Bulletin of Monetary Economics and Banking, Vol. 24 No. 2, 2021, pp. 169 - 180
p-ISSN: 1410 8046, e-ISSN: 2460 9196

PALM OIL PRICE–EXCHANGE RATE NEXUS IN INDONESIA AND MALAYSIA

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ABSTRACT

In this study, we extend the literature analyzing the predictive content of commodity prices for exchange rates by examining the role of palm oil price. Our analysis focuses on Indonesia and Malaysia, the two top producers and exporters of palm oil, and utilizes daily data covering the period from December 12, 2011 to March 29, 2021, which is partitioned into two sub-samples based on the COVID-19 pandemic. Relying on a methodology that accommodates some salient features of the variables of interest, we find that on average the in-sample predictability of palm oil price for exchange rate movements is stronger for Indonesia than for Malaysia. While Indonesia's exchange rate appreciates due to a rise in palm oil price regardless of the choice of predictive model, Malaysia's exchange rate only appreciates after adjusting for oil price. However, both exchange rates do not seem to be resilient to the COVID-19 pandemic as they depreciate amidst dwindling palm oil price. Similar outcomes are observed for the out-of-sample predictability analysis. We highlight avenues for future research and the implications of our results for portfolio diversification strategies.

Keywords: Palm oil; Exchange rate; Predictability; Forecast evaluation; COVID-19.
JEL Classifications: C53; D81; F31; Q02.

Article history:
Received : January 23, 2021
Revised : April 27, 2021
Accepted : May 10, 2021
Available Online : June 30, 2021

https://doi.org/10.21098/bemp.v24i2.1620

I. INTRODUCTION

In this study, we extend the literature on exchange rate predictability by exploring the predictive content of palm oil price for the exchange rates of Indonesia and Malaysia— the two top producers and exporters of palm oil in the world.[1] The work of Meese and Rogoff (1983)[2] provides a strong motivation for revisiting the nexus between commodity prices and exchange rate (see for a review, Salisu *et al*., 2019a; Salisu *et al*., 2020) and given the significance of palm oil to the global economy—it accounts for 35% of the world's vegetable oil demand[3] and is a source of foreign exchange to some emerging economies such as Indonesia and Malaysia,[4] it will not be out of place to expect some co-movements between palm oil and exchange rates, particularly for the countries mentioned (see Figures 1 and 2). Accordingly, we hypothesize that an increase in the price of palm oil will boost the current account balance of palm oil-exporting countries, causing their currencies to appreciate, while currencies of palm oil-importing countries depreciate, *ceteris paribus*. We test this hypothesis using a predictability model that accommodates the salient features of the variables of interest, such as persistence, endogeneity and conditional heteroscedasticity (see Westerlund & Narayan, 2012; 2015),[5] in addition to extending the analysis to include out-of-sample forecasts. We also examine the role of the COVID-19 pandemic in the nexus,[6] by considering the non-pharmaceutical measures such as the social distancing, isolation and quarantine, physical distancing, use of face masks, hand hygiene, total lockdown, among others, which undermined the supply of and the demand for palm oil[7] with probable implications on the flow of foreign exchange receipts from its export. Consequently, we further partition our data sample into pre-COVID-19 and COVID-19 samples and thereafter we render distinct analyses for them in order to tease out the role of the pandemic in influencing the palm oil–exchange rate predictability relationship.

Against this backdrop, we make two contributions to the literature, one of which is the extension of the literature on commodity–exchange rate nexus to include another important commodity price, palm oil, particularly from the perspective of its contribution to foreign exchange earnings of its exporters. While

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1 See https://www.indexmundi.com/agriculture/?commodity=palm-oil&graph=exports

2 This study compares the out-of-sample fit of various structural and time-series exchange rate models and finds that the random walk model performs no worse than any estimated univariate time series model for various dollar exchange rates. In other words, various standard models fail to yield any improvement over the random walk model for exchange rates.

3 https://www.wwf.org.uk/updates/8-things-know-about-palm-oil

4 Indonesia was ranked as the largest exporter of palm oil in 2019, earning US$10.4 billion in foreign exchange from palm oil exporting in that year, while Malaysia was ranked second, earning $8.3 billion from exporting of palm oil (see https://www.worldstopexports.com/palm-oil-exports-by-country/).

