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PREDICTORS OF EXCHANGE RATE RETURNS: EVIDENCE FROM INDONESIA

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ABSTRACT

Using historical time-series data, we investigate Indonesia's exchange rate return predictability. We employ nine predictors, namely stock price, gold price, oil price, commodity price, inflation, balance of payment, total exports, the US T-bill rate, and the US federal fund rate. With historical data, we fail to discover any evidence that these factors predict Indonesia's exchange rate returns. However, we find that oil price, commodity price, inflation, and the US T-bill rate can significantly predict Indonesia's exchange rate returns during the Asian financial crisis. Our findings key implication is that it is the external factors that dominate the evolution of Indonesia's exchange rate, and inflation rate is the only domestic factor for policy makers to control.

Keywords: Exchange rate; Predictors; Inflation; External factors; Indonesia.

JEL Classifications: F30; F31; F37.

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I. INTRODUCTION

Exchange rate predictability constitutes an important subject of research in financial economics. The importance of understanding exchange rate predictability is many. First, factors that predict exchange rates are part of policy makers policy tools (see for example, Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2011 and Rossi and Inoue, 2012). This is relevant because maintaining a stable exchange rate—lowest volatility possible—helps both a country's balance of trade and current account. A depreciation, for example, will make imports expensive (holding exports constant) and, thus, will hurt trade and current account balances. Second, a stable exchange rate ensures macroeconomic stability, which is an important ingredient for economic growth (see, for instance, Collard and Dellas, 2002; An, Kim and You, 2016). Third, a stable exchange rate offers a conducive investment climate in which investor confidence is not dented by unstable exchange rates (see for example Narayan, Sharma, Phan, Liu, 2020). It follows that in order to achieve stable exchange rate and to minimize disruptions to it, understanding the factors that predict exchange rate is important.

Indonesia is a large country with a population of over 260 million, making it the fourth largest in the world. In Southeast Asia, the Indonesian economy is the largest with a GDP of over 1,000 billion USD in 2018 (Trading Economics, 2018). In addition, Indonesia is a member of the G-20 and has the 10th largest economy (in terms of purchasing power parity) (The World Bank, 2018). However, Indonesia's currency is volatile and vulnerable to external and internal factors.

Figure 1 shows Indonesia's currency (rupiah) per US dollar over the period 1983 - 2018. Over this period, Indonesia's currency depreciated, from IDR 970 to IDR 14,907 per 1 US dollar (1,436.80%). Indonesia's currency was very volatile during this period as depicted in Figure 1. Inspired by the literature on the importance of understanding the predictors of exchange rate and the sharp depreciation experienced by the Indonesian rupiah, the goal of our paper is to investigate and understand the factors that predict Indonesia's exchange rate. Our hypothesis is that there are specific factors that matter more to the way Indonesia's exchange rate has evolved over time. In other words, the role of factors will not be homogenous.

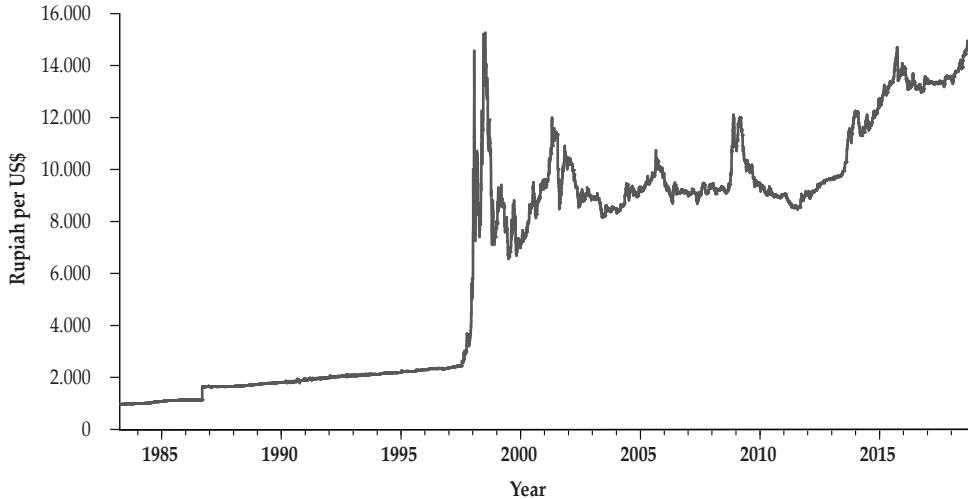
To test our hypothesis, we compile a dataset of the Indonesian exchange rate and its possible predictors. We have nine predictors for which daily time-series data are available covering the sample April 1983 to September 2018. This equates to approximately 35 years of data. The nine predictors are stock price, gold price, oil price, commodities price, inflation, balance of payments, total exports, the US T-bill rate, and the US federal fund rates.

