Jurnal BPPK Volume 15 Nomor 1 Tahun 2022 Halaman 35-48

BADAN PENDIDIKAN DAN PELATIHAN KEUANGAN
KEMENTERIAN KEUANGAN
REPUBLIK INDONESIA

JURNAL BPPK

DETERMINING FACTORS FOR 10-YEAR LOCAL CURRENCY SOVEREIGN BONDS YIELD WITH DYNAMIC REGRESSION MODEL: INDONESIA CASE

Dea Avega Editya,
Department of Econometrics & Business Statistics-Monash University, Australia, Email: dea.avega@kemenkeu.go.id

ARTICLE INFORMATION

ARTICLE HISTORY
Received
08 Mei 2022

Accepted to be published
24 Agustus 2022

KEYWORDS:
sovereign bonds
machine learning
forecasting
dynamic linear regression
ARIMA

ABSTRACT

Sovereign bonds, particularly Local Currency Bonds (LCB) of 10-year tenure, had a strategic role in economy, thus understanding factors affecting its yield's movement would help government to maintain economic stability.
This paper empirically study Indonesia's 10-year LCB and its relationship with several factors; US Treasury (UST) yield, credit default swap (CDS), foreign ownership, central bank's policy rate (policy rate), exchange rate, volatility index (VIX) and primary dealers' trading behavior. The relationship was modelled using Dynamic Regression Model (DRM), with ARIMA errors to absorb the dynamics. Evaluation on the model's performance was conducted by making prediction on the real LCB yield's movement during 2021.
The best model containing 10y-UST yield and its lag-1, 5y-CDS and its lag-1, exchange rate, policy rate and ARIMA errors of AR(1) and AR(2) could perform well in predicting the real yield. This study confirmed that 10y-UST and its lag-1 are the main drivers for the LCB yield's movement, along with compelling influence of the exchange rate.

1. INTRODUCTION

1.1. Background of Study

Indonesian government regularly issue Rupiah-denominated sovereign bonds (conventional and sharia bonds) in the primary market to finance the deficit of the national budget. In 2021, the issuance target for the sovereign bonds is around 80-85% of total deficit financing which amounts to IDR1,006 trillion (DJPPR, 2021b) or equivalent to USD72 Billion (assumed exchange rate for conversion IDR/USD is 14,284.00). As of 2 September 2021, the total outstanding of local currency sovereign bonds (LCB) is IDR4,539 trillion (DJPPR, 2021c) or equivalent to USD318 billion.

According to the Minister of Finance's Regulation about auction of Surat Utang Negara (conventional bonds), the government sells the sovereign bonds through an auction which is conducted every Tuesday, with its announcement to be released three days before the auction day or T-3 (Ministry of Finance, 2019). During a 2-hour auction, investors (both individuals and institutions) can put their bidding in multiple prices through primary dealers, and auction winners will pay their bonds based on their proposed volumes and yields (Ministry of Finance, 2019). In addition to the multiple price (competitive) mechanism, the government also offers the LCB to several non-competitive participants such as Indonesia Central Bank (Bank Indonesia) and Indonesia Deposit Insurance Corporation (Lembaga Penjamin Simpanan) (Ministry of Finance, 2019). This non-competitive buying may also be conducted by primary dealers to complement their competitive bidding purchase. Non-competitive buyers will pay their LCB based on weighted average yield (WAY) from the winning competitive bidding (Ministry of Finance, 2019). The auction mechanism for sharia bonds (Surat Berharga Syariah Negara) is quite the same with of the conventional bonds (Ministry of Finance, 2020).

There are several benchmark series of the LCB offered in the auction. These series represent various maturity times. From published calendar of issuance on the Directorate General of Budget Financing and Risk Management's (DJPPR) website, tenors of conventional bonds benchmark series being auctioned in 2021 are ranging from 5, 10, 15, and 20 years (DJPPR, 2021a). Meanwhile, benchmark tenors of sharia bonds cover 2, 4, 13, and 25 years (DJPPR, 2021a).

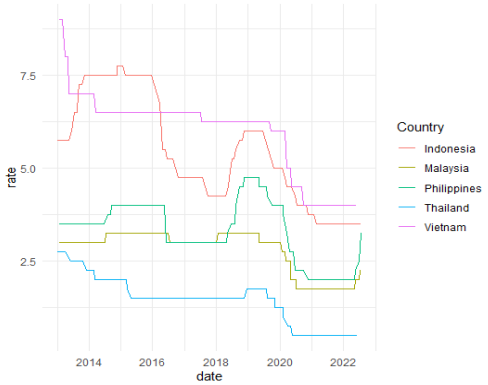
Since 2021, the yield of 10-year (10y) LCB has become one of the macroeconomic's primary indicators with its annually average value (assumption) is stated in the national budget, replacing yield of 3-month tenor (Surat Perbendaharaan Negara/T-bills). This replacement is because the yield of 10y-LCB is considered as having a larger and more significant portion in the nation's cost of borrowing compared to the T-bills (Fiskal, 2021, p. 35).

Moreover, the 10y-yield is said to reflect outlook of long-term economic development and its movement is commonly used as a sign for predicting country's

economic health as explained by Permanasari & Kurniasih (2021), although for having an overview on general economic condition other types of rate indicators are still be considered (Fiskal, 2021).

During a period of 2014-2018, Indonesia is said to have a higher average of 10y-sovereign bonds yield compared to its ASEAN-5 peers (Thailand, Philippines, Malaysia, Vietnam) as well as several other emerging countries with similar credit ratings like Mexico, Columbia, and India (muktiyanto & Aulia, 2019). This condition had made Indonesia to have more expensive debt compared to these countries. As corporates and business use the 10-y yield for benchmarking when borrowing or lending money in medium-long term, one may argue that impact of the expensive sovereign debt could also be spilled over in the national economy. Data indicates that Indonesian borrowers must pay higher interest rate compared to their peers in other ASEAN-5 countries (except Vietnam), as shown in Source: Tradingeconomics, processed

Figure 1.



Source: Tradingeconomics, processed
Figure 1 Interest Rate of ASEAN-5 Countries

Considering the important functions of the 10y-LCB yield in Indonesia's economy, this study analyzes several variables determining the yield and quantify their impact using econometric model. This paper is delivered in the following structure. First, research background and motivation is described in the early section. The next section is discussing some previous studies for variables assumed to have relationship with bonds yield. Third section explains each variable in the analysis and research methodology used to analyze the relationship between predictors and the LCB yield. The rest sections discuss about result and findings from analysis conducted in this study as well conclusion, impact and limitation of the study.

This study provides three new values to existing literatures. First, it offers an alternative to existing econometrics models utilized for analyzing factors that affect the Indonesia's 10y-LCB yield. The model in this study is incorporating a linear regression model that commonly used in many existing studies on the topic such as; Kurniasih & Restika (2015), Muktiyanto & Aulia (2019) and Permanasari & Kurniasih (2021), with an ARIMA model to enhance the regression while still maintain its simplicity form.

Second, this paper is pioneering study on the impact of primary dealers' behavior on the Indonesia's 10y-LCB yield, inspired particularly by similar studies on the US Treasury auction, for instances; Mercer et al. (2013) and Tchuindjo et al. (2015).

Third, this work provides evaluation on the model's performance using machine learning approach by making a prediction on real LCB yield's movement in 2021 based on information available in 2015-2020 (training data).

