 and RTU statistics imply that when OOSR2>0 and RTU<1, our *PO*-based predictability model is preferred over the constant model. Additionally, once again we have estimated an in-sample model using three forecasting horizons (h = 1, h = 3 and h = 6) and produced results using data at both quarterly and monthly frequencies. These statistics are reported in Table 4.

We focus first on quarterly data results from Panel A of Table 4. We note that irrespective of the out-of-sample period and forecasting horizon used, RTU <1 is recorded in the case of *GDP* and *Consp*, supporting the *PO*-based model. On the other hand, OOSR2 statistics are positive in the case of *Consp* and negative for *GDP*. Additionally, with respect to other three aggregate demand components (*Invst*, *GovS*, and *X-M*), we find mixed evidence in support of our proposed *PO*-based forecasting model. For instance, in the case of *GovS*, we find that the *PO*-based predictability model is superior to the constant-only model at forecasting horizons, h = 1, h = 3 and h = 6. In the case of *GovS*, we find that both statistics support our *PO*-based model. However, in the case of *Invst*, RTU statistics are in favour of *PO*-based predictability model but this evidence is not robust when using the OOSR2 statistics.

Results in Panel B reproduces results using monthly data. Our econometric approach remains same as when we used quarterly data. Results for *GDP* are insensitive to the use of different data frequencies. On the other hand, for four aggregate demand components, the evidence in support of the *PO*-based predictability model is dependent either on the forecasting horizon, the out-of-sample periods, or on the two forecasting evaluations statistics.

Our findings can be concluded as follows: (1) There is strong evidence that *PO*-based predictability model outperforms the constant-model consistently for *GDP* followed by *Consp*; and (2) findings in support of the *PO*-based predictability model for *Invst*, *GovS*, and *X-M*, are dependent either on different forecasting horizons; the two out-of-sample periods (50% and 25%); and the two forecasting evaluation statistics (RTU and OOSR2). Overall, our findings imply that *PO* has significant predictability power in order to predict aggregate demand proxied using *GDP*. However, when we disaggregate the components of aggregate demand, we find strong evidence in support of *PO* as a statistically significant predictor for *Consp* and to a limited extent for other aggregate demand variables (*GovS*, *Invst*, and *X-M*).

Table 4.
Out-of-sample Evaluations

Here, we report results for two measures of out-of-sample predictability namely relative Theil U (RTU) and out-of-sample R-squared (OOSR2) statistics based on quarterly (Panel A) and monthly dataset (Panel B). The RTU and OOSR2 statistics measures the performance of our predictive regression model vis-à-vis the constant-only model. The out-of-sample period considered are 50% and 25% of the sample. The results are reported for a one-period ($h = 1$), three-period ($h = 3$) and six-period ($h = 6$) forecasting horizons.

Panel A: Quarterly												
	OOS = 50%						OOS = 25%					
	$h = 1$		$h = 3$		$h = 6$		$h = 1$		$h = 3$		$h = 6$	
Variables	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**
GDP	0.9166	-0.0888	0.7035	-0.2129	0.7715	-0.2242	0.9890	-0.1962	0.7179	-0.1308	0.8376	-0.0416
Consp	0.7639	0.0383	0.5887	0.0249	0.7394	-0.0397	0.7857	-0.0857	0.5595	0.0399	0.6938	0.1245
Invst	1.0630	-0.0701	0.7220	-0.1263	0.7949	-0.2079	1.0862	-0.0825	0.7556	-0.0215	0.7925	-0.0018
GovS	1.0081	-0.7191	0.9631	0.5763	0.6935	0.8786	1.0025	-0.1685	0.9045	0.5462	0.6150	0.8957
X-M	1.0003	0.0000	1.0027	0.0002	1.0012	0.0006	1.0232	-0.8831	1.0062	-0.1674	1.0222	-1.1641
Panel B: Monthly												
	$h = 1$		$h = 3$		$h = 6$		$h = 1$		$h = 3$		$h = 6$	
Variables	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**	**RTU**	**OOSR2**
GDP	0.8711	-0.1045	0.7594	-0.1021	0.6886	-0.2786	0.9732	-0.2134	0.8265	-0.0930	0.7051	-0.1382
Consp	0.8217	-0.0778	0.6842	-0.1748	0.6618	-0.2362	0.7371	0.0173	0.5432	0.0775	0.5397	0.0094
Invst	1.0383	-0.0882	0.7961	-0.0631	0.7266	-0.1675	1.0422	-0.0666	0.8135	0.0278	0.7145	0.0152
GovS	1.0267	-1.0734	1.0294	-1.1622	0.7821	0.7585	1.0154	-0.5417	1.0177	-0.5628	0.7164	0.7288
X-M	0.9968	-0.0005	1.0068	0.0011	1.0047	0.0003	0.8759	-0.1582	0.8832	-0.2190	0.9545	-0.0278

