Analysis on Determining Factors for 10-year Local Currency Sovereign Bonds Yield with Dynamic Regression Model: Indonesia Case

Dea Avega Editya   Dianne Cook

Contents

1 Abstract

We propose three dynamic regression models (DRM) to explain relationship between several predictors and Indonesia's local currency bonds (LCB) yield using time series data from 2015 until 2021. The third model that contains 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) can perform well in predicting real yield of the LCB in 2021 with small forecast error suggesting satisfying explanatory power of the model. Model statistics shows that 10y-UST and its lag-1 are the main factors that driving the LCB yield.

2 Introduction

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 or equivalent to USD72 Billion.[1] As of 2 September 2021, the total outstanding of local currency sovereign bonds (LCB) is IDR4,539 Trillion or equivalent to USD318 billion.[2]

The government sells the sovereign bonds through an auction which is conducted every Tuesday. The announcement will be released three days before the auction day (T-3). 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. 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). 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.

There are several benchmark series of the LCB offered in the auction. These series represent various maturity times. For conventional bonds, tenors of benchmark series in 2021 are ranging from 5, 10, 15, and 20 years. Meanwhile, benchmark tenors of sharia bonds cover 2, 4, 13, and 25 years.

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 treasury bills of tenor 3-month (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. Moreover, the 10y-yield is also reflecting outlook of long-term economic development and its movement is commonly used as a sign for predicting country's economic health.

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 and Aulia 2019). This condition had made Indonesia pays more expensive debt compared to these countries. As corporate and business use the LCB yield for benchmarking when borrowing or lending money in medium-long term, we may argue that the impact of costly debt has also spilled over in the national economy.

Considering the important functions of the 10y-LCB yield in Indonesia's economy, this study will analyze several variables that determine the yield and quantify their impact using the dynamic regression model (DRM) that consist of a linear model with ARIMA errors. This paper will be delivered in several sections. First, we will explain our research's motivation in Section 2. Section 3 will provide explanation of the collected data including some background knowledge from prior studies describing relation between each predictor and the LCB yield. Section 4 will explicate three models of DRM used in this study and several pre-check conducted before building these models. Section 5 and 6 will subsequently cover analysis of the result as well as conclusion and limitation.

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[1]Assumed exchange rate for conversion (IDR/USD) = 14,284.00

[2]ibid

3 Motivation

This paper provides three new values to existing literature. First, it employs exploratory data analysis (EDA) approach in each discussion and analysis. This approach will help us in gaining better intuition of each variable as well as eye-proofing some evidence complementing result from any formal statistic test conducted in this study. Some relationship may also be revealed through visualizations even before taking inference from model. Second, this is the first work that empirically studies the impact of primary dealers' behavior on the 10y-LCB yield in Indonesia. Third, this study also provide evaluation on the model's performance by making prediction of the LCB yield based on information from the predictors and comparing the prediction with the real yield.

The purpose of this work will be to provide insights and policy recommendations for the government 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 help to optimize the national's cost of borrowing which later can improve the economy.

4 Explanation of Collected Data

There are 7 variables used in this paper as explanatory variables to the Indonesia's LCB yield; US Treasury (UST) yield, credit default swap (CDS), foreign ownership, central bank's policy rate (policy rate), exchange rate, volatility index (VIX) and a dummy variable of auction/non-auction days as a proxy to primary dealers' trading behavior. The use of these explanatory variables are following numerous studies that have been conducted previously by various authors.

The UST yield is described by Miyajima er al. (2015) and Muktiyanto et al. (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 et al. whose focus of study is on Indonesia's 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 et al. (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 et. al (2014) and Muktiyanto et al. (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 et al. (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 (2020).

Our fourth predictor variable in this study, the policy rate, is inspired by results from several working papers in Indonesia conducted by Muktiyanto et al. (2019) and Kurniasih et al. (2015). These authors analyze relationship between the predictor with Indonesia's bonds yield. Both studies 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, Mohanty, and Chan 2015), (Gadanecz, Miyajima, and Shu 2018), (Saenong et al. 2020) and (Permanasari and Kurniasih 2021). Miyajima et al. (2015) suggest crucial effect of the exchange rate on the yield in emerging economies, while Gadanecz et al (Gadanecz, Miyajima, and Shu 2018) who use exchange rate volatility and expected exchange rate as predictor variables also confirm the significant relationship. These two studies are inline with a work by Permanasari et al. (2021) who study the effect on Indonesia's bonds yield, suggesting a significant negative-relationship between the exchange rate and the yield. A slight different conclusion is provided by Saenong et al (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. 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 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 (2018).

For the purpose of our study, we will use 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. Our response variable is 10y-Indonesia's LCB yield. All variables (except for Bank Indonesia's policy rate)[3] are collected as time-series data covering period from 2 January 2015 up to 5 August 2021 and will be explained in the following section.

4.1   10y-LCB Yield

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 1. As shown in the plot, the general trend of the yield is decreasing over the period of observations.

Figure 1: 10y-LCB yield movement from Jan 2015 until Aug 2021

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[3]The Bank Indonesia's policy rate is only available from 21 April 2016

If we look at the annual seasonal plot of the LCB yield in figure 2, we see that 2015 and 2018 have a quite similar increasing trend, while 2017 and 2019 have a similar decreasing trend.
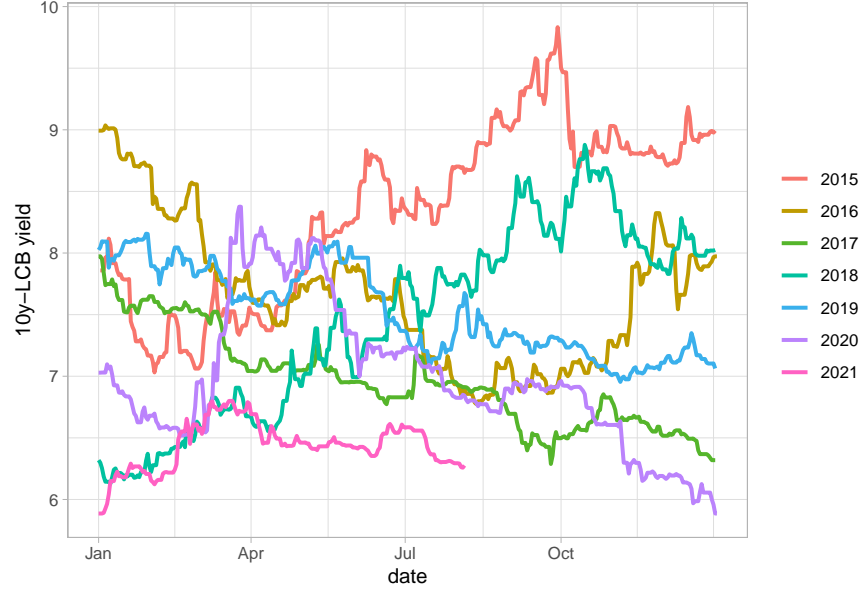