The purpose of this study is to provide insights and policy recommendations for the government, particularly in its role as a public debt manager, in their effort to reduce and stabilize the yield, specifically by giving more understanding on several significant factors that affect the yield. By keeping the yield low and stable, it will optimize the national's cost of borrowing which later can improve the overall economy.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1. Literature Review

The UST yield is described by Miyajima et al. (2015) and Muktiyanto & Aulia (2019) as a significant factor that affecting other countries' bonds yield. Miyajima et al. (2015) conclude that the UST yield, while not a main contributor to the LCB yield in emerging economies, is to some extent affecting the yield. Muktiyanto & Aulia (2019) whose focus of study is on Indonesia's sovereign bonds gives more emphasize on the predictor variable suggesting that the UST yield is not only significant but also has the biggest role in determining the LCB yield of the country. On the contrary, Permanasari & Kurniasih (2021) who also study the same country suggest that the UST yield has no significant effect in determining the LCB yield.

Furthermore, findings from Kim & Lee (2014) and Muktiyanto & Aulia (2019) explain that our second predictor, the CDS, is a significant factor that affecting the yield. The first name, using yield spread decomposition approach, suggest that the CDS as a proxy to default risk has 37% contribution to the spread. Muktiyanto & Aulia (2019) support this finding by suggesting the significant effect of the CDS on the Indonesia's LCB yield.

The effect of foreign ownership on the bonds yield is studied by researchers like Gadanecz et al. (2018) who confirm the significance of the variable in emerging economies. Another study with similar tone by Dachroui et al. (2020) who analyze role of capital flight as a driver of sovereign bonds spreads in Latin America countries, conclude that the spreads are

positively correlated with the capital flight (Dachraoui et al., 2020).

Our fourth predictor variable in this research, the policy rate, is inspired by results from studies in Indonesia conducted by Muktiyanto & Aulia (2019) and Kurniasih & Restika (2015). These authors analyze relationship between the predictor with Indonesia's bonds yield. Both agree that the policy rate significantly affect the yield in a positive direction.

Moreover, some works highlight the effect of exchange rate on the bonds yield (Miyajima et al., 2015), (Gadanecz et al., 2018), (Saenong et al., 2020) and (Permanasari & Kurniasih, 2021). Miyajima et al. (2015) suggest crucial effect of the exchange rate on the yield in emerging economies, while Gadanecz et al. (2018) who use exchange rate volatility and expected exchange rate as predictor variables also confirm the significant relationship. These two studies are in line with a work by Permanasari & Kurniasih (2021) who study the effect on Indonesia's bonds yield, suggesting a significant positive-relationship between the exchange rate and the yield. A slight different conclusion is provided by Saenong et al (2020) who argue that the effect on the Indonesia's bonds yield only significant in the short run but find to be insignificant in the long run.

Meanwhile, relationship between our sixth predictor-the VIX and the bonds yield is said to be significant by several researchers like Miyajima et al. (2015), Izadi et al. (2018) and Dachraoui et al. (2020). Miyajima et al. (2015) find the significant relationship in several emerging markets being observed, while Izadi et al. (2018) also find the similar effect in all 24 developed countries in North America, Europe and Pacific Rim regions. In addition, Dachraoui et al. (2020) confirm the significant effect in Latin America countries.

Other researches like Tchuindjo et al. (2015), Endo (2020), Nyborg et al. (2004), Mercer et al. (2013), and Ferrari et al. (2018) took different angle by looking at primary dealers system and its impact on bonds yield. Nyborg et al. (2004), Mercer et al. (2013) and Tchuindjo (2015) concern on primary dealers trading behavior in US Treasury bonds auction that potentially could result in higher yield. Endo (2020) study role of primary dealers in low income economies, while Ferrari et al. (2018) focus on the effect of primary dealers' funding constraints on sovereign bonds yield in 9 Euro countries. The last name conclude that the constraints can lead to higher yield spread (Ferrari et al., 2018).

2.2. Hypothesis

Based on the literature review, this study starts with an assumption that several risks can affect the movement of Indonesia's LCB yield 10-y. These risks are represented by variables: US Treasury (UST) yield and foreign ownership (external risk), 5-y credit default swap (default risk), volatility index and central bank's policy rate (financial market risk), USD/IDR exchange rate (external risk), and a dummy variable of auction/non-auction days as a proxy to primary dealers' trading behavior (system risk).

3. RESEARCH METHODOLOGY

This paper uses quantitative method by collecting secondary data from various sources such as Bloomberg, Ministry of Finance and Bank Indonesia. The data being used are historical timeseries (backward approach) consisting of 10y-UST yield, 5y-Indonesia's CDS, foreign ownership, Bank Indonesia's policy rate, exchange rate (USD/IDR), Indonesia's VIX, dummy variable of auction/no-auction days as a proxy to Indonesia's primary dealers' behavior, as well as 10y-Indonesia's LCB yield as a response variable. All variables (except for Bank Indonesia's policy rate (the rate is only available from 21 April 2016) are covering period of 2 January 2015 up to 5 August 2021. Each variable will be explained in the following sub-sections.

In explaining relationship between response variable and its predictors, this study employs dynamic regression model (DRM). There are two main advantages of using this type of model. First, it uses "easy to interpret" linear regression model. Second, it enables us to combine the regression with ARIMA model to handle subtle timeseries dynamics (Hyndman, Rob and Athanasopoulos, n.d.). Thus, DRM in this study consist of a linear regression model and an ARIMA model.

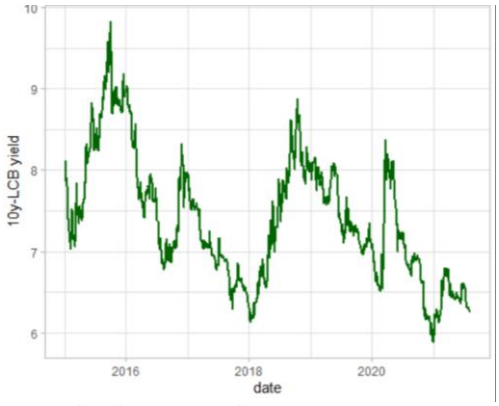
Furthermore, this work starts with building DRM containing full predictors. The next step is building DRM that contains only significant predictors. Lastly, lagged version of the significant predictors is included in a new DRM, with number of lags is chosen based on metrics. The final step is to select the best DRM by looking at model's accuracy. Performance of the best DRM is evaluated by fitting the model on the testing data to make a prediction on the real yield's movement in 2021. Data wrangling, analysis and visualization process are conducted solely in R software with the use of several R libraries. All variables covered in this research are explained as follow:

3.1. Response Variable

3.1.1. 10y-LCB Yield (lcb_10y)

Yield can be described as expected return demanded by investors in exchange of borne risks. The 10y-LCB yield data used in this study is using Indonesia's generic yield of 10-year maturity as a proxy to the LCB yield. The data is retrieved from Bloomberg platform using ticker code "GRR" (global summary of government bill, note, and benchmark bond rates for individual countries).

Timeseries visualization of the LCB yield can be seen in Figure 2. As shown in the plot, the general trend of the yield is decreasing over the period of observations.



Source: Bloomberg, processed
Figure 2. Trend of 10-y LCB yield. The general trend is decreasing.

3.2. External Risk

3.2.1. 10y-US Treasury Yield (ust_10y)

The United States of America (US) government's bonds for medium-long term maturity is commonly named as US Treasury bonds (UST bonds). The UST bonds of various maturities are generally used as a benchmark for other countries' sovereign bonds of equivalent maturity (Du et al., 2018). The bonds are considered as the safest instrument hence issuers of other countries usually give extra premium over the UST bonds yield to compensate additional risks taken by investors when purchasing non-UST bonds (Kim & Lee, 2014). Thus, our hypothesis is that the 10-y UST yield influences the Indonesia's LCB yield.