5 A number of studies involved in return predictability have demonstrated that accounting for these salient features improves forecast outcomes (see for example, Bannigidadmath and Narayan, 2015; Narayan and Gupta, 2015; Phan et al., 2015; Salisu et al., 2019b,c; Sharma et al., 2019).

6 Quite a number of studies have established a strong link between exchange rate and the COVID-19 pandemic (see Iyke, 2020; Iyke & Ho, 2021a; Narayan 2020a, b; Narayan et al., 2020a), although they only test for in-saple predictability. Evidence of predictability in-sample does not mean out-of-sample predictability.

7 See https://www.tridge.com/stories/palm-oil-prices-rise-to-nine-year-high-in-2021;https://biofuels-news.com/news/palm-oil-prices-to-fall-amid-coronavirus-uncertainty-globally/

we acknowledge the work of Aziz and Applanaidu (2017) on the same countries, we extend this study to include the out-of-sample predictability contents of palm oil price for their exchange rates' movements because reliance on in-sample predictability may lead to biased outcomes (see Campbell & Thompson, 2008; Rapach & Zhou, 2013). Second, we account for the role of COVID-19 pandemic in the nexus by partitioning the data into pre-COVID-19 and COVID-19 samples, motivated by the findings of Iyke (2020) and Narayan (2020a, 2020b), which lend support to a strong connection between the COVID-19 pandemic and the exchange rates of both developed and emerging markets.[8]

Finally, for the purpose of robustness, we control for other factors such as crude oil price (see also Ferraro *et al*., 2015; Salisu *et al*., 2019a, 2020) and uncertainty due to pandemics and epidemics (see Feng *et al*., 2021; Iyke, 2020; Narayan 2020a, b; Narayan *et al*., 2020a; Olasehinde-Williams *et al*., 2021), given their strong connections with exchange rates. For instance, a recent study by Salisu *et al*. (2021) provides evidence in support of the inclusion of Uncertainty to Pandemics and Epidemics (*UPE*) in the predictability of exchange rates. This study covers an array of Asian countries including Malaysia and therefore extending it to cover Indonesia would not be inapt. Similarly, studies such as Sharma *et al*. (2019) and Shangle and Solaymani (2020), respectively, provide evidence linking macroeconomic fundamentals in Indonesia and Malaysia to oil price movements; and Nusair and Olson (2021) analyze the role of oil price in selected Asian economies including Indonesia and Malaysia. Beyond the two countries, several studies have demonstrated the link between oil and exchange rate (see Ferraro *et al*., 2015; Salisu *et al*., 2019a, 2020, among others). Therefore, the consideration of the above-mentioned control variables in the predictability of exchange rate is justified.

In all, we find that the predictability of palm oil price for exchange rate movements is stronger for Indonesia than for Malaysia. While the exchange rate of the former appreciates due to a rise in palm oil price regardless of the predictive model, that of the latter only appreciates after controlling for oil price. However, both exchange rates do not seem to be resilient to the COVID-19 pandemic as they depreciate amidst dwindling palm oil price, thus validating the literature on COVID-19 and exchange rates, which suggests adverse effects of the pandemic on exchange rates (see Feng *et al*., 2021; Iyke, 2020; Narayan, 2020a, b; Narayan *et al*., 2020a; Olasehinde-Williams *et al*., 2021). Similar outcomes are observed for the out-of-sample predictability analysis as, on average, the palm oil-based model outperforms the benchmark model for Indonesia based on the full sample and at a longer horizon, while the reverse is the case for Malaysia. Our results advance the literature on exchange rate forecasting by justifying the inclusion of another important commodity price in the predictive model, particularly for countries where such a commodity plays a significant role.

[8] In fact, the literature showing the connection between COVID-19 pandemic and different financial markets is now well developed. Studies such as Salisu & Vo (2020), Salisu et al. (2020), Liu et al. (2020), Salisu & Sikiru (2020) and Sharma (2020), Iyke and Ho (2021b), among others focus on equity markets; for the foreign exchange market, see Iyke (2020), Narayan (2020a&b), Narayan et al. (2020a), among others; for the energy market, see Apergis and Apergis (2020), Devpura and Narayan (2020), Liu et al. (2020), Narayan (2020c), Prabheesh et al. (2020), Salisu and Adediran (2020), among others.