Figure 2: Seasonal Plot of 10y-LCB Yield

Looking further to the probability distribution of the yield-divided by year, semester and week in month as shown in figure 3, we can see that the yield is generally more volatile in the first semester (as indicated by longer interquartile ranges) than the second semester with exception for 2020.
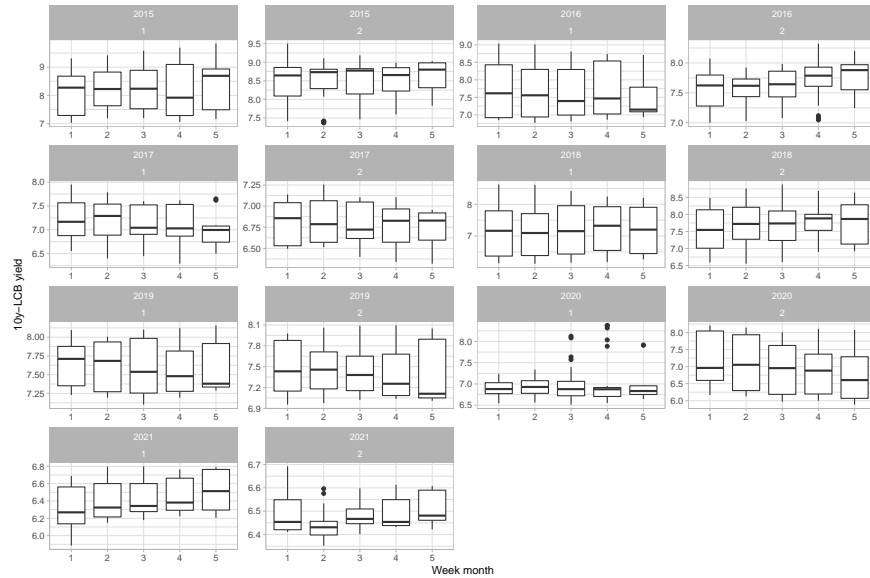

Figure 3: Probability distribution of 10y-LCB yield by semester and week in month

Furthermore, as yield is associated with risks, we will group our explanatory variables based on several relevant risk categories, which are external risk, default risk, financial market risk, macroeconomic risk and system risk.

4.2 External risk

4.2.1 10y-US treasury yield

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. The UST bonds are considered as the safest instrument hence issuers from other countries usually give extra premium over the UST bonds yield to compensate additional risks taken by investors when purchasing non-UST bonds. Thus, our hypothesis is that the 10-y UST yield has an effect on 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 4. The general trend of the UST yield is decreasing.

Figure 4: 10y-UST yield movement from Jan 2015 until Aug 2021

Moreover, timeseries of the predictor and the 10y-LCB yield with adjusted scale can be seen in figure 5. From the figure, we may conclude that these two variables seem to move toward the same direction, except for 2020 in which both variables were obviously moving in the opposite way.

Figure 5: Timeseries of 10y-LCB yield and 10y-UST yield (adjusted scale)

Looking at the annual seasonal plot of the UST yield in figure 6, we see that all years before 2019 have a relatively stable trend.
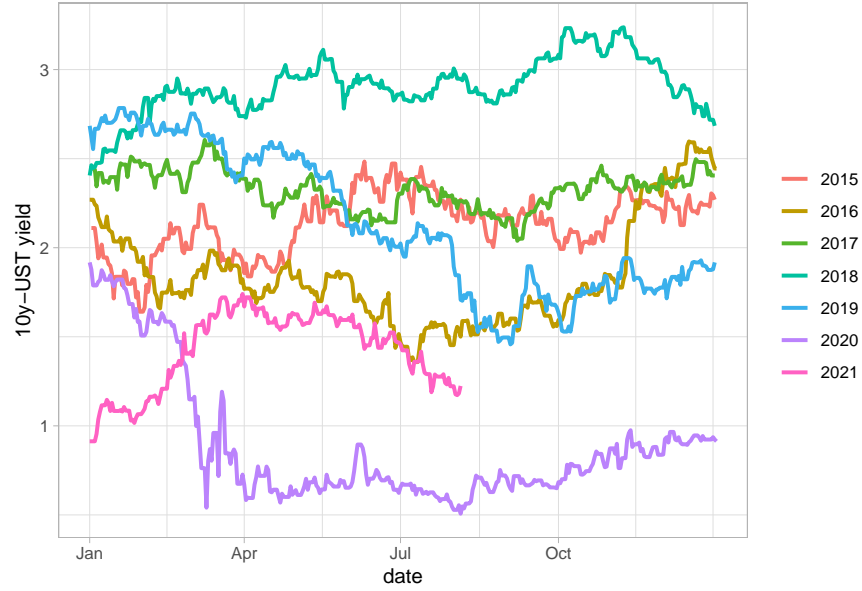

Figure 6: Seasonal plot of 10y-UST yield

Probability distribution of 10y-UST yield for all years in observation is illustrated in figure 7. In most years, the distribution is equal between first and second semester. Particularly for 2018, the UST yield looks more volative in the first semester than the second one. The opposite case is occurred in 2020, where the volatility is higher in the second semester than the first one.
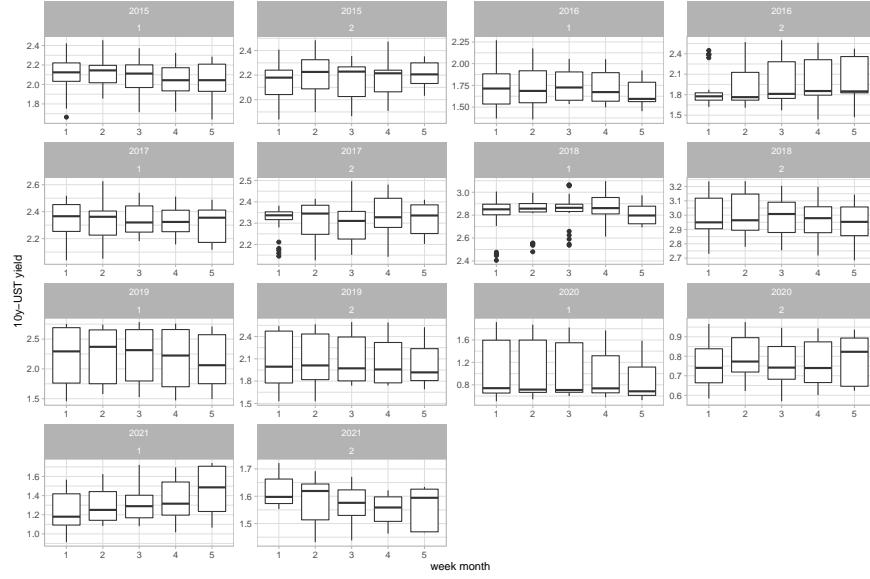
Figure 7: Probability distribution of 10y-UST yield by semester and week in month