The UST yield data used in this study is sourced from Bloomberg with the same ticker code "GRR" specifically of the 10-year maturity. Timeseries visualization of the predictor variable is shown in Figure 3. The general trend of the UST yield is decreasing.

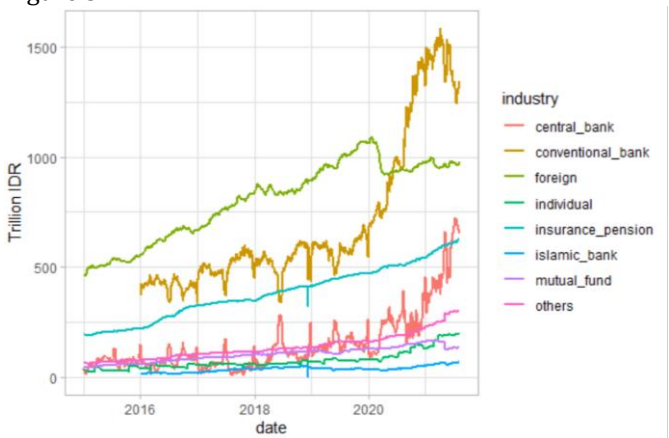
Source: Bloomberg, processed
Figure 3. Trend of 10-year UST yield. The general trend is decreasing.

3.2.2. Foreign Ownership (foreign)

As per 21 July 2021, foreign investors are holding IDR963 Trillion or 22.73% of total bonds ownership (DJPPR, 2021b, p. 12). The historical data of changes in the foreign ownership is shown in Figure 4. The general trend of the changes is increasing.

Source: Indonesian Ministry of Finance, processed
Figure 4. Trend of foreign ownership in Indonesia's bonds. The general trend is increasing.

The foreign investor's share in the government bonds (including the 10y-LCB) has been reduced dramatically since 2020 due to a huge upsize in both central bank and conventional bank's holdings in the LCB, although the long trend is increasing as shown in Figure 5.



Source: Indonesian Ministry of Finance, processed
Figure 5. Total bonds ownership by industry. Colors represent various industries

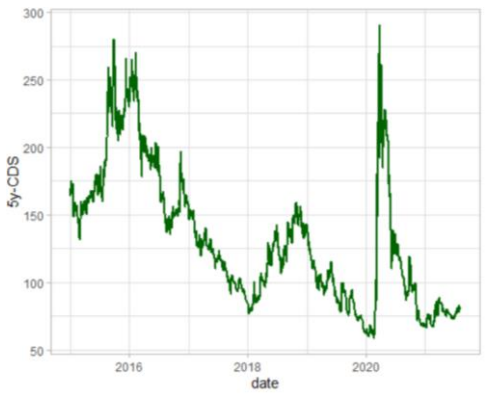
The figure shows daily changes in the LCB ownership, grouped by several industries from January 2015 until early August of 2021 (data before 2018 for conventional and Islamic bank are not shown in the plot due to different classification names).

3.3. Default Risk

3.3.1. 5y-Credit Default Swap (cds_5y)

A credit default swap (CDS) is described by Codogno et al. (2003) as “a derivative contract that allows investors to hedge against the default of a borrower”, and “provides a market-based measure of the credit-risk premium” (2003). Furthermore, CDS spreads can be seen as indication of the perceived credit risk by investors (2003). This study uses data of Indonesia’s 5y-CDS which is gathered from Bloomberg platform.

Time series of the CDS can be seen in Figure 6. The general trend of the CDS is declining, with the highest jump occurred in March 2020 due to announcement of early cases of covid19 in Indonesia.



Source: Bloomberg, processed
Figure 6. Trend of 5-y Indonesia's CDS. The general trend is decreasing.

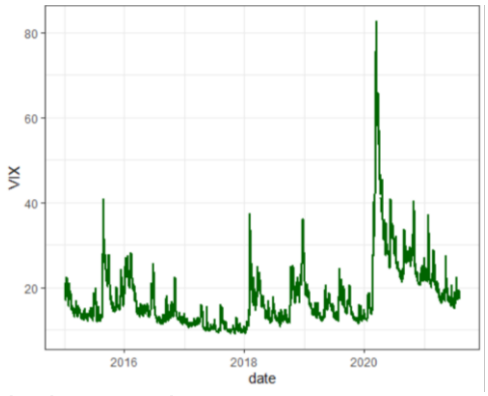
3.4. Financial Market Risk

3.4.1. Volatility Index (vix)

Volatility Index-a shorter term for Chicago Board Options Exchange's (CBOE) Volatility Index, was first introduced by the CBOE to measure the relative strength of short-term price changes of the S&P 500 index (SPX) in real-time (Whaley, 2009). One of the main purposes of the VIX Index as suggested by Whaley (2009) is it can be used to quantify expected short-term volatility and to track historical volatility using index option prices. Moreover, the index is practically used by investors to measure shock/fear in a stock market, thus it is also known as Fear Index.

After successful implementation in the USA, the index is now used globally to quantify the volatility of country's stock market. Data of Indonesia's VIX Index used in this study is retrieved from Bloomberg platform.

Historical VIX of the country can be seen in Figure 7. During years of observation, the highest jump in the VIX was happened in March 2020 where Indonesia reported its covid19 cases for the first time.



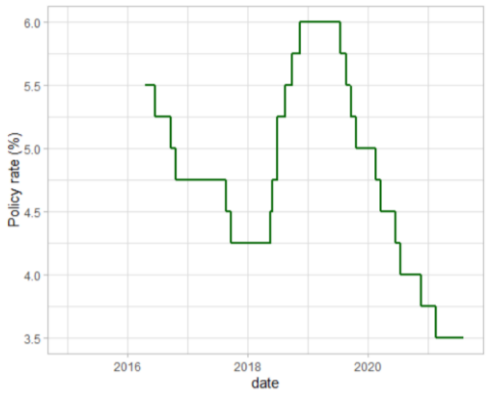
Source: Bloomberg, processed
Figure 7. Trend of Indonesia's VIX. The general trend is flat.

3.4.2. Policy Rate (pol_rate)

Policy rate is a product of monetary authority used as a tool to manage liquidity in money market (Bank Indonesia, n.d.). The ultimate aim of the policy rate is helping the authority to achieve their inflation target (n.d.). In Indonesia, the rate is periodically announced to public by Bank Indonesia (BI) as an output of monthly BI Board of Governors' meeting. As explained by Muktiyanto & Aulia (2019), the rate is expected to be transmissioned in money market, which in turn can affect deposit and loan rate, and finally influence asset valuation including stocks and bonds. Before 19 August 2016, the rate used 12-month BI certificate as a reference rate, and after the date it uses 7-day Reverse Repo Rate (7d-RRR) as a new reference rate (Bank Indonesia, n.d.).

Since historical data of the 12-month BI certificate is no longer available in the BI's website, this study is only collecting data of the 7d-RRR which has been officially published since 21 April 2016. Thus, the data of the policy rate used in this study is ranging from that date until 5 August 2021 (the data is downloaded from BI's website at https://www.bi.go.id/id/statistik/indikator/bi-7day-rr.aspx).

Historical data of the rate is visualized in Figure 8. The general trend of the rate is declining.



Source: Bank Indonesia, processed
Figure 8. Timeseries of BI's policy rate. The general trend is decreasing.

3.5. Macroeconomic Risk

3.5.1. Exchange Rate of USD/IDR (exchange_rate)

The data for foreign exchange (fx) rate of USD against Rupiah is using middle rate, calculated from Bank Indonesia's buy and sell fx rates of each working day (the fx data is downloaded from https://www.bi.go.id/en/statistik/informasi-kurs/transaksi-bi/Default.aspx). For non-working days, data is imputed from the rate of a previous working day.