II. DATA AND METHODOLOGY

Our study utilizes daily data on palm oil price and exchange rates of Indonesia and Malaysia covering the period from December 12, 2011 to March 29, 2021, based on data availability; we use the US dollar as the reference currency.[9] In addition, and to bring to the fore, the role of the pandemic on the nexus between the two variables, we further partition the full sample (i.e. from December 12, 2011 to March 29, 2021) into the pre-COVID-19 sample (from December 12, 2011 to December 31, 2019) and COVID-19 sample (from January 01, 2020 to March 29, 2021). Thereafter, we construct a predictive model that hinges on the trade channel (Amano & van Norden, 1998; Bénassy-Quéré *et al*., 2007), whereby an increase in palm oil price will be followed by an appreciation of the currencies of large palm oil exporters (Indonesia and Malaysia, in this case), given an increase in foreign exchange supply, which further strengthens the current accounts and balance of payments of these countries. On the one hand, an increase in palm oil price will cause a depreciation in the currencies of palm oil dependent countries, given the deterioration of the current accounts in order to settle high import bills of palm oil imports, *ceteris paribus*. Thus, we hypothesize a negative relationship between palm oil price and exchange rates of large palm oil exporters. To test this hypothesis, we use a predictive model of exchange rate in which palm oil price serves as a predictor with some salient features of both the predictand and predictor series, such as endogeneity, conditional heteroscedasticity and persistence effects, are accommodated in the estimation process (see Westerlund & Narayan, 2012, 2015)[10] as follows:

$$r_t = \alpha_1 + \sum_{i=1}^{5} \alpha_{2i}^{adj} poil_{t-i} + \lambda(poil_t - \rho poil_{t-1}) + \mu_t \tag{1}$$

where r_t is the predictand series and it is measured as the logarithm return of the exchange rate; α_1 is the constant intercept; *poil* is the predictor series and it is measured as the logarithm of palm oil price; μ_t is the zero mean idiosyncratic error term; and the coefficient α_{2i}^{adj} is the measure of the impact of *poil* on the exchange rate (after accounting for persistence and endogeneity bias)[11], where the underlying null hypothesis of no predictability involves a joint (Wald) test as $\sum_{i=1}^{5} \alpha_{2i}^{adj}$, as we account for a maximum number of five lags given the 5-day daily data frequency and capture more dynamics in the estimation process. Consequently, there are three possibilities involving this test: (i) when $\sum_{i=1}^{5} \alpha_{2i}^{adj} > 0$ (the exchange rate depreciates with an increase in palm oil price); (ii) when $\sum_{i=1}^{5} \alpha_{2i}^{adj} < 0$ (the exchange rate appreciates with an increase in palm oil price); and (iii) when $\sum_{i=1}^{5} \alpha_{2i}^{adj} = 0$ (the exchange rate remains unchanged under the same condition as the previous).

Note that there is no control variable in Equation (1). Therefore, for robustness purposes, we adjust the exchange rate for two other factors—movements in oil

[9] Data used in this study are freely downloadable at investing.com

[10] Recent studies analyzing the nexus between commodity prices and exchange rates have documented the need to account for these effects (see Salisu et al., 2019a; Salisu et al., 2020). Some technical details on how to account for these effects are well documented in Weslerlund & Narayan (WN, 2012, 2015).

[11] See WN (2012, 2015) for a discussion of the methodology.

price and uncertainty due to pandemics and epidemics (*UPE*).[12] As noted earlier, Sharma *et al*. (2019) and Shangle & Solaymani (2020), respectively, show that changes in macroeconomic fundamentals in Indonesia and Malaysia can be linked to oil price fluctuations (see also, Nusair & Olson, 2021). In the same vein, there is an emerging body of literature linking the movements in exchange rates to the COVID-19 pandemic (see Iyke, 2020; Narayan, 2020a,b; Narayan *et al*., 2020a). However, to circumvent parameter proliferation, we follow a two-step procedure when controlling for these additional factors. We first adjust the predictand series for the two factors distinctly by regressing the exchange rate return (r_t) on each of the control variables (i.e. $r_t=\alpha+\beta Control_t+\varepsilon_t$) and thereafter, the adjusted series obtained after the estimation (i.e. $r_t=\alpha+\varepsilon_t$) is used to replace the predictand (r_t - without control variable) in Equation (1) and the analyses are replicated for the adjusted series, accordingly. For ease of reference, we refer to Equation (1) without control variables as Model 1 in the results tables, while the equations that account for oil price and *UPE* are, respectively, denoted as Models 2 and 3.