The yearly correlation between the 10y-UST yield and the 10y- lCB yield is shown in figure 8. The plot indicates a positive linear correlation between the two variables in all observed years, except for 2020 that suggests a negative correlation.
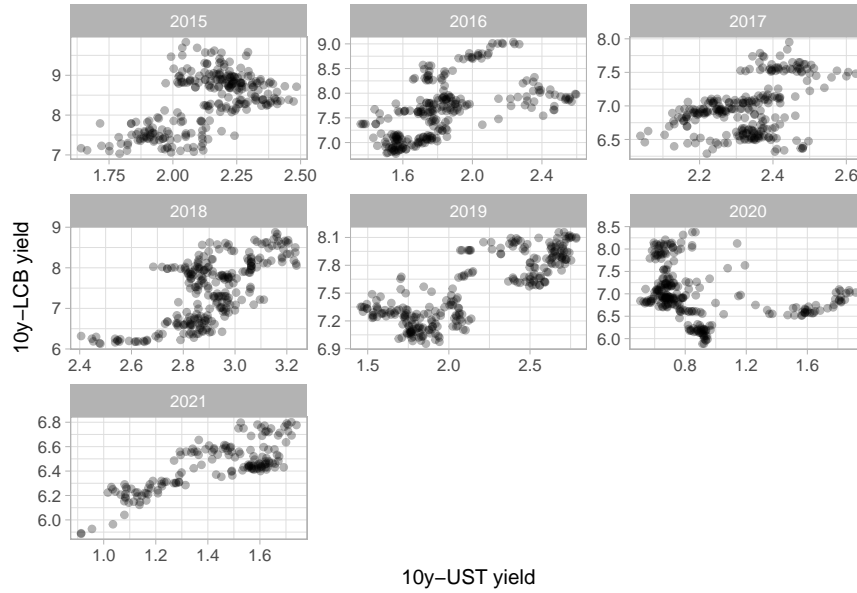

Figure 8: Correlation between 10y-UST yield and 10y-LCB yield

4.2.2 Foreign Ownership

As per 29 July 2021, foreign investors are holding IDR965 Trillions or 22.5% of total bonds ownership. The historical data of changes in the foreign ownership is shown in figure 9. The general trend of the changes is increasing.
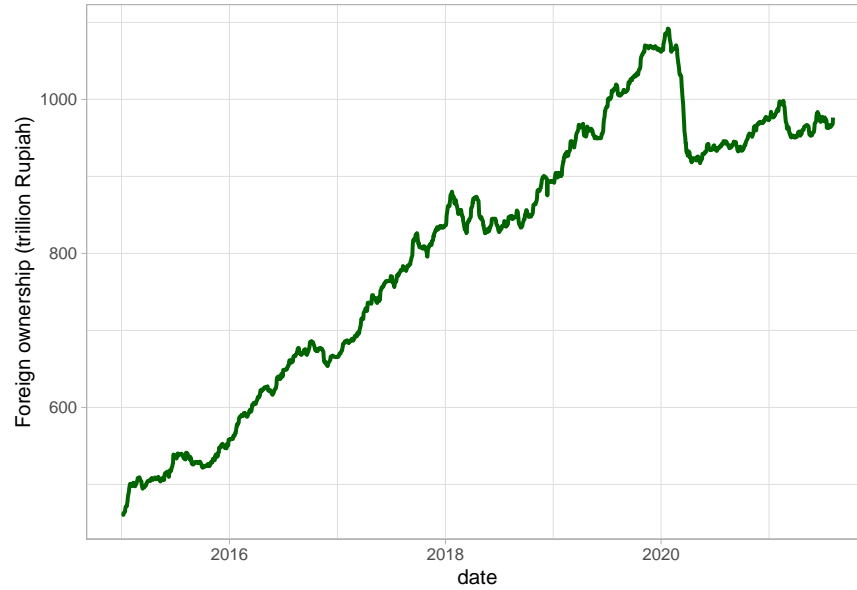
Figure 9: Changes in foreign ownership from Jan 2015-Aug 2021

If we look at the annual seasonal plot of the foreign ownership in figure 10, we see that all years have a relatively stable upwards trend, with exception for 2020 and 2021 in which the ownership were slightly declining.
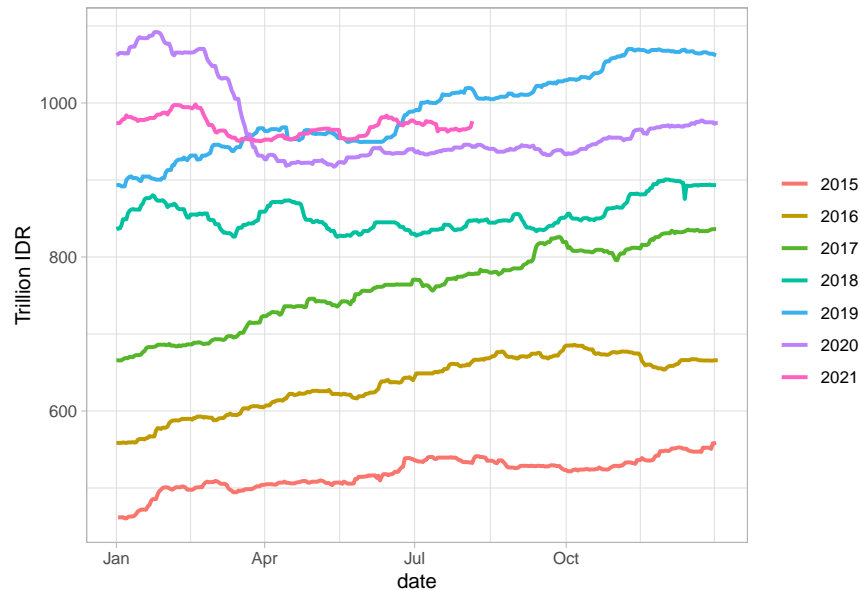
Figure 10: Seasonal plot of foreign ownership portion