Historical data of the exchange rate is visualized in Figure 9. The general trend of the rate is increasing.

Source: Bank Indonesia, processed
Figure 9. Trend of USD/IDR rate. The general trend is increasing.

3.6. System Risk

3.6.1. Primary Dealer Behavior (auction_day)

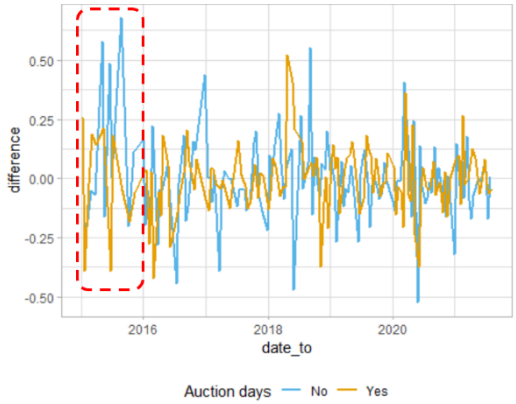
Primary dealer system in Indonesia has been established since 2007 based on the Minister of Finance's Regulation (PMK) No. 144/PMK.08/2006. The system is expected to run several functions as shown in more developed economies. Arnone & Arden (2003) describe role of primary dealers as intermediary between debt managers and investors in primary market, bookmakers and bonds distributors, liquidity provider between primary and secondary market, promoter of continuous market and efficient price discovery, and adviser to government.

As stated on DJPPR's website, in 2021 there are 20 primary dealers of conventional bonds comprise of 16 conventional banks and 4 securities companies. For sharia bonds, there are also 20 primary dealers consist of 13 conventional banks, 3 Islamic banks and 4 securities companies. Primary dealers are required to participate in every auction and to bid for a minimum quantity of the total offering amount (Ministry of Finance, 2019). They can bid both on behalf of their customers and for their own accounts (2019). As primary dealers can participate in competitive bidding in primary market as well as buy and sell in secondary market, they have direct contribution on forming yield of sovereign bonds (Tchuindjo, 2015).

Tchuindjo (2015) writes that primary dealers will make bilateral contracts for the offered securities as soon as auction announced, known as pre-sale or when-issued market. Mercer et al. (2013) argue that they will be able to "discover" the ultimate auction price since in pre-sale period. Many primary dealers are also believed to often short in the when-issued market (Nyborg & Strebulaev, 2004) which encourages them to bid aggressively and assign lower prices to the auctioned securities (Tchuindjo, 2015), meaning higher demanded yields.

Thus, analysis in this study is based on an assumption that primary dealers' strategic behavior in the auctions can affect sovereign bonds yield. To check this assumption, dummy variables of "auction days" (written in the model output as auction_day1) is used representing the pre-sale/when-issued period and "non-auction days" that representing regular workdays. Referring to Nyborg et al. (2004) pre-sale period is described as days started from the day of auction announcement (T-3) until a moment before bonds is distributed on the day of settlement (T+2). For simplicity, this study defines auction days as days started from T-3 until T+1. Here, the day of settlement (T+2) is excluded since bonds is usually distributed by the Central Bank in the morning of the settlement day. In addition, data only includes auction days that offer benchmark series of the 10y-sovereign bonds in the auction day (T). Before 2019, the 10y-series is not regularly offered in the auction.

To check if the yield difference of these two periods is significant or not, a new variable of "difference" is created by subtracting yield of the last day from of the first day for each period (auction and non-auction). The difference of yield in each period can be seen in Figure 10.



Source: Bloomberg, processed
Figure 10. Yield difference of first and last day in auction and non-auction days categories. Colors represent each category. The difference is generally not distinguishable.

From the figure, we can see that in 2015 and 2016 yield difference in auction days tend to be negative which indicate that the yield of the first day in the period of auction are mostly higher than of the last day. On the other hand, the yield of the first day in the period of non-auction are mostly lower than of the last day. That means yield tend to increase preceding an auction event which support the argument of Tchuindjo (2015). Nevertheless, this seems not to be the case in more recent years as differences between auction and non-auction periods become indistinguishable and more converging to zero.

4. RESULTS AND FINDINGS

Before constructing the DRM, this study applies two preliminary testing as a standard procedure for implementing linear regression with time series variables. First test is to check multicolinearity between the predictors fitted in the linear regression model. Second test is to check cointegration of all variables combination, as ARIMA model requires all variables to be stationary unless if they are cointegrated (Hyndman, Rob and Athanasopoulos, n.d.).

4.1. Preliminary Test

4.1.1. Multicolinearity Test

For conducting multicolinearity test, this study builds a linear model with the LCB yield as a response and remaining variables as predictors. Then, variance inflation factor (VIF) of all predictors is calculated. The result can be seen Table 1.

Table 1. Statistical resut of multicolinearity test

Statistic result of multicolinearity test

variable	VIF
ust_10y	2.08
vix	3.48
cds_5y	7.39
pol_rate	2.30
foreign	8.90
exchange_rate	3.55
auction_day	1.02

* Threshold used for multicolinearity indication is 10

From the result, all VIF values are still below 10 as the upper threshold of multicolinearity, with two variables; 5y-CDS and foreign ownership, have values exceed the conservative threshold of 5. However, since the dataset used in this study is considered large this study will use the upper threshold for multicolinearity indication as suggested by Jongh et al. (2015). Thus, all predictors can pass the multicolinearity test and be included in DRM.

4.1.2. Cointegration Test

For checking cointegration between variables, this study is using Johansen procedure (Johansen, 1991) since this testing method enable us to use combination of more than two timeseries (the Johansen procedure is conducted in R using library urca). As a requirement for the test, all timeseries must be at the same level of order integration one I(1).

Using Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) to check required difference for all variables, the foreign ownership variable is the only variable that need to be double differenced, or in other words this variable is in order of integration I(2) instead of I(1). Thus, a single differenced version of this variable will be used (diff_foreign) so as to make its integration order I(1) in the cointegration testing. No seasonal differencing is needed for all variables. Full result of the KPSS test can be seen in Table 2.

Table 2. Result unit root test

unit root	value	unit root	value
lcb_10y_kpss_stat	7.96	foreign_ndiffs	2.00
lcb_10y_kpss_pvalue	0.01	foreign_nsdiffs	0.00
lcb_10y_ndiffs	1.00	cds_5y_kpss_stat	13.19
lcb_10y_nsdiffs	0.00	cds_5y_kpss_pvalue	0.01
ust_10y_kpss_stat	8.29	cds_5y_ndiffs	1.00
ust_10y_kpss_pvalue	0.01	cds_5y_nsdiffs	0.00
ust_10y_ndiffs	1.00	exchange_rate_kpss_stat	15.07
ust_10y_nsdiffs	0.00	exchange_rate_kpss_pvalue	0.01
vix_kpss_stat	5.29	exchange_rate_ndiffs	1.00
vix_kpss_pvalue	0.01	exchange_rate_nsdiffs	0.00
vix_ndiffs	1.00	pol_rate_kpss_stat	5.59
vix_nsdiffs	0.00	pol_rate_kpss_pvalue	0.01
foreign_kpss_stat	24.86	pol_rate_ndiffs	1.00
foreign_kpss_pvalue	0.01	pol_rate_nsdiffs	0.00

* ndiffs = required regular difference, nsdiffs = required seasonal difference

The Johansen procedure is conducted using trace statistic method that produce eigenvalues (λ), rank of the matrix (shown in Table 3) and eigenvector associated with the highest eigenvalue (shown in Table 4).