IV. ROBUSTNESS CHECKS

In this section, we undertake robustness tests. More specifically, we will use adjusted-GDP as a dependent variable in our proposed predictability model depicted by Equation (1). To do so, we have considered three control variables, namely *EXR*, *FDI*, and *INF* to adjust *GDP*. Our approach includes following three steps. In step one, we estimate the following regression:

$$GDP_t = \alpha + \gamma Con_{t-1} + \varphi_t \tag{2}$$

Here, GDP_t denotes Indonesia's economic growth and *Con* denotes a control variable. Equation (2) is a bivariate model and, therefore, it will be estimated individually for each control variable (*EXR*, *FDI*, and *INF*).

In the second step, we extract the estimated constant, $\hat{\alpha}$, and the residuals, $\hat{\varphi}$, from Equation (2). The adjusted-GDP (denoted by *GDP**) is then computed as follows:

$$GDP^* = \hat{\alpha} + \hat{\varphi} \tag{3}$$

In the final step, our predictability model remains same as Equation (1), however, we will use *GDP** instead of *GDP* as the dependent variable. Here, *GDP** denotes three GDP-adjusted series, namely *GDP_EXR*, *GDP_FDI*, and *GDP_INF*.

We have considered robustness check for both in-sample and out-of-sample evaluations. Our approach remains the same as discussed in Section III. We begin with reading results for in-sample predictability from Table 5. We find that *PO* is a statistically significant predictor of adjusted-GDP (namely *GDP_FDI* and *GDP_INF*) at $h = 3$ when we consider quarterly data. On the other hand, when monthly data is used, *PO* is found to be a statistically significant predictor of three adjusted-GDP series (*GDP_EXR*, *GDP_FDI*, and *GDP_INF*) at $h = 6$. Overall, we conclude that our findings remain unchanged irrespective of the *GDP* series used for predictability. In other words, our results imply that *PO* is a statistically significant predictor of *GDP* (adjusted-GDP) at $h = 3$ and $h = 6$, when we use data at quarterly and monthly frequencies, respectively.

Finally, in unreported results, we also undertake a robustness test for different out-of-sample periods. The main conclusions do not change. Tabulated results are available upon request.

Table 5.
Robustness Check for in-sample Predictability Test

In this table, we report in-sample predictability test results for adjusted-GDP. We have used three control variables, namely Exchange Rate (EXR), Foreign Direct Investment (FDI), and Inflation Rate (INF) to adjust GDP. Our approach includes following two steps. First, we estimate the following regression model: $GDP_t = \alpha + \gamma Con_{t-1} + \varphi_t$. Here, *GDP* denotes percentage change in real GDP and *Con* denotes control variable. Second, we extract constant, $\widehat{\alpha}$ and residual, $\widehat{\varphi}_t$, from estimated model and the sum of $\widehat{\alpha}$ and $\widehat{\varphi}_t$ provides us with adjusted-GDP. Given, we have three control variables, we conduct this approach three times for each control variable and obtain three adjusted-GDP series, namely GDP_EXR, GDP_FDI, and GDP_INF. Finally, we estimate our predictability model using these adjusted-GDP series. Finally, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quarterly			Panel B: Monthly		
	$h = 1$			$h = 1$	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP_EXR	0.3190***	0.0049	*GDP_EXR*	0.1628*	0.0758
GDP_FDI	0.1309	0.2944	*GDP_FDI*	0.0651	0.4990
GDP_INF	0.2562	0.1076	*GDP_INF*	0.1109	0.2617
	$h = 3$			$h = 3$	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP_EXR	-0.0939	0.4512	*GDP_EXR*	-0.0265	0.8358
GDP_FDI	-0.2945**	0.0147	*GDP_FDI*	-0.1316	0.3047
GDP_INF	-0.1979**	0.0475	*GDP_INF*	-0.0847	0.4800
	$h = 6$			$h = 6$	
Variables	**coefficient**	***p*-value**	**Variables**	**coefficient**	***p*-value**
GDP_EXR	-0.0408	0.8096	*GDP_EXR*	-0.2333*	0.0565
GDP_FDI	-0.1739	0.3166	*GDP_FDI*	-0.3306***	0.0047
GDP_INF	0.3622	0.1683	*GDP_INF*	-0.2992***	0.0080