Our econometric approach is inspired by Westerlund and Narayan (WN, 2015), commonly known as the Westerlund Narayan Flexible Generalised Least Squares (WN-FGLS) estimator (see also Westerlund and Narayan, 2012). We use the WN-FGLS estimator to test the null hypothesis of no predictability of the Indonesian exchange rate.¹ The motivation for using the WN-FGLS estimator has roots in the features of our dataset: namely, the existence of predictor persistency

¹ Devpura, Narayan, and Sharma (2018) and Sharma (2016) use the same model to predict stock returns and gold price returns, respectively.

Figure 1.
Indonesian Rupiah Against the US Dollar

This figure plots Indonesia's exchange rate per US dollar over the period 04 April 1983 – 14 September 2018. Data is sourced from the Global Financial Database (2018).



and endogeneity, and model heteroskedasticity. These features are easily accommodated by the WN-FGLS estimator; see also applications in Sharma (2016).

Our main finding is that when we consider a historical time period of data (1983 to 2018), there is no evidence that any one of the nine predictors predicts Indonesia's exchange rate. However, when we consider a relatively recent time period (namely, the post-Asian Financial Crisis (AFC) period), we find that of the nine predictors, oil price, commodity price, inflation and foreign short-rate (the US T-bill rate) are instrumental in predicting Indonesia's exchange rate. In our story, therefore, we show that while it is the external factors that dominate the evolution of Indonesia's exchange rate, inflation remains the key domestic monetary policy tool that can be used to maintain exchange rate stability.

Our contributions to the literature are twofold. First, there is a relatively scarce literature on Indonesia's exchange rate predictability (see for instance Narayan et al., 2020; Juhro and Phan, 2018). Narayan et al., (2020) examine whether forward premiums predict spot exchange rate returns for 16 currencies that follow floating regimes and another 34 currencies (including Indonesia) that follow other regimes. They document forward premium significantly predicts Indonesia's spot exchange rate returns. However, this evidence is not replicated in out-of-sample test evaluations, suggesting that the predictability of Indonesia exchange rate is not robust. On the other hand, Juhro and Phan (2018) test whether global economic policy uncertainty (EPU) predicts exchange rates and their volatility in 10 ASEAN countries. They document strong evidence of predictability in the case of Indonesia. The main drawback of these two studies is that their choice of predictor variables is restricted to commonly used predictors, namely the forward premium and EPU. Even though both studies have considered multiple currencies, they do not consider a wide range of predictors. We fill this gap by considering an extensive list of predictors. We also consider the longest time-

series data possible. Despite using a rich dataset, we do not find any evidence that commonly known predictors predict Indonesia's exchange rate over the 1983 to 2018 period. However, the predictability relationship becomes visible only in a recent time period, particularly when we consider the period marked by the AFC.

Two implications, one policy-oriented and one that sets the agenda for future research, are in order. For Indonesian policy makers, inflation stands as the most important factor. The role of the central bank—namely, Bank Indonesia is, therefore, important in its quest to maintain a stable inflation rate (see for example, Narayan, 2019). This policy objective which has been impressively met by the central bank will be key in keeping Indonesia's exchange rate stable. Fittingly, it is important to highlight that most predictors relevant to exchange rate of Indonesia are external, suggesting that what happens in the international market with respect to, for instance, commodity prices and interest rates will have ramifications for Indonesia's exchange rate. For future research, the message is that not finding predictability (or even finding predictability) is very much a data sample driven fact. When we shorten the sample and consider a period (post-AFC) when Indonesia's exchange rate was more dynamic, we do find evidence of predictability. This type of sub-sampled data analysis should not be ignored when modelling financial time-series data of Indonesia.

Our second contribution is to the international literature aimed at predicting exchange rates. In this literature, terrorist attacks (Narayan et al. 2018); monetary fundamental variables (Molodtsova et al., 2011 and Rossi and Inoue, 2012); forward premiums (Narayan et al., 2020); the US government shutdowns (see Sharma et al. 2019); and commodity prices (see Chen and Rogoff, 2003; Chen, Rogoff, and Rossi, 2010) have been shown to predict exchange rate returns.² A common feature of these studies is that they show the role of non-conventional factors predicting exchange rates; we add to this the case of Indonesia, where conventional factors are able to predict returns. The implication is that future studies can consider for Indonesia the role of non-conventional factors.