In the final set up of the methodology, we extend the predictive model as expressed in Equation (1) to include the out-of-sample period and, thereafter, we compare the forecast performance of this (palm oil-based) model with a benchmark (random walk) model. The Clark and West (2007) approach is used to judge the superiority of the models. The forecast analysis is rendered for multiple out-of-sample (15-day, 30-day and 60-day) ahead forecast horizons, while the 75/25 sub-sampling is used for the in-sample/out-of-sample evaluations.

III. EMPIRICAL RESULTS

We begin the discussion of results with the predictability outcome by looking at the statistical significance of the predictability parameter as well as the direction of relationship (see Table 1). We hypothesize that an increase in the price of palm oil would increase the producing/exporting country's dollar receipts to boost its reserves, thus leading to an appreciation in its (domestic) currency relative to the reference currency. Turning to the results, we find that Indonesia's currency appreciates throughout the periods considered, except for the COVID-19 period, irrespective of the predictive model (i.e. with or without adjusting for oil price and *UPE*), while Malaysia's currency only appreciates during the pre-COVID period after adjusting for oil price. Nonetheless, we find consistent results for the two countries during the COVID-19 period, whereby both exchange rates depreciate in response to an increase in palm oil price regardless of the choice of model. This

[12] The *UPE* index developed by Baker et al. (2020) covers all forms of pandemics and epidemics since 1986 and is regularly updated. Therefore, it is not restricted to COVID-19 pandemic. The *UPE* measure utilizes four sets of terms, namely (i) E: economic, economy, financial; (ii) M: "stock market", equity, equities, "Standard and Poors"; (iii) V: volatility, volatile, uncertain, uncertainty, risk, risky; (iv) ID: epidemic, pandemic, virus, flu, disease, coronaviruses (i.e. COVID-19, MERS & SARS), Ebola, H5N1, H1N1 and tracing across approximately 3,000 newspapers, they obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID. A number of studies have documented the suitability of the *UPE* index as a measure of uncertainty associated with all forms of known pandemics and epidemics in predictability analysis (see Salisu & Adediran, 2020; Salisu & Sikiru, 2020, among others).

further asserts the influence of the COVID-19 pandemic on commodity prices (see Elleby *et al*., 2020; Borgards *et al*., 2021) and the exchange rate (see Aslam *et al*., 2020; Narayan, 2020a,b; Narayan *et al*., 2020a). Our results equally attest to the heat felt by the Indonesian economy, which has hitherto experienced stability until the outbreak of the pandemic (see Susilawati *et al*., 2020). In the same vein, our findings in relation to Malaysia show that diversification of export from palm oil to high-tech products (see Rasiah, 2015) could make its exchange rate to respond differently to palm oil fundamentals.

On the relative performance of our predictive model using the Clark & West (2007) test in Table 2, the results obtained somewhat align with the predictability results. Expectedly consistent with predictability results earlier), the palm oil-based model outperforms the benchmark model for Indonesia, on average, based on the full sample and at a longer horizon, while the reverse is the case for Malaysia. Narrowing to the sub-samples, we find evidence of outperformance of palm oil-based model over the benchmark model for Malaysia during the COVID-19 and the pre-COVID-19 periods, albeit with the *UPE*-adjusted model, while it is only evident for Indonesia before the pandemic after controlling for *UPE*. These results further validate the evidence reported in Salisu *et al*. (2021), which supports the inclusion of *UPE* in a predictive model of exchange rates in selected Asian economies (perhaps due to the fact that some of the well-known epidemics and pandemics such as COVID-19, MERS & SARS emanated from the region). Further evaluation of the comparative performance of the three palm oil-based models using the RMSE statistics supports the adjustment of the exchange rate returns for some other important factors, such as oil price and *UPE* (see Table 3), as the model without adjustment (i.e. Model 1 without control) produces the least RMSE value over the forecast horizons. Overall, while it may be difficult to beat the forecast prowess of a random walk model for exchange rate (Moosa, 2013; Moosa & Burns, 2014; Ferraro *et al*., 2015), accounting for important drivers and fundamentals may offer better forecast outcomes (see also, Salisu *et al*., 2019a, 2020; Narayan *et al*., 2020b).