Table 3. Rank of matrix from Johansen's procedure

	lev_10pct	lev_5pct	lev_1pct	test_stat
r <= 6 |	6.50	8.18	11.65	2.39
r <= 5 |	15.66	17.95	23.52	12.92
r <= 4 |	28.71	31.52	37.22	25.45
r <= 3 |	45.23	48.28	55.43	57.32
r <= 2 |	66.49	70.60	78.87	97.05
r <= 1 |	85.18	90.39	104.20	208.93
r = 0 |	118.99	124.25	136.06	868.11

Table 4. Eigenvalues of variable's linear combination

lambda	value
0.289	lambda1
0.056	lambda2
0.020	lambda3
0.016	lambda4
0.006	lambda5
0.005	lambda6
0.001	lambda7

The first hypothesis, r=0, tests for the presence of cointegration between all seven variables included. Since the test statistic exceeds the 1% level

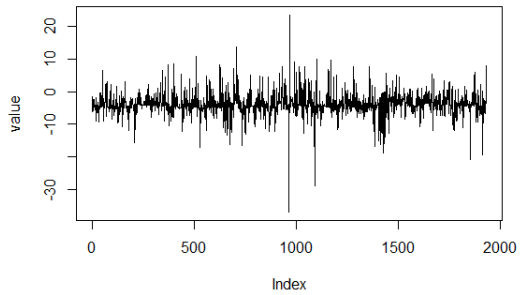
significantly (868.11), it is a strong evidence to reject the null hypothesis of no cointegration.

Other test statistics for r <= 1, r <= 2 and r <= 3 also show that the null hypothesis of no cointegration can be rejected. However, for the higher rank of matrix the null hypothesis cannot be rejected. Hence, it can be concluded that to form linear combination that poses cointegration we need at least 4 combinations of the variables. **Using all combination of the 7 variables can perfectly make these timeseries cointegrated.**

Table 5. Component of eigenvector for variable 10-y LCB yield corresponding with the largest eigenvalue (lambda1)

	lcb_10y
lcb_10y	1.000
ust_10y	0.222
vix	0.122
dif_foreign	1.584
cds_5y	-0.008
exchange_rate	-0.001
pol_rate	-0.599

Summing up cointegration values (produced from matrix multiplication of eigenvector in Table 5 with its corresponding variable), the stationary of the linear combination of all timeseries can be visualized as shown in Figure 11.



Source: R software output
Figure 11. Stationarity of cointegrated variables. Values from the linear combination of variables are not significantly different from zero.

From the figure, long-run effect of all combined variables seems not significantly different from zero (white noise) meaning that they are all cointegrated.

4.2. Building Dynamic Regression Model (DRM)

Regarding the result from the previous section, the general equation for DRM can be written down as follow:

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + \beta_5 x_{5t} + \beta_6 x_{6t} + \beta_7 x_{7t} + \eta_t$$

where (x_i) represent each predictor and (η_t) is an ARIMA error.

Summary statistic of the data is shown in Table 6.

Table 6. Summary statistic of the data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
lcb_10y	2,408	7.39	0.77	5.89	6.82	7.91	9.83
ust_10y	2,408	1.98	0.66	0.51	1.60	2.41	3.24
vix	2,408	17.63	7.88	9.14	12.69	20.54	82.69
dif_foreign	2,407	0.21	2.06	-20.96	-0.19	0.78	17.30
cds_5y	2,408	131.71	50.20	58.38	92.03	159.98	290.82
exchange_rate	2,408	13,888.72	649.97	12,444	13,337	14,309.2	16,741
pol_rate	1,933	4.78	0.75	3.50	4.25	5.25	6.00
auction_day	2,408	0.38	0.49	0	0	1	1

4.2.1. Full and Smaller DRM

The first step of building DRM is to include all predictors in the model (full DRM), with model's statistics can be seen in Table 7. The ARIMA error specification is chosen automatically by fable library using stepwise algorithm that looking for the smallest AIC, AICc and BIC of some possible models. This process results in 2 non-seasonal ARIMA; ar1, ar2 and 1 seasonal ARIMA; sar1.

From the table, all predictors seem significant on 5% level except for vix, dif_foreign, auction_day1 as well as sar1). From the significant predictors, variables that pose positive correlation with the LCB yield are 10y-UST yield, 5y-CDS, and exchange rate, while policy rate poses negative correlation.

Table 7. Full model's statistic

term	estimate	std.error	statistic	pval
ar1	0.1181	0.02	4.98	0.00
ar2	-0.0527	0.02	-2.30	0.02
sar1	-0.0398	0.02	-1.73	0.08
ust_10y	0.1370	0.03	4.71	0.00
cds_5y	0.0036	0.00	14.00	0.00
exchange_rate	0.0004	0.00	12.97	0.00
vix	0.0012	0.00	1.76	0.08
pol_rate	-0.0765	0.04	-2.06	0.04
dif_foreign	-0.0002	0.00	-0.60	0.55
auction_day1	-0.0009	0.00	-0.30	0.76

Regarding the result, it is preferable to build a smaller model containing only significant variables (removing vix, dif_foreign, auction_day1, and sar1). The statistic for smaller model is shown in Table 8.

Table 8. Smaller model's statistic

term	estimate	std.error	statistic	pval
ar1	0.1242	0.02	5.28	0.00
ar2	-0.0527	0.02	-2.30	0.02
ust_10y	0.1220	0.03	4.39	0.00
cds_5y	0.0038	0.00	15.97	0.00
exchange_rate	0.0004	0.00	13.09	0.00
pol_rate	-0.0772	0.04	-2.09	0.04

The next step is to compare model's performance of both models using the second-order Akaike Information Criterion (AICc). The better model is indicated by a lower value of the AICc.

Table 9. Model estimation for the full and smaller model

model	.model	AICc
Full model	ARIMA(lcb_10y ~ ust_10y + cds_5y + exchange_rate + vix + pol_rate + dif_foreign + auction_day)	-6594
Smaller model	ARIMA(lcb_10y ~ ust_10y + cds_5y + exchange_rate + pol_rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6596

From Table 9, the smaller model looks only slightly better than the full model AICc (-6596 vs -6594) but is preferred since it can explain the LCB yield with 3 less variables.

4.2.2. DRM with Lagged Predictors

It is reasonable that some significant predictors in the model may have delayed impact on the response variable (Hyndman, Rob and Athanasopoulos, n.d.). This is particularly possible for predictors that have daily changed values such as 10y-UST yield, 5y-CDS, and exchange rate. Thus, some lagged versions of these predictors are added into the smaller model, and later compare the AICc value of the new model to the smaller model without lags.

The DRM with lagged effects can be written as follow:

$$y_t = \beta_0 + \gamma_0 x_{it} + \gamma_1 x_{it-1} + \ldots + \gamma_k x_{it-k} + \eta_t$$

where (x_i) represent each predictor, γ_k is lagged effect and (η_t) is an ARIMA process.

For this purpose, appropriate number of lags for each predictor is selected by comparing the AICc of the predictor's models. The models used in comparison consist of four models, first is a model with only one original predictor against the LCB yield, second is a model with one original predictor and its lag-1 version, third is a model with one original predictor, its lag-1 and lag-2 versions, and fourth is a model with one original predictor, its lag-1, lag-2 and lag-3 versions.

The data for the models is restricted as it is important to ensure that the models use same fitting period when comparing number of lags (Hyndman, Rob and Athanasopoulos, n.d.).

The result of comparing AICc for each different predictors can be seen in Table 10. For 10y-UST yield, lag-1 can moderately reduce AICc (5274) thus is preferred, compared to lag-2 and lag-3 which add more complication to the model but with minor improvement on the AICc. For 5y-CDS, the best lag for the predictor is lag-1 (AICc is 3200). Furthermore, for exchange rate, the original version (lag 0 or no lag) can produce the best AICc (5547) compared to its lag versions.