The paper is organized as follows. Section II discusses the data and method used in the empirical investigations. Section III analyses the empirical outcomes of the study and Section IV provides the robustness tests outcomes. Finally, Section V concludes the paper.

II. DATA AND METHODOLOGY

A. Data

We use daily time-series data over the period 4 April 1983 to 14 September 2018. Our sample size consists of 92,500 observations. Our dependent variable is Indonesia's exchange rate which is sourced from Indonesia Stock Exchange. We convert Indonesia's exchange rate (vis-à-vis US dollar) into log return form. In addition, we consider nine predictor variables, namely stock price, gold price, oil

² Some of these predictor variables are borrowed from the literature on the determinants of exchange rate (see, for example, Eslamloueyan and Kia, 2015; and Jakab and Kovacs, 2000). Another strand of literature which is closely related to our study includes the predictability of exchange rate with the Taylor Rule fundamentals (see, for example, Alba, Park, and Xie, 2015).

price, commodity price, inflation, balance of payment (BoP), export (in natural log), the US Treasury bill 1-year rate (US T-bill), and the US federal fund rate. All nine predictor variables are sourced from *Bank Indonesia*. Our choice of data is strictly based on data availability for Indonesia.

B. Methodology

Our research is closely related to the work of Devpura et al. (2018), Sharma (2016), Narayan et al. (2014a, 2014b), and Narayan et al. (2013). The common focus of these studies is on time-series predictability. We do not repeat the details of the WN predictability test here given that it has been extensively covered by the literature (see, for example, Sharma, 2016; Narayan et al., 2014a, 2014b; Narayan et al., 2013). Our predictability model takes the following form:

$$ERET_t = \alpha + \beta Predictor_{t-1} + \varepsilon_{ERET,t} \quad (1)$$

where, $ERET_t$ is Indonesia's exchange rate return, computed as $\log(ER_t/ER_{t-1}) * 100$. is the exchange rate index. The variable *Predictor* contains one of the nine predictor variables. Therefore, we estimate the above predictability model nine times, one at a time for each of the nine-predictor variable. The null hypothesis of no predictability is tested by setting $H_0 : \beta = 0$.

This study also obtains two out-of-sample forecasting evaluation statistics, namely the relative Theil U (RTU) and the out-of-sample R-squared (OOSR2) statistics, which compare the performance of our proposed predictability model with the constant-only (benchmark) model for Indonesia's exchange rate returns. When $OOSR2 > 0$ our proposed predictor-based forecasting model beats the benchmark model. When the $RTU > 1$, it indicates that the benchmark model is better. Moreover, if $RTU = 1$, it implies both models have equal strength.

III. EMPIRICAL FINDINGS

This section is organized into four parts. The first part discusses some preliminary analysis of data. The second part presents the in-sample and out-of-sample predictability test results. We report robustness test outcomes in the final part of this section.

A. Preliminary analysis

The starting point is to examine selected descriptive statistics of the data as reported in Table 1. The mean and standard deviation (SD) of all 10 variables are in column 2 and column 3, respectively, and, for the period 1983 – 2018, are 0.03% (mean) and 1.19 (SD). The reported mean for all predictor variables is positive, except in the case of BoP. Out of all nine predictors, the least volatile predictor is the US federal fund rate while exports are the most volatile.

Table 1.
Descriptive Statistics and Unit Root Test Results

This table reports some commonly used descriptive statistics. In columns 2 and 3, we report the mean and Standard Deviation (SD), respectively. In columns 4 and 5, we report ADF unit root test results. We allow a maximum of eight lags. The Schwarz Information Criterion (SIC) is used to select the optimal lag length (LL), which is reported beside the test statistics in square brackets. Except in the case of exchange rate returns, we allow for both an intercept and a time trend while conducting a unit root test. We only allow for an intercept in the case of exchange rate returns.