Table 1.
Predictability Results for Exchange Rates

This table reports estimates of the slope (predictability) coefficients of the predictor series, which is palm oil price, denoted as $\sum_{i=1}^{5}\alpha_{2i}^{adj}$ in the case of Model 1 (i.e. Equation (1) without control variable). Models 2 and 3 involve a two-step procedure, whereby the first step requires regressing the exchange rate return on a control variable, i.e. $r_t=\alpha+\beta Control_t+\varepsilon_t$, while the second step involves using the adjusted exchange rate return (i.e. $r_t=\alpha+\varepsilon_t$) as the new regressand in Equation (1). Thus, Model 2 adjusts for oil price, while Model 3 adjusts for *UPE*. The Wald test is used to determine the joint significance of $\sum_{i=1}^{5}\alpha_{2i}^{adj}$, while values in "( )" are the corresponding standard errors. Lastly, "a" (1%), "b" (5%) and "c" (10%) indicate statistical significance, and the decision is based on the *F*-statistic.

	Full sample (12/12/2011-29/3/2021)			**Pre-COVID (12/12/2011-31/12/2019)**			**COVID-19 sample (1/1/2020-29/3/2021)**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Malaysia	0.0009	0.0026[b]	-0.0016	-0.1697[a]	0.0240[a]	0.0083[a]	0.2115[a]	0.2783[a]	0.2240[a]
	(0.0017)	(0.0013)	(0.0022)	(0.0085)	(0.0027)	(0.0021)	(0.0372)	(0.0303)	(0.0253)
Indonesia	-0.0163[a]	-0.0179[a]	-0.0553[a]	-0.0473[a]	-0.0372[a]	-0.0604[a]	0.3863[a]	0.3741[a]	0.0230
	(0.0015)	(0.0021)	(0.0006)	(0.0018)	(0.0021)	(0.0046)	(0.0200)	(0.0226)	(0.0189)

Table 2.
Clark and West out-of-sample Forecast Evaluation Results

This table shows the Clark-West test results. Model 1 does not account for any control variable, whereas Models 2 and 3 account for oil price and *UPE*, respectively. Essentially, Models 2 and 3 involve a two-step procedure, whereby the first step requires regressing the exchange rate return on each of the control variables, i.e. $r_t=\alpha+\beta Control_t+\varepsilon_t$, while the second step involves using the adjusted exchange rate return (i.e. $r_t=\alpha+\varepsilon_t$) as the new regressand in Equation (1). Thus, Model 2 adjusts for oil price, while Model 3 adjusts for *UPE*. For the Clark and West test, the values reported in square brackets are the *t*-statistics. We compare each of the palm oil-based models (i.e. Models, 1, 2 and 3) with a random walk model and a positive and significant value indicates that the palm oil-based model beats the random walk model, while the reverse is the case if the null hypothesis is not rejected (or may imply equality of forecast performance of the two competing models). Lastly, "a" (1%), "b" (5%) and "c" (10%) indicate statistical significance.