V. IMPLICATIONS OF OUR FINDINGS

One aspect of our work that we would like to draw attention to is the role that the current COVID-19 pandemic is playing in influencing both the financial and economic systems globally. There is an emerging literature on this; see Ali, Alam, and Rizvi (2020); Fu and Shen (2020); Qin, Zhang, and Su (2020); Iyke (2020a,b); Gu, Ying, Zhang and Tao (2020); Haroon and Rizvi (2020a, b); He, Sun, Zhang, and Li (2020); He, Niu, Sun and Li (2020); Liu, Sun and Zhang (2020); C.T. and Prabheesh (2020); Chen, Liu and Zhao (2020); Mishra, Rath and Das (2020); Ming, Zhou, Ai, Bi, and Zhong (2020); Phan and Narayan (2020); Salisu and Akanni (2020); Shen, Fu, Pan, Yu, and Chen (2020); Wang, Zhang, Wang and Fu (2020); Yue, Korkmaz, and Zhou (2020); Yu, Xiao and Li (2020), Liu, Pan and Yin (2020); Qin, Huang, Shen, and Fu (2020); and Xiong, Wu, Hou, and Zhang (2020); and Zhang, Hu and Ji (2020).

A subset of this literature has shown that oil prices due to COVID-19 have created financial and economic market uncertainties. These uncertainties are likely to have implications for forecasting macroeconomic time-series data. Our study does not consider the effects of COVID-19 in predicting aggregate demand for Indonesia. Future studies should use the above-mentioned studies as a benchmark to explore the implications of forecasting models, including the performance of the WN estimator when faced by a shock such as COVID-19.

VI. CONCLUSION

This study undertakes an in-sample and out-of-sample predictability analysis of aggregate demand (real GDP) and its four components (namely *Consp*, *Invst*, *GovS*, and *X-M*) based on *PO*. Our data for Indonesia cover the 2008 to 2019 period. We unveil the following findings. First, we show that *PO* is a statistically significant predictor of *GDP*. However, our results are dependent on different forecasting horizons and different data frequencies. More specifically, when we use data at quarterly frequency, *PO* significantly predicts *GDP* at $h = 3$, whereas at monthly frequencies, the significant evidence of predictability is observed at $h = 6$. Additionally, we use two out-of-sample evaluation statistics, OOSR2 and RTU and document that the *PO*-based predictability model outperforms the benchmark constant-only model using RTU statistics; however, the same cannot be concluded using OOSR2 statistics.

In addition, we examine whether the four components of aggregate demand are predictable using *PO*. Overall, we document strong evidence of predictability in the case of *Consp* compared to *Invst*, *GovS*, and *X-M*. This finding implies that *Consp* plays a major role in moving aggregate demand with respect to *PO*.

REFERENCES

Ali, M., Alam, N., Rizvi, S.A.R. (2020). Coronavirus (COVID-19) – An Epidemic or Pandemic for Financial Markets. *Journal of Behavioral and Experimental Finance*, 100341.

Apergis, N., and Apergis, E. (2020). Can the COVID-19 Pandemic and oil Prices Drive The US Partisan Conflict Index. *Energy Research Letters*, 1(1), 13144. https://doi.org/10.46557/001c.13144.

Bittencourt, M. (2012). Inflation and Economic Growth in Latin America: Some Panel Time-Series Evidence. *Economic Modelling,* 29, 333-340.

Burdekin, R.C.K., Denzau, A.T., Keil, M.W., Sitthiyot, T., Willett, T.D. (2004). When Does Inflation Hurt Economic Growth? Different Nonlinearities for Different Economies. *Journal of Macroeconomics,* 26, 519-532.