Table 10. Selecting appropiate number of lag for each predictor based on AICc

variable	.model	AICc
ust_10y	lag0	5277
ust_10y	lag1	5274
ust_10y	lag2	5271
ust_10y	lag3	5270
cds_5y	lag0	3204
cds_5y	lag1	3200
cds_5y	lag2	3201
cds_5y	lag3	3202
exchange_rate	lag0	5547
exchange_rate	lag1	5548
exchange_rate	lag2	5549
exchange_rate	lag3	5550

Based on the result, **a new model is built with two lagged predictors which are lag-1 of 10y-UST and lag-1 of 5y-CDS**. The AICc value for this model together with the AICc of the two previous models are shown in Table 11.

Table 11. Model estimation for full model with no lags, smaller model with no lags, and smaller model with chosen lags

	.model	AICc
full model no lags	ARIMA(lcb_10y ~ ust_10y + cds_5y + exchange_rate + vix + pol_rate + dif_foreign + auction_day)	-6594
smaller model no lags	ARIMA(lcb_10y ~ ust_10y + cds_5y + exchange_rate + pol_rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6596
smaller model with lags	ARIMA(lcb_10y ~ ust_10y + lag(ust_10y, 1) + cds_5y + lag(cds_5y, 1) + exchange_rate + pol_rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6677

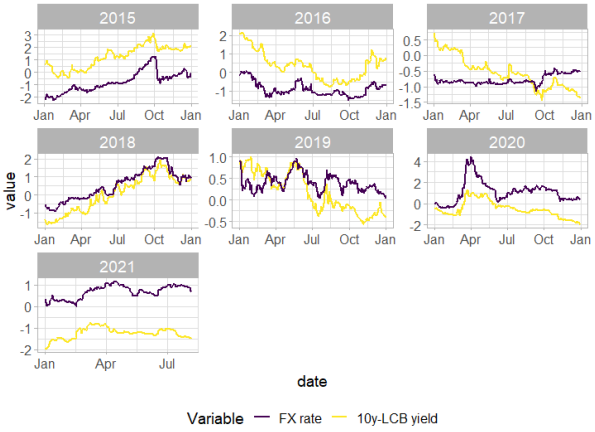
The smaller model with lags is the best DRM since its AICc (-6676) is significantly lower than "no-lags" models of both the full and the smaller model (-6594 and -6596).

4.3. Analysis

4.3.1. Interpretation of The Best DRM

As displayed in Table 12, all variables including their lags version are significant on 5% level except for AR(2) (ARIMA error lag-2) that is only significant on 10% level. It's also observed that the biggest factors driving the LCB yield are the 10y-UST yield together with its lag-1 version, which is in line with arguments of Miyajima et al. (2015) and Muktiyanto et al. (2019) but contradict finding of Permanasari et al. (2021) saying the UST yield has no significant effect. For a single factor, the lag-1 UST yield is the most important driver for Indonesia's bonds yield (indicated by its large estimate coefficient), meaning that today's yield level is mostly affected by the UST yield of yesterday.

Moreover, it is also noticed that the exchange rate is such a quite powerful factor in determining the yield since a moderate increase in the exchange rate, i.e., 1000 USD/IDR, will boost the yield about 40bps (0.4%) on average. This finding supports arguments of Miyajima et al. (2015), Gadanecz et al. (2018) and Permanasari & Kurniasih (2021). As visualized in Figure 12, the exchange rate and the LCB yield (adjusted scale) seem to have a strong positive correlation suggested by similar patterns in all observed years (except for 2017).



Source: Bloomberg & Bank Indonesia, processed
Figure 12. Time series of 10y-LCB yield and exchange rate (adjusted scale) observed in 2015-2021. These two variables were almost perfectly moving in such a parallel way.

Other significant factors are policy rate that agree with results from Kim & Lee (2014) and Muktiyanto & Aulia (2019), as well as 5y-CDS (Muktiyanto & Aulia, 2019; Permanasari & Kurniasih, 2021) but with relatively low effect on the LCB yield.

Distinguished from what Permanasari & Kurniasih (2021) argue, this study found that policy rate has negatively affect the LCB yield, i.e., increased policy rate will decrease the LCB yield, which at first seems counter intuitive. Nevertheless, as explained by Gadanecz et al. (2018), with more attractive interest rate more capital inflow will enter financial market, thus may help reduce the exchange rate (strengthen local currency). This effect will in turn decrease yield, which may reflect more investor's confident on holding sovereign bonds.

Table 12. Statistic of the smaller model with lags

term	estimate	std.error	statistic	pval
ar1	0.1241	0.02	5.33	0.00
ar2	-0.0421	0.02	-1.83	0.07
ust_10y	0.1383	0.03	5.05	0.00
lag(ust_10y, 1)	0.2036	0.03	7.48	0.00
cds_5y	0.0041	0.00	17.03	0.00
lag(cds_5y, 1)	0.0018	0.00	7.20	0.00
exchange_rate	0.0004	0.00	11.21	0.00
pol_rate	-0.0752	0.04	-2.07	0.04

Interpretation from each significant coefficient can be described as follow (the effect of each predictor on the response is assuming other factors hold constant):

a. for 1% increase in lag-1 LCB yield (represented as ARIMA error lag-1 or AR(1)), the LCB yield will increase about 12bps (on average)
b. for 1% increase in 10y-UST yield, the LCB yield will increase about 14bps (on average)
c. for 1% increase in lag-1 10y-UST yield, the LCB yield will increase about 20bps (on average)
d. for 10 points increase in 5y-CDS, the LCB yield will increase about 4bps (on average)
e. for 10 points increase in lag-1 5y-CDS, the LCB yield will increase about 2bps (on average)
f. for 1000 USD/IDR increase in exchange rate (Rupiah weakened by 1000), the LCB yield will increase about 40bps (on average)
g. for 1% increase in policy rate, the LCB yield will decrease about 7bps (on average)

4.3.2. Model Performance

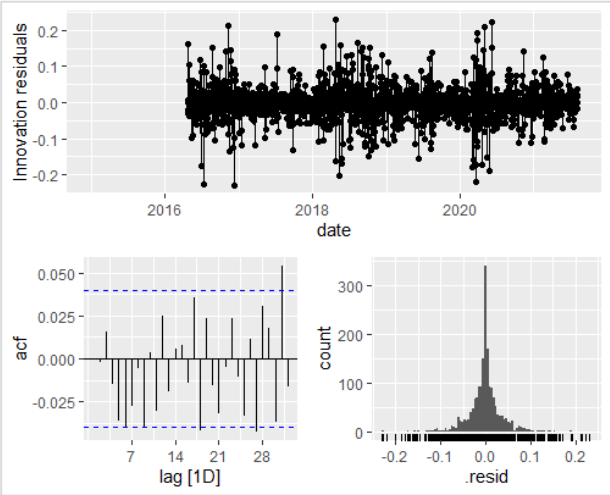
This sub-section is discussing model evaluation of the best DRM (smaller model with lags) conducted by predicting the real LCB yield's movement based on information from the model, and finally check its prediction accuracy.

4.3.2.1. Residual Check

Before using machine learning approach to predict the yield's movement, it is important to first check if residuals from the chosen DRM is resembling a white noise. The aim is to make sure that there is no significant information left in the residuals that should be used in our model (Hyndman, Rob and Athanasopoulos, n.d.).