Variable	Mean	SD	ADF [LL]	p-value
Exchange Rate Returns	0.0295	11.972	-13.3385 [32]	0.0000
Stock Price	1617.8	1863.6	-1.0263 [6]	0.9388
Gold Price	650.5	4.334.843	-1.8273 [0]	0.6916
Oil Price	42.5322	28.7103	-2.5552 [5]	0.3013
Commodity Price	316.6	172.75	2.0655 [1]	0.5645
Inflation	9.5815	11.4036	-3.8099 [23]	0.0160
Balance of Payment	-3231.4	10391	-1.9136 [0]	0.6472
Export	13.736	0.6064	-2.7512 [0]	0.2158
US T-Bill	3.6256	2.8137	-1.5777 [20]	0.8020
US Federal Fund Rate	3.9544	3.0799	-1.4166 [23]	0.8564

To the Augmented Dickey and Fuller test: we do not reject the null hypothesis of a unit root in the case of any of the nine predictors. This indicates that all nine predictors are non-stationary. The only stationary variable is our dependent variables—the Indonesian exchange rate returns.

Additionally, to ascertain that all predictor variables are highly persistent, we have estimated first-order autoregressive (AR (1)) model for all nine predictors. We report these results in Table 2 (see column 2) and discover all values are close to one. This is a strong evidence supporting predictor persistency. Next, we conduct the heteroskedasticity test. Our approach is simple using an AR(8) model and test the null hypothesis of “no ARCH”. The LM-ARCH test suggest statistical significance for six out of nine predictor variables. This indicates that stock price, gold price, oil price, commodity price, the US T-bill, and the US federal fund rate are heteroskedastic. For the remaining three variables (namely, inflation, BoP, and exports), we do not reject the null hypothesis.

The endogeneity test following WN is in Table 3. We find that three predictor variables (gold price, oil price, and commodity price) are endogenous to the exchange rate returns. For the remaining six predictors, we do not find evidence of endogeneity. Overall, we conclude that we do need to control for persistency, endogeneity and heteroskedasticity while conducting predictability tests. This justifies the use of the WN-FGLS predictability estimator.

Table 2.
Persistency and ARCH Effects

In this table, we report results for persistency and heteroskedasticity. In column 2, we report the first-order autoregressive (AR (1)) coefficient of predictor variables which provides a measure of predictor persistency. In column 3, we report *F*-statistics obtained from Lagrange Multiplier (LM) ARCH effects test. The null hypothesis tested is “no ARCH”. Finally, * denotes statistical significance at the 10% level.

Variable	AR (1)	<i>F</i> -statistics
Stock Price	1.0002	185.9417*
Gold Price	0.9998	92.1615*
Oil Price	0.9993	247.3944*
Commodity Price	0.9996	204.6288*
Inflation	0.9989	0.0072
Balance of Payment	0.9994	0.0014
Export	0.9998	0.0067
US T-Bills	0.9996	327.7490*
US Federal Fund Rate	0.9966	167.6465*

Table 3.
Endogeneity test

This table reports endogeneity test results. This test is based on regressing the error-term from the predictive regression model on the error-term from the AR (1) model of the predictor variable. Finally, *** denotes statistical significance at the 1% level.

Variable	θ	<i>t</i> -stat	<i>p</i> -value
Stock Price	-0.0048***	-9.9553	0.0000
Gold Price	-0.0039***	-2.6450	0.0082
Oil Price	-0.0307***	-2.7157	0.0066
Commodity Price	-0.0077***	-3.0577	0.0022
Inflation	0.0017	0.0720	0.9426
Balance of Payment	0.0000	1.1926	0.2331
Export	0.4624	0.2673	0.7892
US T-Bills	-0.1581	-0.6833	0.4944
US Federal Fund Rate	0.0093	0.1845	0.8536

B. Predictability test results

In-sample predictability test results are in Table 4. The WN-FGLS coefficient and its corresponding *t*-statistics are reported in columns 2 – 3. Interestingly, we find no evidence of predictability regardless of the predictor used. In other words, we conclude that all the nine commonly known predictors failed to significantly predict Indonesia’s exchange rate returns.

Table 4.
In-sample Predictability

This table reports in-sample predictability test result. Here, we report the bias-adjusted FGLS estimator proposed by Westerlund and Narayan (WN, 2012, 2015). The coefficient of the predictor and the *t*-statistics associated with the null hypothesis of “no predictability” are reported.

Variable	Coefficient	<i>t</i> -statistics
Stock Price	-0.0000	-0.6535
Gold Price	-0.0000	-1.0274
Oil Price	-0.0004	-0.9296
Commodity Price	-0.0001	-0.8858
Inflation	-0.0018	-0.6115
Balance of Payment	-0.0000	-1.1716
Export	-0.0069	-0.3337
US T-Bills	0.0048	1.0915
US Federal Fund Rate	0.0042	1.7942

In addition, we consider out-of-sample forecasting evaluations. We use data for three in-sample periods, 25%, 50%, 75% in order to generate recursive forecasts of the exchange rate returns for the remaining 75%, 50%, and 25% of the sample, respectively.