C.T., V., and Prabheesh, K.P. (2020). Implications of COVID-19 Pandemic on The Global Trade Networks. *Emerging Markets Finance and Trade*, 56, 2408-2421 https://doi.org/10.1080/1540496X.2020.1785426.

Chen, C., Liu, L., and Zhao, N. (2020). Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The Case of COVID-19. *Emerging Markets Finance and Trade*, 56, 2298-2309; https://doi.org/10.1080/1540496X.2020.1787150.

Cooke, M. F. (2012). In the Name Of Poverty Alleviation: Experiments with Oil Palm Smallholders and Customary Land in Sabah, Malaysia. *Asia Pacific Viewpoint*, 53, 240–253.

Devpura, N., and Narayan, P.K. (2020). Hourly Oil Price Volatility: The role of COVID-19. *Energy Research Letters*, 1(2), 13683. https://doi.org/10.46557/001c.13683.

Devpura, N., Narayan, P.K., and Sharma, S.S. (2018). Is Stock Return Predictability Time-Varying? *Journal of International Financial Markets, Institutions & Money*, 52, 152–172.

Directorate General of Estate Crops Indonesia (2017). *Tree Crop Estate Statistics of Indonesia 2015–2017: Palm Oil.* Jakarta: Ministry of Agriculture.

Fu, M., & Shen, H. (2020). COVID-19 and Corporate Performance in The Energy Industry. *Energy Research Letters*, 1, 12967. https://doi.org/10.46557/001c.12967

Gil-Alana, L.A., and Monge, M. (2020). Crude Oil Prices and COVID-19: Persistence of the shock. *Energy Research Letters*, 1(1), 13200. https://doi.org/10.46557/001c.13200.

Gu, X., Ying, S., Zhang, W., and Tao, Y. (2020). How Do Firms Respond To COVID-19? First Evidence from Suzhou, China. *Emerging Markets Finance and Trade*; 56, 2181-2197; https://doi.org/10.1080/1540496X.2020.1789455.

Gunby, P., Jin, Y., Reed, W.R. (2017). Did FDI Really Cause Chinese Economic Growth? A Meta-Analysis. *World Development*, 90, 242-255.

Hamilton, J.D. (1983). Oil and the Macroeconomy Since World War II. *Journal of Political Economics* 91, 228-248.

Hamilton, J.D. (2003). What Is An Oil Shock? *Journal of Econometrics*, 113, 363-398.

Haroon, O., Rizvi, S.A.R., (2020a). COVID-19: Media Coverage and Financial Markets Behaviour - A Sectoral Inquiry. *Journal of Behavioral and Experimental Finance*, 100343.

Haroon, O., and Rizvi, S.A.R. (2020b). Flatten The Curve and Stock Market Liquidity—An Inquiry Into Emerging Economies. *Emerging Markets Finance and Trade*, 56, 2151-2161; https://doi.org/10.1080/1540496X.2020.1784716.

He, P., Niu, H., Sun, Z., and Li, T. (2020). Accounting Index of COVID-19 Impact On Chinese Industries: A Case Study Using Big Data Portrait Analysis. *Emerging Markets Finance and Trade*, 56, 2332-2349; https://doi.org/10.1080/1540496X.2020.1785866.

He, P., Sun, Y., Zhang, Y., and Li, T. (2020). COVID-19's Impact on Stock Prices across Different Sectors—An Event Study Based on The Chinese Stock Market. *Emerging Markets Finance and Trade*, 56, 2198-2212; https://doi.org/10.1080/1540496X.2020.1785865

Huang, F-S. (2017). Explaining The Nonlinearity Of Inflation And Economic Growth: The Role of Tax Evasion. *International Review of Economics and Finance*, 52, 436-445.

Huang, W., and Zheng, Y. (2020). COVID-19: Structural Changes in the Relationship Between Investor Sentiment and Crude Oil Futures Price. *Energy Research Letters*, 1(2), 13685. https://doi.org/10.46557/001c.13685.

Iyke, B. (2020a). COVID-19: The Reaction of US Oil and Gas Producers to the Pandemic. *Energy Research Letters*, 1(2), 13912. https://doi.org/10.46557/001c.13912.

Iyke, B.N. (2020b). The Disease Outbreak Channel of Exchange Rate Return Predictability: Evidence from COVID-19. *Emerging Markets Finance and Trade*, 56, 2277-2297; https://doi.org/10.1080/1540496X.2020.1784718.