Probability distribution of the ownership for all years of observation is shown in figure 11. In general, the changes of foreign ownership in more recent years (2018, 2019 and 2021) looks more volatile in the second semester than the first one. This is not the case for 2020 in which more volatility is shown in the first semester with decreasing median from IDR1000 trillion to around IDR950 trillion. It is as expected since Indonesia started to experience its covid19 pandemic in the first semester that may trigger foreign bonds

holders to reduce their exposure in the country. Furthermore, the median amount of foreign ownership was slightly increasing in the second semester of 2020 possibly due to a more confident bonds market as the Bank Indonesia had started to step into the market.
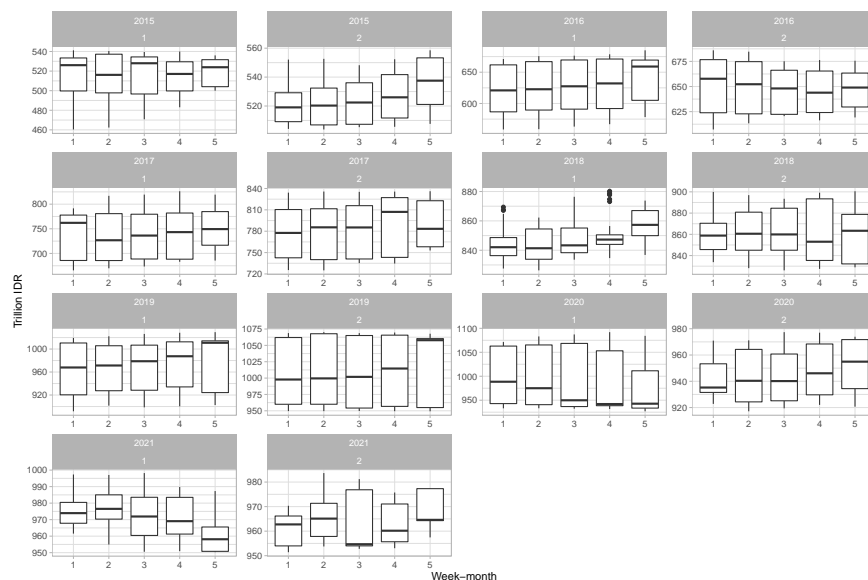
Figure 11: Probability distribution of foreign ownership

The foreign investor's share in the government bonds (including the 10y-LCB) has been reduced dramatically since 2020 due to an increase in both central bank and conventional bank's holdings in the LCB, as shown in figure 12. The figure shows daily changes in the LCB ownership, grouped by several industries from Jan 2015 until early August of 2021 (data before 2018 for conventional bank and islamic bank are not shown in the plot due to different classification names).

Figure 12: Total proportion of bonds ownership by industry from Jan 2015-Aug 2021

Starting from mid of 2020, the Central Bank (Bank Indonesia) seems to move aggressively in purchasing the government bonds through Quantitative Easing (QE) program in order to absorb l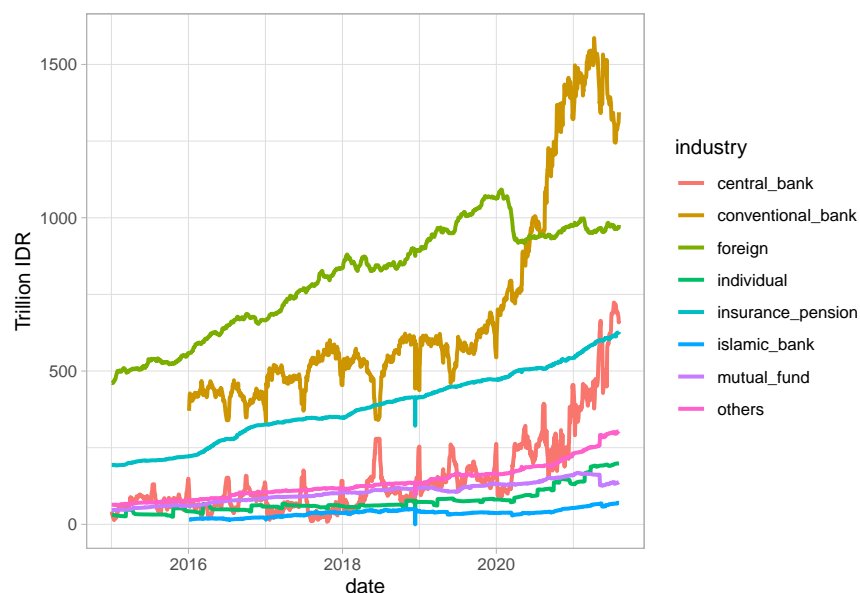arger issuance of the bonds which aimed to support large financing for covid19 pandemic. The monetary authority also introduced mandatory purchase regulation for the conventional banks that requires them to buy some minimum amount of the bonds and hold it as their liquidity assets, thus the bank's ownership were also growing big and even exceeding the ownership amount of foreign investors. Another interesting pattern from the plot is that the banks and the central bank always move in the opposite direction although in the long run both have similar upward trends. This is because of the central bank's function as "a stopper" responsible for backing up issuance of the LCB, to maintain stability of the yield's movement. However, LCB hold by the central bank is still under the amount of foreign ownership.

Timeseries of the foreign ownership and the yield is visualized in figure 13. From this figure we can see that most of the time these two variables are moving in opposite direction, except for 2020.