	Full sample (12/12/2011-29/3/2021)			Pre-COVID (12/12/2011-31/12/2019)			COVID-19 sample (1/1/2020-29/3/2021)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
				Malaysia					
h=15	-0.0001	-0.0002	-0.0001	0.0010^{c}	0.0005	0.0009^{c}	0.0078^{b}	0.0096^{a}	0.0078^{b}
	[-0.3143]	[-0.3932]	[-0.3173]	[1.4430]	[0.9180]	[1.5132]	[1.8901]	[2.2902]	[1.6981]
h=30	-0.0001	-0.0002	-0.0001	0.0010^{c}	0.0005	0.0010^{c}	0.0078^{a}	0.0095^{a}	0.0083^{b}
	[-0.3140]	[-0.3943]	[-0.3167]	[1.5378]	[0.9828]	[1.6196]	[2.0140]	[2.3934]	[1.8435]
h=60	-0.0001	-0.0001	-0.0001	0.0010^{c}	0.0005	0.0010^{c}	0.0062^{b}	0.0075^{a}	0.0084^{a}
	[-0.2177]	[-0.3042]	[-0.2215]	[1.5605]	[1.0126]	[1.6380]	[1.7706]	[2.0783]	[2.0700]
				Indonesia					
h=15	0.0005	0.0005	0.0004	0.0004	0.0005	0.0006^{c}	-0.0021	-0.0026	0.0053
	[1.2456]	[1.2104]	[1.1018]	[1.1733]	[1.1971]	[1.3459]	[-0.1407]	[-0.1789]	[0.3900]
h=30	0.0007^{c}	0.0007^{c}	0.0005^{c}	0.0004	0.0005	0.0006^{c}	-0.0019	-0.0024	0.0052
	[1.6435]	[1.6054]	[1.4943]	[1.1805]	[1.2190]	[1.3379]	[-0.1346]	[-0.1713]	[0.4036]
h=60	0.0006^{c}	0.0006^{c}	0.0005^{c}	0.0004	0.0005	0.0005^{c}	-0.0010	-0.0016	0.0073
	[1.4952]	[1.4887]	[1.3984]	[1.1413]	[1.1815]	[1.2887]	[-0.0789]	[-0.1277]	[0.6278]

Table 3.
Root Mean Square Error Forecast Evaluation Results

This table shows the forecast evaluation results. RMSE is the Root Mean Square. Model (M)1 does not account for any control variable, whereas Models 2 and 3 account for oil price and *UPE*, respectively. Essentially, Models 2 and 3 involve a two-step procedure, whereby the first step requires regressing the exchange rate return on each of the control variables, i.e. $r_t=\alpha+\beta Control_t+\varepsilon_t$, while the second step involves using the adjusted exchange rate return (i.e. $r_t=\alpha+\varepsilon_t$) as the new regressand in Equation (1). Thus, Model 2 adjusts for oil price, while Model 3 adjusts for *UPE*.

	Full sample (12/12/2011-29/3/2021)			Pre-COVID (12/12/2011-31/12/2019)			COVID-19 sample (1/1/2020-29/3/2021)		
	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M 3
				Malaysia					
h=15	0.4509	0.4500	0.4508	0.4733	0.4689	0.4733	0.3560	0.3525	0.3563
h=30	0.4493	0.4484	0.4492	0.4721	0.4677	0.4721	0.3555	0.3524	0.3567
h=60	0.4465	0.4456	0.4465	0.4690	0.4646	0.4690	0.3464	0.3441	0.3450
				Indonesia					
h=15	0.3735	0.3735	0.3737	0.3808	0.3795	0.3803	0.7172	0.7171	0.6929
h=30	0.3785	0.3784	0.3787	0.3800	0.3787	0.3796	0.7046	0.7043	0.6829
h=60	0.3821	0.3821	0.3823	0.3774	0.3761	0.3770	0.6725	0.6723	0.6512

Figure 1.
Time Series Plot of USD/MYR Against Palm Oil Price

This figure plots the time-series daily data on USD/MYR against palm oil price, whereby MYR denotes Malaysian Ringgit. The sample covers the period from December 12, 2011 to March 29, 2021. The source of the data is investing.com.