Kadarusman, Y., B., Pramudya, E., P. (2019). The Effects of India and China On The Sustainability of The Palm Oil Production In Indonesia: Towards A Better Understanding Of The Dynamics of Regional Sustainability Governance. *Sustainable Development*, 27, 898-909.

Kilian, I. (2011). Are The Responses of the US Economy Asymmetric in Energy Price Increases and Decreases? *Quantitative Economics*, 2, 419-453.

Lee, J., Yue, C. (2017). Impacts of the US Dollar (USD) Exchange Rate on Economic Growth and the Environment in the United States. *Energy Economics*, 64, 170 – 176.

Li, T. M. (2016). Situating Transmigration in Indonesia's Oil Palm Labour Regime. In R. Cramb & J. McCarthy (Eds.), *the Oil Palm Complex: Smallholders, Agribusiness and the State in Indonesia and Malaysia* (pp. 354–377). Singapore: NUS Press.

Liu, D., Sun, W., and Zhang, X. (2020). Is the Chinese Economy Well Positioned to Fight The COVID-19 Pandemic? The Financial Cycle Perspective. *Emerging Markets Finance and Trade*, 56, 2259-2276; https://doi.org/10.1080/1540496X.2020.1787152.

Liu, L., Wang, E. Z., & Lee, C. C. (2020). Impact of the COVID-19 Pandemic on the Crude Oil and Stock Markets in the US: A Time-Varying Analysis. *Energy Research Letters*, 1, 13154. https://doi.org/10.46557/001c.13154.

Liu, T., Pan, B., and Yin, Z. (2020). Pandemic, Mobile Payment, and Household Consumption: Micro-Evidence from China. *Emerging Markets Finance and Trade*, 56, 2378-2389; https://doi.org/10.1080/1540496X.2020.1788539.

Ming, W., Zhou, Z., Ai, H., Bi, H., and Zhong, Y. (2020). COVID-19 and Air Quality: Evidence from China. *Emerging Markets Finance and Trade*, 56, 2422-2442; https://doi.org/10.1080/1540496X.2020.1790353.

Mishra, A.K., Rath, B.N., and Dash, A.K. (2020). Does the Indian Financial Market Nosedive Because of The COVID-19 Outbreak, in Comparison to After Demonetisation and The GST? *Emerging Markets Finance and Trade*, 56, 2162-2180; https://doi.org/10/1080/1540496X.2020.1785425.

Narayan, P. K. (2020). Oil Price News and COVID-19 - Is There Any Connection?. *Energy Research Letters*, 1, 13176. https://doi.org/10.46557/001c.13176.

Narayan, P.K., Sharma, S., Poon, W.C., Westerlund, J. (2014). Do Oil Prices Predict Economic Growth? New Global Evidence. *Energy Economics*, 4, 137-146.

Obidzinski, K., Andriani, R., Komarudin, H., & Andrianto, A. (2012). Environmental and Social Impacts of Oil Palm Plantations and Their Implications for Biofuel Production in Indonesia. *Ecology and Society*, 17, 25.

Obidzinski, K., Dermawan, A., & Hadianto, A. (2014). Oil Palm Plantation Investments in Indonesia's Forest Frontiers: Limited Economic Multipliers and Uncertain Benefits for Local Communities. *Environment, Development and Sustainability*, 16, 1177–1196.

Phan, D.H.B., and Narayan, P.K. (2020). Country Responses and the Reaction of The Stock Market to COVID-19—A Preliminary Exposition. *Emerging Markets Finance and Trade*; 56, 2138-2150; https://doi.org/10.1080/1540496X.2020.1784719

Phan, D.H.B., Sharma, S.S., Tran, V.T. (2018). Can Economic Policy Uncertainty Predict Stock Returns? Global Evidence. *Journal of International Financial Markets, Institutions and Money*, 55, 134-150.

Potter, L. (2012). New Transmigration 'Paradigm' in Indonesia: Examples from Kalimantan. *Asia Pacific Viewpoint*, 53, 272–287.