Figure 13: Time series of 10y-LCB yield and foreign percentage (adjusted scale)

The yearly correlation between the foreign ownership and the 10y-LCB yield can be seen in figure 14. In general, the plot shows negative correlation between these two variables, except for 2015.
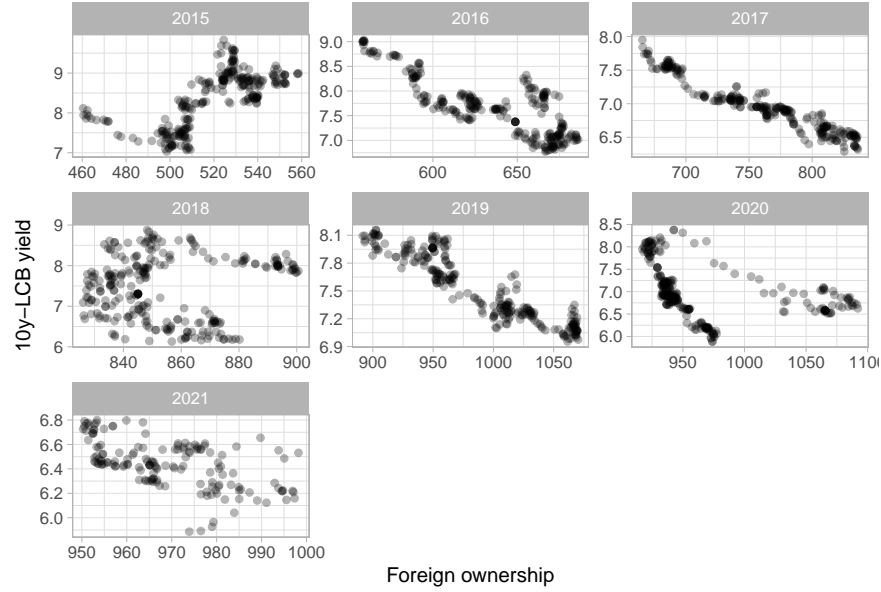
Figure 14: Correlation between foreign ownership and 10y-LCB yield

4.3 Default risk (5y-credit default swap)

A credit default swap (CDS) is a derivative contract that allows investors to hedge against the default of a borrower. This provides a market-based measure of the credit-risk premium. As mentioned by Codogno et al. (2003), CDS spreads can be seen as indication of the perceived credit risk by investors. 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 15. The general trend of the CDS is declining, with the highest jump occurred in early 2020 due to announcement of early cases of covid19 in March 2020.

Figure 15: Indonesia's 5y-CDS from Jan 2015-Aug 2021

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Checking at the annual seasonal plot of the 5y-CDS in figure 16, we see that the observed trends are quite the same with the trend of the LCB yield, in which 2015 and 2018 have an increasing trend, whereas 2017 and 2019 have a decreasing trend.
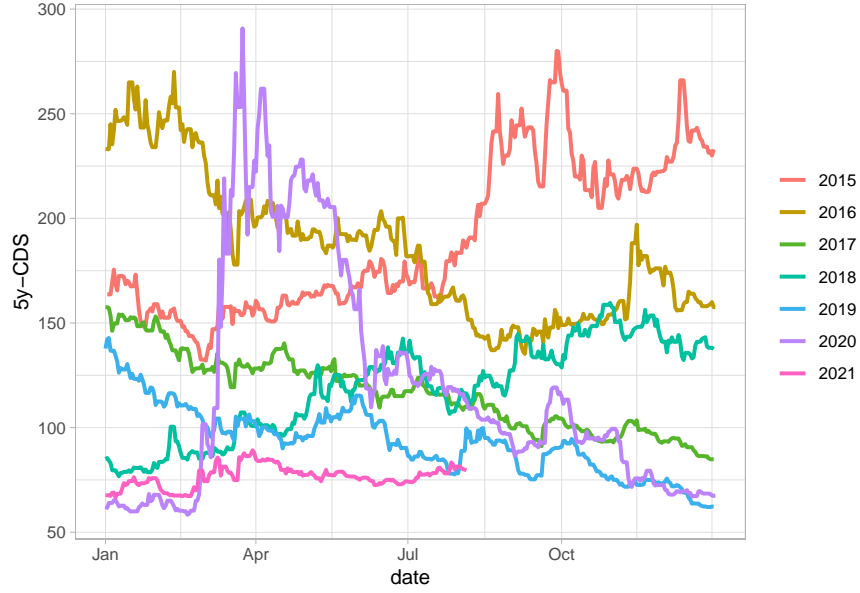
Figure 16: Seasonal plot of 5y-CDS

Probability distribution of the CDS is shown in figure 17. There is no obvious different between first and second semester for each year of observation, except for 2020 in which the CDS looks more highly volatile in the second semester than the first one. In addition, the first semester of 2020 has some noticeable outliers, with the highest value is about 300.
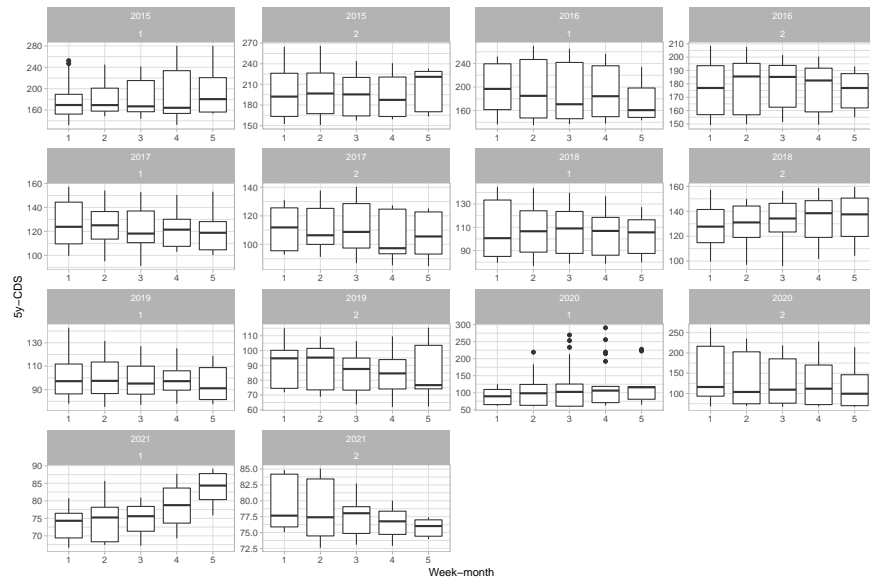
Figure 17: Probability distribution of 5y-CDS by semester and week in month

Time series of the CDS and the yield can be seen in figure 18. From the visualization we can see that the

pattern of these two variables are really similar, and both are moving towards the same direction.