Table 5 describes the results. We report the OOSR2 and RTU statistics. Irrespective of the out-of-sample periods considered for forecasting evaluations, we do not find any significant evidence of predictability using our model. The OOSR2 statistics is found to be less than zero for all nine predictors, which indicates the constant-only model outperforms our proposed predictor-based models. Similarly, the RTU statistics are reported greater than value one in majority of the cases, which again supports the benchmark model. The only exceptions are BoP, exports, and the US federal fund rate-based predictor models, where we find some evidence in support of our proposed model vis-à-vis constant-only model. Overall, results obtained using both in-sample and out-of-sample predictability tests are consistent.

Table 5.
Out-of-sample Forecasting Evaluations

This table reports out-of-sample forecasting evaluations, namely relative Theil U (RTU) and out-of-sample R-squared (OOSR2). Here, we use data for three in-sample periods, 25%, 50%, and 75%, to generate recursive forecasts of exchange rate returns for the remaining 75%, 50%, and 25% of the sample, respectively. The RTU and OOSR2 statistics measure the performance of our predictive regression model vis-a-vis the constant-only model.

Variable	Out-of-sample periods	OOSR2	RTU
Stock Price	02/12/1992 – 09/14/2018 (75%)	0.0125	1.0061
	12/25/2000 – 09/14/2018 (50%)	0.0581	1.0312
	11/04/2009 – 09/14/2018 (25%)	0.1144	1.0631
Gold Price	02/12/1992 – 09/14/2018 (75%)	0.0016	1.0007
	12/25/2000 – 09/14/2018 (50%)	0.0083	1.0040
	11/04/2009 – 09/14/2018 (25%)	0.0268	1.0135

Table 5.
Out-of-sample Forecasting Evaluations (Continued)

Variable	Out-of-sample periods	OOSR2	RTU
Oil Price	02/12/1992 – 09/14/2018 (75%)	0.0011	1.0005
	12/25/2000 – 09/14/2018 (50%)	0.0072	1.0035
	11/04/2009 – 09/14/2018 (25%)	0.0131	1.0064
Commodity Price	02/12/1992 – 09/14/2018 (75%)	0.0013	1.0006
	12/25/2000 – 09/14/2018 (50%)	0.0065	1.0031
	11/04/2009 – 09/14/2018 (25%)	0.0130	1.0064
Inflation	02/12/1992 – 09/14/2018 (75%)	0.0003	1.0001
	12/25/2000 – 09/14/2018 (50%)	0.0080	1.0003
	11/04/2009 – 09/14/2018 (25%)	0.0023	1.0009
Balance of Payment	02/12/1992 – 09/14/2018 (75%)	0.0003	0.9999
	12/25/2000 – 09/14/2018 (50%)	0.0012	1.0006
	11/04/2009 – 09/14/2018 (25%)	0.0030	0.9998
Export	02/12/1992 – 09/14/2018 (75%)	0.0000	0.9999
	12/25/2000 – 09/14/2018 (50%)	0.0004	1.0001
	11/04/2009 – 09/14/2018 (25%)	0.0018	1.0007
US T-Bills	02/12/1992 – 09/14/2018 (75%)	0.0003	1.0001
	12/25/2000 – 09/14/2018 (50%)	0.0008	1.0003
	11/04/2009 – 09/14/2018 (25%)	0.0002	0.9999
US Federal Fund Rate	02/12/1992 – 09/14/2018 (75%)	0.0005	1.0002
	12/25/2000 – 09/14/2018 (50%)	0.0035	1.0016
	11/04/2009 – 09/14/2018 (25%)	0.0001	0.9998

IV. ROBUSTNESS TEST

In this section, we discuss robustness test results. Our data sample covers the 1997 Asian Financial Crisis (AFC). Thus, we believe it is important to check whether our main findings discussed earlier are distorted due to the AFC period. To overcome this shortcoming of our earlier analysis, we divide data sample into three sub-samples, namely pre-crisis (04 April 1983 – 14 August 1997), crisis (15 August 1997 – 31 December 1998), and post-crisis (01 January 1999 – 14 January 2018) periods.³

Our approach in conducting in-sample predictability test remains the same. We test for the presence of persistency, endogeneity, and heteroskedasticity over the three sub-sample periods. Overall, our findings suggest that we do need to control for these features of the data while examining the predictability irrespective of the sub-sample periods.⁴

³ These sub-sample periods are used in number of previous studies (see, for example, Choi and Papaioannou, 2009).