A visualization check is conducted using gg_tsresiduals function from library feasts to show the innovation residuals. From the residuals plot as seen in Figure 13 (residuals from year 2015 are not shown in the figure since policy rate variable in the model is only available from 2016), we can see that residuals of the estimated ARIMA model (2,1,0)(0,0,0) seems not significantly different from a white noise since its mean is not far from zero.

There are some noticeable outliers in the residuals which are mostly due to some shocks occurred in several past years, for example a US-China trade war event in 2018 and covid19 pandemic in early 2020. From the ACF plot, residuals of most recent lags (1 up to lag-14) are still considerably located inside blue lines indicating no concerning spikes of residuals.



Source: R software output
Figure 13. Innovation residuals of the model. All plots indicate residuals are not different from zero

The visualization check is complemented with a formal test of Ljung-Box test (LJUNG & BOX, 1978). From the test result, we can confirm that the residuals are similar to white noise since the p-value produced (with lag = 21) is large (0.24).

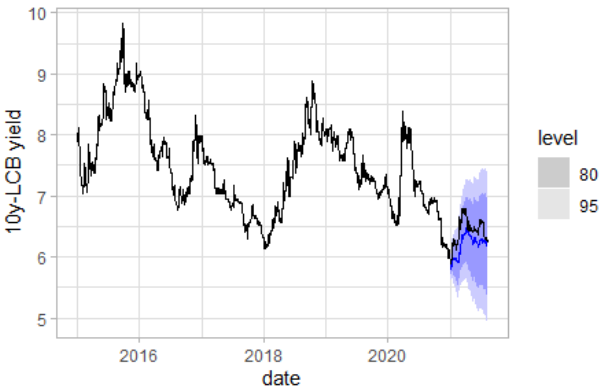
Table 13. Ljung-Box test on innovation residuals

lb_stat	lb_pvalue
25.12276	0.24

4.3.3. Yield Prediction Using the Best DRM

After confirming that our timeseries resemble a white noise, the next step is making a prediction on the real 10y-LCB yield. The prediction is based on the fitted model of training data. For this purpose, this study separate data into training and testing. The training data contains all observations up to 31 December 2020, while the testing data spares all observations from 1 January 2021 until 8 August 2021.

Since our goal is to predict the real 10y-LCB yield, real data of the predictors are used instead of forecasting each of these exogenous variables. The prediction is conducted using library forecast in R and the result can be seen in Figure 14.



Source: R software output
Figure 14. Performance of model in predicting real 10y-LCB yield. Black line represents the real yield, blue line is the prediction. The prediction seems closely follow the real yield's movement.

From the plot, the selected DRM seems to capture the LCB yield's dynamics (trend and volatility) well. The gaps between prediction and real yield are mostly small along the forecast horizon, and the real yield is still mostly covered inside the 80% prediction interval band. Another thing to notice here is that the prediction interval looks quite wide. This is because we use information from quite short-range timeseries (5 years long) and at the same time our forecast horizon is quite long (7 months) hence more uncertainty is associated with the prediction.

From Table 14, the DRM seems to have very low prediction error indicated by small score of Root Mean Score Error (RMSE) and Mean Absolute Score Error (MASE) that are 0.26 and 1.78 consecutively.

Table 14. Forecast error of the smaller model with lags

.model	RMSE	MASE
ARIMA(lcb_10y ~ ust_10y + lag(ust_10y, 1) + cds_5y + lag(cds_5y, 1) + exchange_rate + pol_rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	0.26	1.78

5. CONCLUSIONS

This study is starting the analysis with 7 predictors assumed to have correlation with the 10y-LCB yield. The predictors are 10y-UST yield, 5y-Indonesia's CDS, foreign ownership, Bank Indonesia's policy rate, exchange rate (USD/IDR), Indonesia's VIX as well as a dummy variable of auction/no-auction days as a proxy to Indonesia's primary dealers' behavior. After modeling the relationship between these predictors with the LCB yield using DRM, several predictors are not significant enough on 5% level which are VIX, foreign ownership (in differenced version), as well as auction/non-auction days. Thus, in the second model these insignificant variables are excluded to build smaller DRM. Comparing the AICc from full and smaller DRM, we see that smaller DRM is preferred since it can slightly reduce the AICc with 3 less variables.

Furthermore, as it is reasonable to include lagged effect of variables in a time series model, we also include lag-1 of the UST yield and lag-1 of the CDS in the smaller DRM. The result is that the smaller DRM with several lagged predictors significantly reduce the AICc score. In addition, during evaluation of model performance, the DRM also quite well in predicting the real 10y-LCB yield with small prediction error as indicated by RMSE and MASE (0.26 and 1.78 consecutively). Thus, we can confidently say that the variables in the smaller DRM with lags are very important determiners for the LCB yield. These variables are significant on 5% level, consisting of lag-1 of the LCB yield (AR(1)), 10y-UST yield and its lag-1 version, 5y-CDS and its lag-1 version, exchange rate, and policy rate. The only insignificant variable in the model is the lag-2 LCB yield (AR(2).

From the model statistics, the lag-1 of the LCB yield, the 10y-UST yield and its lagged version, the 5y-CDS and its lagged version, the foreign ownership, and the exchange rate (USD/IDR) are all have positive correlation with the LCB yield. Meanwhile, the policy

rate seems to have a negative correlation with the yield. Moreover, we can argue that the most important factors that driving the LCB yield are the 10y-UST yield together with its lag-1 version. For a single factor, the lag-1 UST yield is the most important driver for Indonesia's bonds yield as it has the biggest estimated coefficient.

In addition, we also notice that the exchange rate is considerably a quite powerful factor in determining the yield since a moderate increase in the exchange rate, i.e., 1000 USD/IDR, will significantly increase the yield about 40 bps (0.4%) on average. A weakened currency may reflect worse economic condition that decrease investor's confident in holding sovereign bonds. As a result, more yields are requested by the investors for buying the bonds.

6. IMPLICATION AND LIMITATION

From the result, this study suggests that finding appropriate level of foreign exchange rate and maintaining its stability can directly impact level and stability of the LCB yield. Adjusting policy rate to its optimum level may also indirectly reduce and stabilize the LCB yield as suggested by the best DRM, possibly because more capital inflow will enter financial market thus help to steady the exchange rate. (Gadanecz et al., 2018). In addition, direction and movement of 10y-UST and its lag-1 can be another useful indicator to predict the 10y-LCB movement accurately.

There are several limitations from this study. First, the range of most timeseries used in this study are quite short, i.e., 5 years and even shorter for the variable policy rate that only cover 4-years long data. Second, several observed years indicate non-regular patterns that are really different from previous years, for example there was a big shifting from foreign dominance in the bonds ownership to the conventional banks since early 2020, possibly due to an implemented mandatory purchase regulation aimed to reduce and stabilize the LCB yield during pandemic as well as more intention in holding secure assets during inconducive market condition. Moreover, Bank Indonesia also became more aggressive in absorbing the bonds issued by the Government during quantitative easing program, as an implementation of a joint-effort to fund covid-19 recovery programs.

These new policies in fact weaken the explanatory power of our model at least for two reasons, first, since the model assumes similar pattern from previous years will continue to occur in the future. Second, abrupt changes in the policy may also cause our foreign ownership predictor to be insignificant.

Lastly, this study only includes several predictors considered as major factors based on prior studies that can be conveniently accessed from either Bloomberg platform or official website. Other variables data that are not publicly shared or need formal and rigid bureaucracy are not included considering time constraint of this study. Hence, future scope of study can include other variables assumed to have correlation with the LCB yield, for example current account deficit and market liquidity during auction period related to a prior study about the effect of primary dealer's budget constraint by Ferrari et al. (2018). In addition, future internal study on the effect of primary dealer's industry type can also be conducted by the government (since the data is strictly confidential), for example by using mixed-effect model, to see if any trading behavior from several particular industries have interesting effect on the yield (i.e. foreign vs local primary dealers, different type of investors represented by primary dealers such as pension fund, insurance and conventional banks).