Figure 18: Time series of 10y-LCB yield and 5y-CDS (adjusted scale)

The yearly correlation between the CDS and the yield is shown in figure 19. The plot shows strong relationship between the two variables in all observed years.
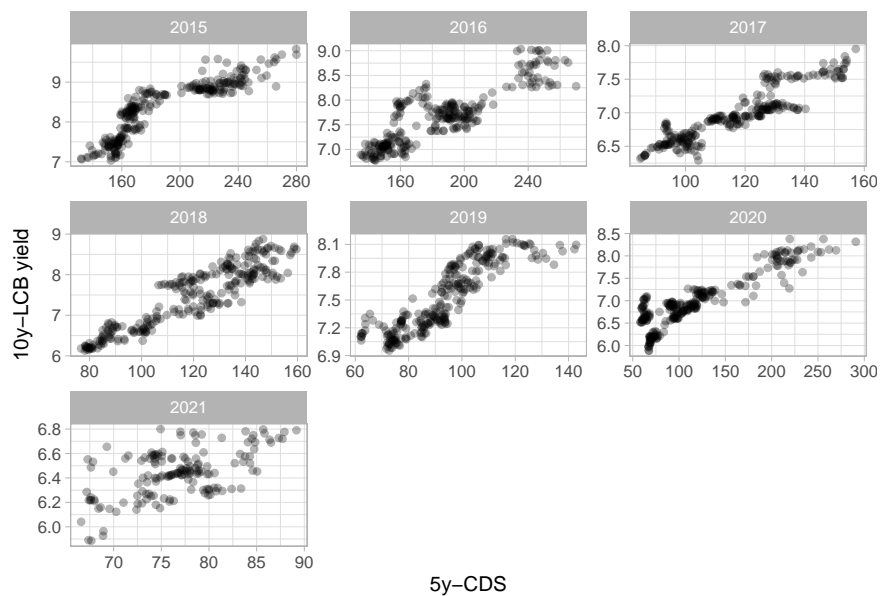
Figure 19: Correlation between 5y-CDS and 10y-LCB yield

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4.4 Financial market risk

4.4.1 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. 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 20. During years of observation, the highest jump in the VIX was happened in early 2020 where Indonesia reported its covid19 cases for the first time.
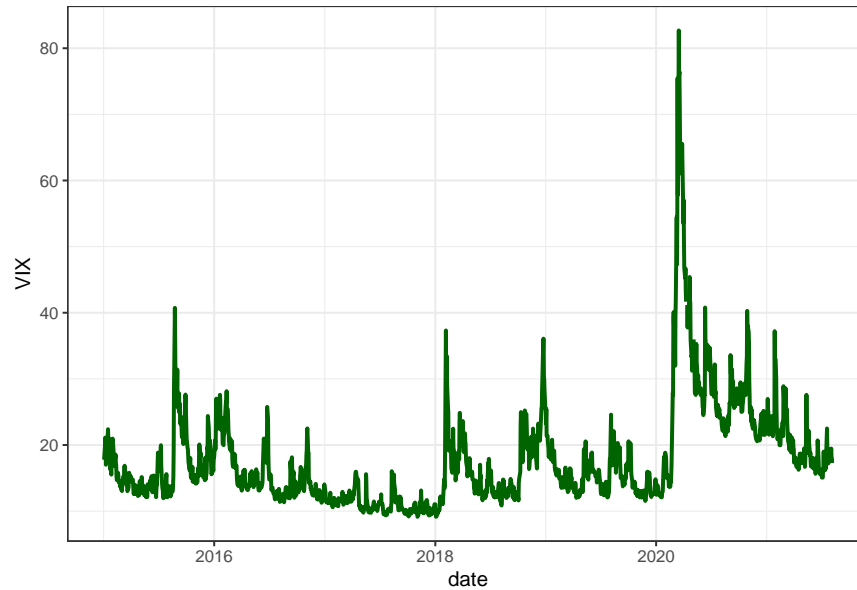
Figure 20: Volatility index of Indonesia from Jan 2015-Aug 2021

Reviewing the annual seasonal plot of the VIX in figure 21, we see that the most years show a relatively stable trend with maximum value is around 40. The exceptional pattern observed is in 2020 that showing a huge leap in March.
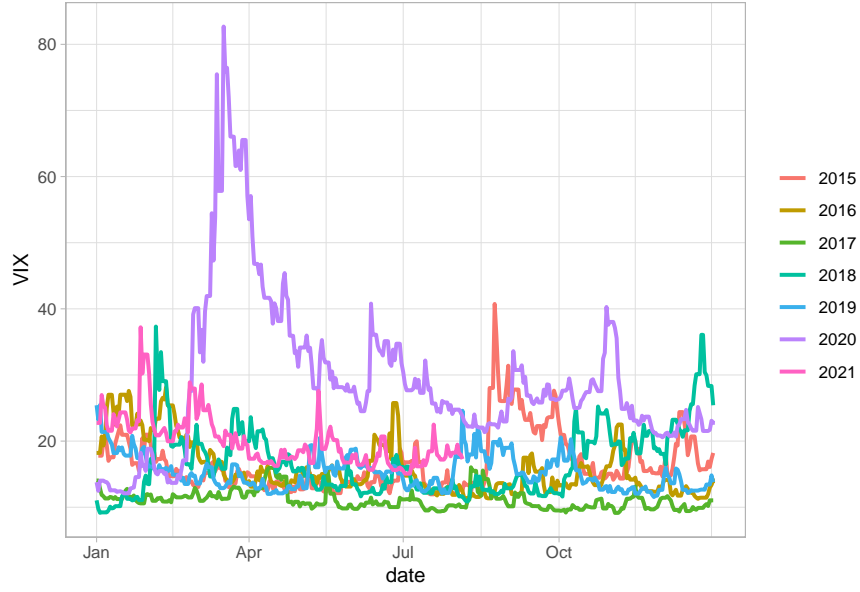
Figure 21: Seasonal plot of VIX