Prabheesh, K.P., Padhan, R., and Garg, B. (2020). COVID-19 and the Oil Price—Stock Market Nexus: Evidence From Net Oil-Importing Countries. *Energy Research Letters*, 1(2), 13745. https://doi.org/10.46557/001c.13745

Qin, M., Zhang, Y. C., & Su, C. W. (2020). The Essential Role of Pandemics: A Fresh Insight into the Oil Market. *Energy Research Letters*, 1, 13166. https://doi.org/10.46557/001c.13166

Qin, X., Huang, G., Shen, H., and Fu, M. (2020). COVID-19 Pandemic and Firm-Level Cash Holding—Moderating Effect Of Goodwill and Goodwill Impairment. *Emerging Markets Finance and Trade*, 56,2243-2258; https://doi.org/10.1080/1540496X.2020.1785864

Salisu, A.A., and Adediran, I.A. (2020). Uncertainty Due to Infectious Diseases and Energy Market Volatility. *Energy Research Letters*, 1(2), 14185. https://doi.org/10.46557/001c.14185

Salisu, A.A., and Akanni, L.O. (2020). Constructing a Global Fear Index for COVID-19 Pandemic. *Emerging Markets Finance and Trade*, 56, 2213-2230; https://doi.org/10.1080/1540496X.2020.1785424

Santika, T., Wilson, K.A., Budiharta, S., Law, E.A., Poh, T.M., Ancrenaz, M., Struebig, M.J., Meijaard, E. (2019). Does Oil Palm Agriculture Help Alleviate Poverty? A Multidimentional Counterfactual Assessment of Oil Palm Development in Indonesia. *World Development*, 120, 105-117.

Sharma, S. S. (2016). Can Consumer Price Index Predict Gold Price Returns? *Economic modelling*, 55, 269-278.

Sharma, S.S. (2019). Which Variables Predict Indonesia's Inflation? *Bulletin of Monetary Economics and Banking*, 22, 87-102.

Sharma, S.S., Tobing, L., Azwar, P. (2018). Understanding Indonesia's Macroeconomic Data: What Do We Know and What Are the Implications? *Bulletin of Monetary Economics and Banking*, 21, 229-264.

Shen, H., Fu, M., Pan, H., Yu, Z., and Chen, Y. (2020). The Impact of the COVID-19 Pandemic on Firm Performance. *Emerging Markets Finance and Trade*; https://doi.org/10.1080/1540496X.2020.1785863.

United States Department of Agriculture, F.A. Service (Eds.) (2020). *Oilseeds and Products Annual*. Report Number ID2020_0004, United States Department of Agriculture, Washington, DC, USA.

Vinayagathasan, T. (2013). Inflation and Economic Growth: A Dynamic Panel Threshold Analysis of Asian Economies. *Journal of Asian Economics*, 26, 31-41.

Wang, Y., Zhang, D., Wang, X., and Fu, Q. (2020). How Does COVID-19 Affect China's Insurance Market? *Emerging Markets Finance and Trade*; https://doi.org/10.1080/1540496X.2020.1791074.

Westerlund, J., and Narayan, P.K. (2012). Does the Choice of Estimator Matter When Forecasting Returns? *Journal of Banking and Finance*, 36, 2632-2640.

Westerlund, J., and Narayan, P.K. (2015). Testing for Predictability in Conditionally Heteroskedastic Stock Returns. *Journal of Financial Econometrics*, 13, 342-375.

Xiong, H., Wu, Z., Hou, F., and Zhang, J. (2020). Which Firm-Specific Characteristics Affect The Market Reaction of Chinese Listed Companies to The COVID-19 Pandemic? *Emerging Markets Finance and Trade*, 56, 2231-2242; https://doi.org/10.1080/1540496X.2020.1787151.

Yu, Z., Xiao, Y., and Li, Y. (2020). The Response of the Labor Force Participation Rate to an Epidemic: Evidence from a Cross-Country Analysis. *Emerging Markets Finance and Trade*, 56, 2390-2407; https://doi.org/10.1080/1540496X.2020.1784717.

Yue, P., Korkmaz, A.G., and Zhou, H. (2020). Household Financial Decision Making Amidst the COVID-19 Pandemic. *Emerging Markets Finance and Trade*, 56, 2363-2377; https://doi.org/10.1080/1540496X.2020.1787149.

Zhang, D., Hu, M., Ji, Q. (2020). Financial Markets Under the Global Pandemic of COVID-19. *Finance Research Letters*, 101528.