⁴ We do not report these preliminary results into the paper as we do not find any change in results irrespective of three different sub-samples. However, all results are available upon request.

The in-sample predictability test results are in Table 6. Now we do find some evidence of predictability of exchange rate returns when we use oil price, commodity price, inflation, and the US T-bill rate as predictor variables. More specifically, we find that oil price and inflation statistically significantly predict exchange rate returns during the crisis and post-crisis periods, respectively. On the other hand, the commodity price and the US T-bill significantly predict exchange rate returns during pre-crisis period.

Table 6.
Robustness Check

This table reports robustness check results by controlling for the 1997 Asian Financial Crisis. More specifically, we examine in-sample predictability for data divided into three sub-sample. These three sub-samples include pre-crisis (04/04/1983 – 08/14/1997), crisis (08/15/1997 – 12/31/1998), and post-crisis (01/01/1999 – 09/14/2018) periods. Finally *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% levels of significance, respectively.

Variable	Periods	Coefficient	t-statistics
Stock Price	Pre-crisis	-0.0000	-0.3534
	Crisis	-0.0249	-0.5149
	Post-crisis	0.0000	0.7468
Gold Price	Pre-crisis	0.0000	0.1808
	Crisis	-0.0023	-0.7250
	Post-crisis	0.0000	0.3054
Oil Price	Pre-crisis	-0.0003	-0.8153
	Crisis	0.0181	1.3159
	Post-crisis	0.0003	0.5985
Commodity Price	Pre-crisis	-0.0007	-0.7429
	Crisis	0.0137*	1.7281
	Post-crisis	0.0002	0.5222
Inflation	Pre-crisis	-0.0042	-1.3385
	Crisis	-0.0174**	-2.2070
	Post-crisis	-0.0001	-0.0330
Balance of Payment	Pre-crisis	-0.0000	-1.0857
	Crisis	0.0001	-1.1002
	Post-crisis	-0.0001*	-1.8097
Export	Pre-crisis	-0.0000	-0.3726
	Crisis	-49.463	-0.9212
	Post-crisis	0.0238	0.8463
US T-Bills	Pre-crisis	-0.0012	-0.1799
	Crisis	1.5998**	2.0810
	Post-crisis	0.0022	0.4173
US Federal Fund Rate	Pre-crisis	-0.0010	-0.4108
	Crisis	0.7162	1.2541
	Post-crisis	0.0030	0.4333

V. CONCLUDING REMARKS

In this paper, we test whether the nine variables, namely stock price, gold price, oil price, commodity price, inflation, balance of payment, total exports, the US T-bill rate, and the US federal fund rate, can predict Indonesia's exchange rate. Our in-sample predictability test based on daily data shows that the nine predictors fail to predict Indonesian exchange rate returns. However, when we test further by considering data characterized by the Asian financial crisis, we find exchange rate predictability resulting from commodity price, inflation, and the US T-bill rate. This style of predictability is tantamount to a structural break-based predictability—a proposal offered by Devpura et al. (2019).

We argue that while external factors dominate the evolution of Indonesia's exchange rate, inflation remains important. Since inflation is a domestic factor, it can be utilized by the Bank Indonesia in its policy formulation to conduct stable monetary policy.

As a last point about future research, we believe the current coronavirus (COVID-19) pandemic will have significant effects on predictability of exchange rates; see recent studies by Phan and Narayan (2020) and Iyke (2020) on how COVID-19 has impacted exchange rates. In addition, there is now an evolving literature showing that COVID-19 is influencing factors that are responsible for exchange rate predictability like, for instance, oil prices and to some extent stock returns (Haroon and Rizvi, 2020; Devpura and Narayan, 2020; Prabheesh et al. 2020; Gil-Alana and Monge, 2020; Narayan, 2020; Liu et al. 2020; Qin et al. 2020; Huang and Zheng, 2020; and Iyke, 2020b; He, Sun, Zhang and Li 2020; He, Niu, Sun, and Li, 2020). Based on evidence reported in these studies, we predict that COVID-19 will also have an impact on the evolution of Indonesia's exchange rate. Future studies should specifically model the role of COVID-19 in the financial stability of Indonesia's economy.

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