The probability distribution of VIX as visualized in figure 22 shows no significant different between VIX in first and second semester of each year of observation, except for 2016 in which the volatility of VIX in first semester is much higher than the second semester.
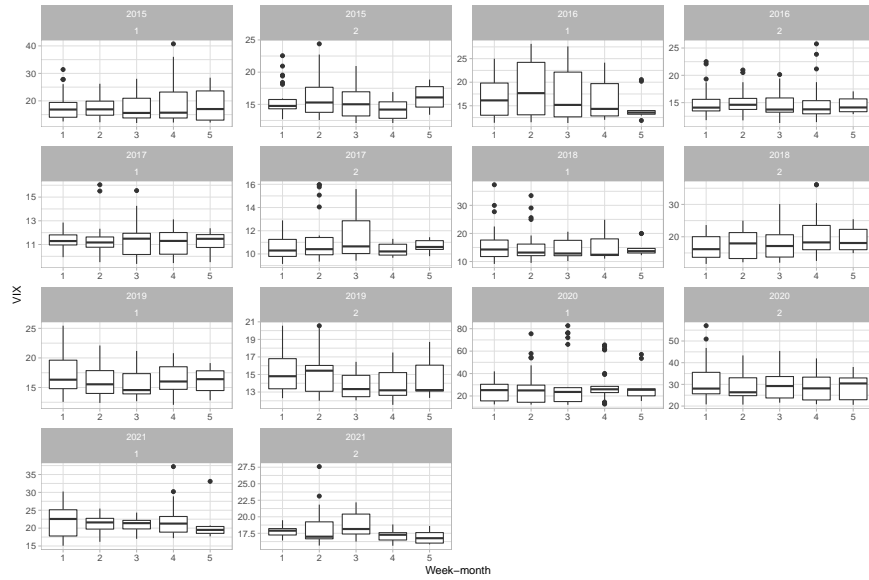
Figure 22: Probability distribution of VIX by semester and week in month

From figure 23, the two variables seem to move towards the same direction in all years of observation. One noticeable difference is that the VIX looks much more volatile than the yield.

Figure 23: Time series of 10y-LCB yield and VIX (adjusted scale)

The yearly correlation between the VIX and the yield is shown in figure 24. In general, the plot shows a positive linear correlation between the two variables in most observed years. Particularly in 2015 and 2018, the relationship looks non-linear, while in 2021 the VIX looks negatively correlated with the yield.
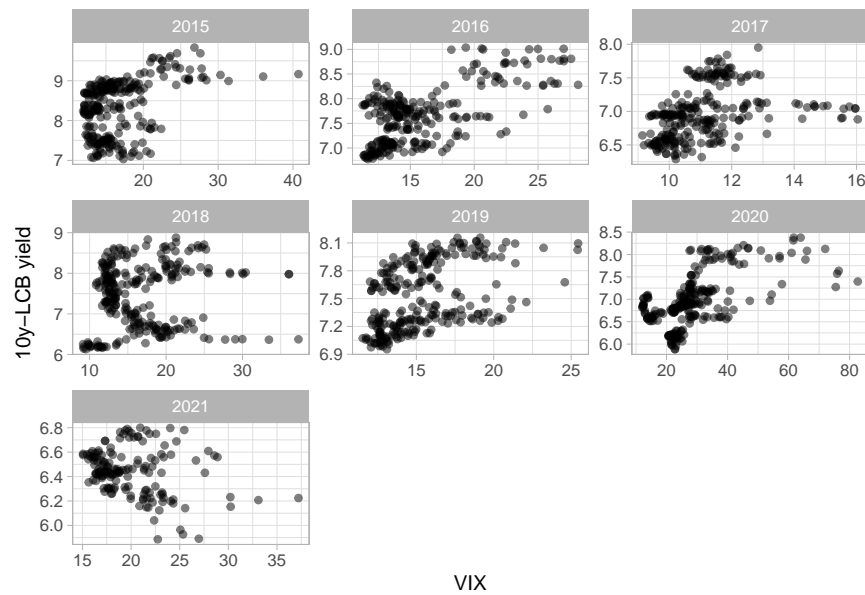
Figure 24: Correlation between VIX and 10y-LCB yield

4.4.2 Policy rate

Policy rate is a product of monetary authority used as a tool to manage liquidity in money market. The ultimate aim of the policy rate is helping the authority to achieve their inflation target. In Indonesia, the rate is periodically announce to public by Bank Indonesia (BI) as an output of monthly BI Board of Governors'

meeting. As explained by Muktiyanto (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.

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 existed since 21 April 2016. Thus, the data of the policy rate[4] used in this study will be ranging from that date until 5 August 2021.

Historical data of the rate is visualized in figure 25. The general trend of the rate is declining.
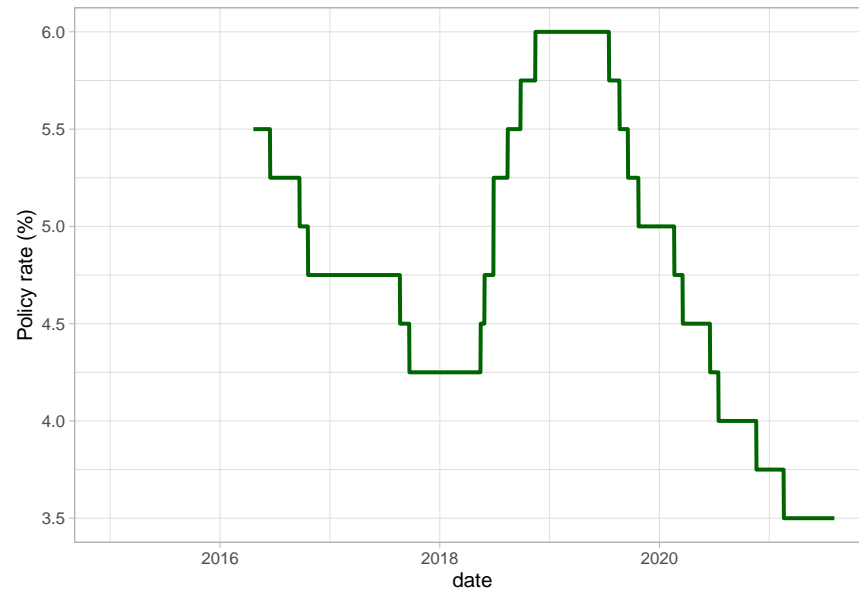
Figure 25: Changes in policy rate from Jan 2015-Aug 2021

Figure 26 indicates that the correlation between the policy rate and the yield are mostly positive and linear, with exception for 2020 in which the correlation looks non-linear, and for 2021 the correlation looks linear but negative.