ACKNOWLEDGEMENT

The author would like to particularly thank Director of Business Analytics Program at Monash University-Professor Dianne Cook, for her great advice and patience in supervising this research. Her advice was very useful for example in defining structure of the writing, choosing appropriate visualizations during exploratory data analysis as well as suggesting model for the timeseries.

In addition, this report also owes a big thank you Professor Rob Hyndman-Head of Econometrics and Business Statistics Department at Monash University for his useful feedback to author's question during completion of this research as well as his lecture on applied forecasting.

Moreover, this work would not have been possible without support from several colleagues at Directorate General of Budget Financing and Risk Management (DJPPR) under Ministry of Finance that provide most of the data in the analysis and facilitate fruitful discussion on the variables used.

REFERENCES

Arnone, M., & Iden, G. (2003). *Primary Dealers in Government Securities: Policy Issues and Selected Countries' Experience* (WP/03/45). https://www.imf.org/external/pubs/ft/wp/2003/wp0345.pdf

Bank Indonesia. (n.d.). *BI 7-Day Reverse Repo Rate*. Retrieved July 23, 2022, from https://www.bi.go.id/en/fungsi-utama/moneter/bi-7day-rr/default.aspx

Codogno, L., Favero, C., & Missale, A. (2003). Yield spreads on EMU government bonds. *Economic Policy*, *37*, 503–532. https://doi.org/10.1111/1468-0327.00114_1

Dachraoui, H., Smida, M., & Sebri, M. (2020). Role of capital flight as a driver of sovereign bond spreads in Latin American countries. *International Economics*, *162*, 15–33. https://doi.org/10.1016/j.inteco.2020.04.002

DJPPR. (2021a). *Calendar of Issuance of Sovereign Bonds*. https://www.djppr.kemenkeu.go.id/page/load/

1332

DJPPR. (2021b). *DJPPR Biweekly Investor Update*. https://www.djppr.kemenkeu.go.id/page/loadViewer?idViewer=10795&action=download

DJPPR. (2021c). *Oustanding Position of Sovereign Bonds*. https://www.djppr.kemenkeu.go.id/page/load/22

Du, W., Im, J., & Schreger, J. (2018). The U.S. Treasury Premium. *Journal of International Economics*, *112*, 167–181. https://doi.org/10.1016/J.JINTECO.2018.01.001

Endo, T. (2020). The primary dealer system in lower-income economies. *Emerging Markets Review*, *45*. https://doi.org/10.1016/j.ememar.2020.100715

Ferrari, M., Stolz, S., & Wedow, M. (2018). Do primary dealer funding constraints impact sovereign bond liquidity and yields: evidence for nine Euro area countries. *Empirical Economics 2018 56:6*, *56*(6), 1855–1891. https://doi.org/10.1007/S00181-018-1451-6

Fiskal, B. K. (2021). *KERANGKA EKONOMI MAKRO*. 35. https://fiskal.kemenkeu.go.id/files/kemppkf/file/kem_ppkf_2021.pdf

Gadanecz, B., Miyajima, K., & Shu, C. (2018). Emerging market local currency sovereign bond yields: The role of exchange rate risk. *International Review of Economics & Finance*, *57*, 371–401. https://doi.org/10.1016/J.IREF.2018.02.004

Hyndman, Rob and Athanasopoulos, G. (n.d.). *Chapter 10 Dynamic regression models | Forecasting: Principles and Practice*. Retrieved October 26, 2021, from https://otexts.com/fpp3/dynamic.html

Izadi, S., & Hassan, M. K. (2018). Impact of international and local conditions on sovereign bond spreads: International evidence. *Borsa Istanbul Review*, *18*(1), 41–51. https://doi.org/10.1016/J.BIR.2017.08.002

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica*, *59*(6), 1551. https://doi.org/10.2307/2938278

Jongh, P. de, Jongh, E. de, Pienaar, M., Gordon-Grant, H., Oberholzer, M., & Santana, L. (2015). The impact of pre-selected variance inflation factor thresholds on the stability and predictive power of logistic regression models in credit scoring. *ORiON*, *31*(1), 17–37. https://doi.org/10.5784/31-1-162

Kim, J., & Lee, C. (2014). A Decomposition of Korean Sovereign Bond Yields: Joint Estimation Using Sovereign CDS and Bond Data. *Asia-Pacific Journal of Financial Studies*, *43*(6), 918–947. https://doi.org/10.1111/AJFS.12077

Kurniasih, A., & Restika, Y. (2015). The influence of Macroeconomic Indicators and Foreign Ownership on Government Bond Yields: A Case of Indonesia. *Mediterranean Journal of Social Sciences*. https://doi.org/10.5901/MJSS.2015.V6N5S5P34

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

LJUNG, G. M., & BOX, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303. https://doi.org/10.1093/BIOMET/65.2.297

Mercer, J. M., Moore, M. E., Whitby, R. J., & Winters, D. B. (2013). Price Discovery in the Treasury-Bill When-Issued Market. *Financial Review*, *48*(1), 1–24. https://doi.org/10.1111/J.1540-6288.2012.00354.X

Ministry of Finance. (2019). *Minister of Finance's Regulation no. 168/PMK.08/2019*. www.jdih.kemenkeu.go.id

Ministry of Finance. (2020). *Minister of Finance's Regulation No. 195/PMK.08/2020*. https://jdih.kemenkeu.go.id/in/dokumen/peraturan/2f0eefb5-a9ee-4419-7e5c-08d8a338ef1f

Miyajima, K., Mohanty, M. S., & Chan, T. (2015). Emerging market local currency bonds: Diversification and stability. *Emerging Markets Review*, *22*, 126–139. https://doi.org/10.1016/j.ememar.2014.09.006

muktiyanto, ihda, & Aulia, M. (2019). Determinan Tingkat Imbal Hasil (Yield) Surat Berharga Negara (SBN) Domestik. *Kajian Ekonomi Dan Keuangan*, *3*(1), 18–30. https://doi.org/10.31685/KEK.V3I1.190

Nyborg, K. G., & Strebulaev, I. A. (2004). Multiple Unit Auctions and Short Squeezes. *The Review of Financial Studies*, *17*(2), 545–580. https://doi.org/10.1093/RFS/HHG038

Permanasari, I., & Kurniasih, A. (2021). Factors Affecting the Yield of Indonesia Government Bonds 10 Years. *European Journal of Business and Management Research*, *6*(1), 243–248. https://doi.org/10.24018/EJBMR.2021.6.1.753

Saenong, Z., Muthalib, A. A., Adam, P., Rumbia, W. A., Millia, H., & Saidi, L. O. (2020). Symmetric and asymmetric effect of crude oil prices and exchange rate on bond yields in Indonesia. *International Journal of Energy Economics and Policy*, *10*(2), 95–100.

https://doi.org/10.32479/IJEEP.8878

Steele, J. M. (2003). *Advanced information on the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel Time-series Econometrics: Cointegration and Autoregressive Conditional Heteroskedasticity*. http://www-stat.wharton.upenn.edu/~steele/HoldingPen/NobelPrizeInfo.pdf

Tchuindjo, L. (2015). Pre-auction short positions and impacts on primary dealers' bidding behavior in US Treasury auctions. *Journal of Banking & Finance*, *59*, 193–201. https://doi.org/10.1016/J.JBANKFIN.2015.06.006

Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, *35*(3), 98–105. https://doi.org/10.3905/JPM.2009.35.3.098