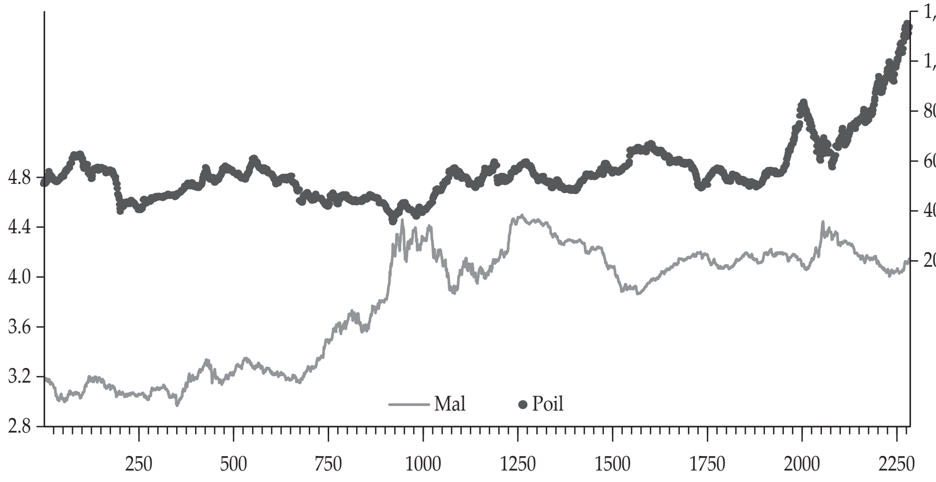
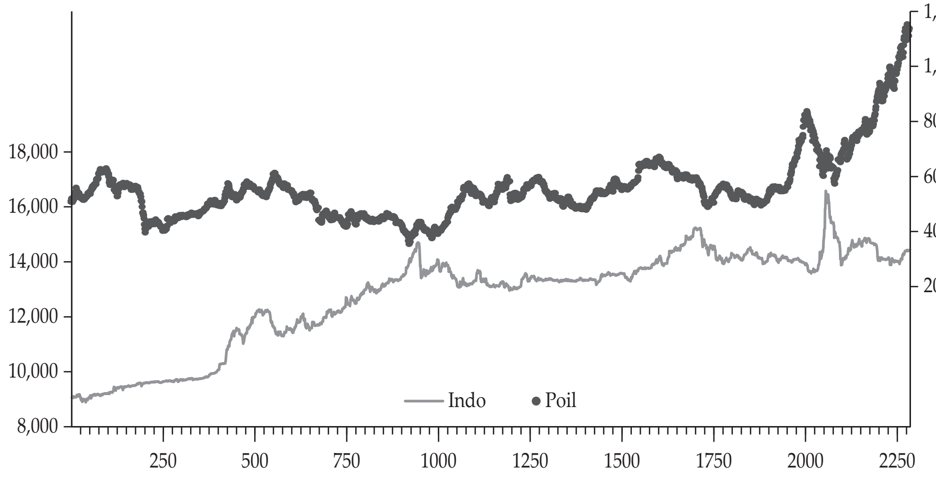


Figure 2.
Time Series Plot of USD/IDR Against Palm Oil Price

Figure 2 plots the time-series daily data on USD/IDR against palm oil price, whereby IDR denotes Indonesian Rupiah. The sample covers the period from December 12, 2011 to March 29, 2021. The source of the data is investing.com.



IV. CONCLUSION

The literature examining the role of commodity prices in the predictability of exchange rate movements is increasingly gaining prominence (see for example, Ferarro & Rogoff, 2015; Salisu *et al.*, 2019a, 2020), with mixed findings regarding whether they are capable of beating a random walk model, which is historically found to offer better out-of-sample forecasts for exchange rates (Moosa, 2013; Moosa & Burns, 2014; Ferraro *et al*., 2015). Thus, we contribute to this strand of literature by considering palm oil price, which has received very little attention despite being a significant contributor to world's vegetable oil demand and a major source of foreign exchange receipts for Indonesia and Malaysia, the two major palm oil producers in the world. We construct a predictive model in which palm oil serves as a predictor, while also controlling for oil price and uncertainty due to pandemics and epidemics. In all, we find that the in-sample predictability of palm oil price for exchange rate movements is stronger for Indonesia than for Malaysia. While the exchange rate of Indonesia appreciates in response to a rise in palm oil price irrespective of the predictive model (i.e. with or without adjusting for oil price and *UPE*), except for the COVID-19 period (where both exchange rates depreciate), Malaysia's exchange rate only appreciates during the pre-COVID period after controlling for oil price. We observed similar outcomes for the out-of-sample predictability analysis as the palm oil-based model outperforms the benchmark model for Indonesia, on average, based on the full sample and at a longer horizon, while the reverse is the case for Malaysia. We set aside, for future research, the economic significance of the forecast results.

ACKNOWLEDGEMENT:
Authors acknowledge helpful comments and suggestions from the Managing Editor and two anonymous referees of this journal. We take responsibility for any errors/omissions.

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