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[4]The data is downloaded from Bank Indonesia's website at https://www.bi.go.id/id/statistik/indikator/bi-7day-rr.aspx.
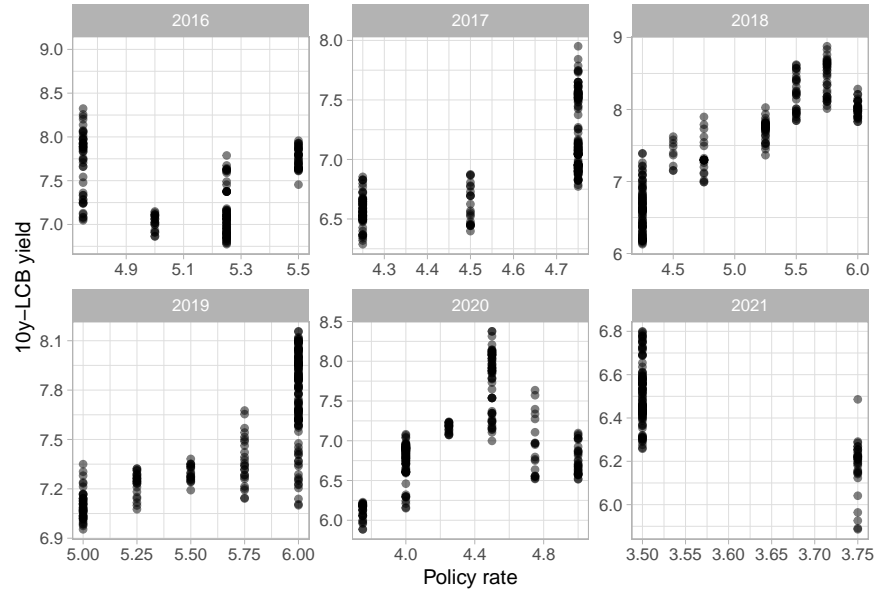
Figure 26: Correlation between policy rate and 10y-LCB yield

Time series of the rate and the yield for each year of observation can be seen in figure 27. The visualization indicates that these two variables are mostly moving towards the same direction, with the most obvious parallel patterns are seen in 2018, 2019 and 2020.
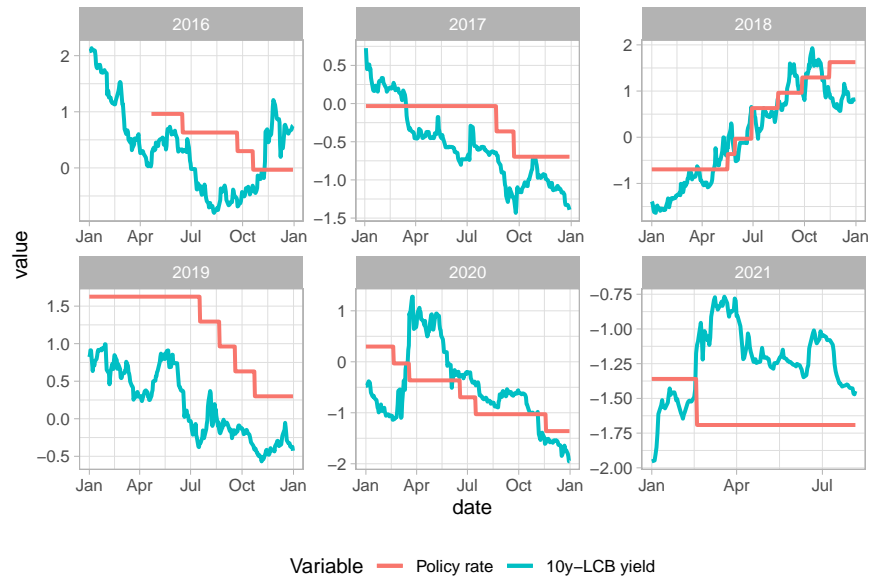
Figure 27: Time series of 10y-LCB yield and policy rate (adjusted scale)

4.5 Macroeconomic risk (exchange rate of USD/IDR)

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.[5] 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 28. The general trend of the rate is increasing.

Figure 28: Foreign exchange rate USD/IDR from Jan 2015 until Aug 2021

Looking at the annual seasonal plot of the exchange rate in figure 29, we see that 2015 and 2018 have an increasing trend. Furthermore, 2020 has the lumpiest trend with a big jump around March-April. The rest of years seems to have a relatively stable pattern

Probability distribution of the exchange rate can be seen in figure 30. In the figure, we can conclude that the exchange rate is relatively more volatile in first semester than second semester in most of years, with an exception for 2017 which shows the opposite.

Adjusting the scale of variables of LCB yield and Exchange Rate, we visualize the movement of these variables for each year as seen in figure 31. From the figure, we may conclude that both variables seem to move toward the same direction. Particularly in 2015, 2016, 2018, 2020 and 2021, these two variables were almost perfectly moving in such a parallel way.

The yearly correlation between the exchange rate and the yield is shown in figure 32. The plot shows a strong positive relationship between the two variables in all observed years, except for 2017 which has a quite different pattern. For 2018, the relationship between these two indeed looks perfectly linear.

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[5]The foreign exchange data is downloaded from https://www.bi.go.id/en/statistik/informasi-kurs/transaksi-bi/Default.aspx
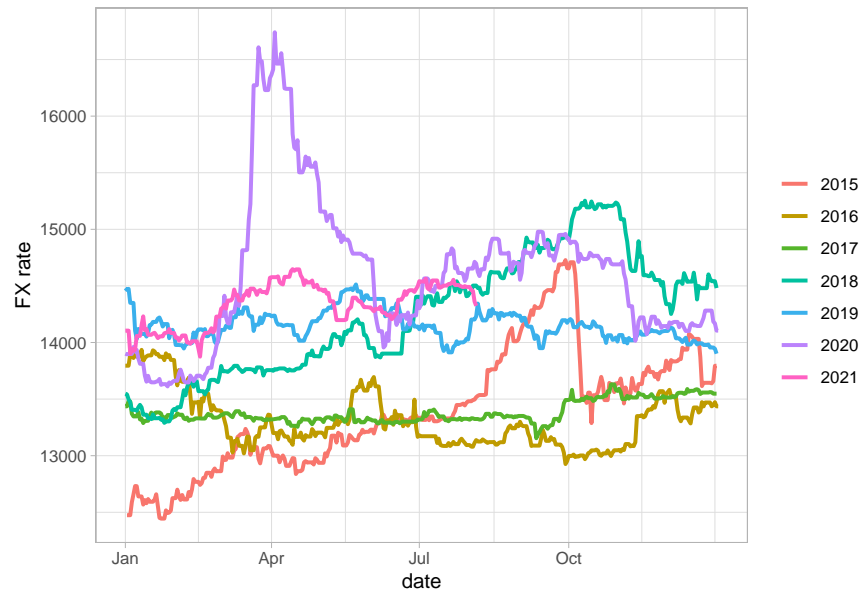
Figure 29: Seasonal plot of exchange rate USD/IDR
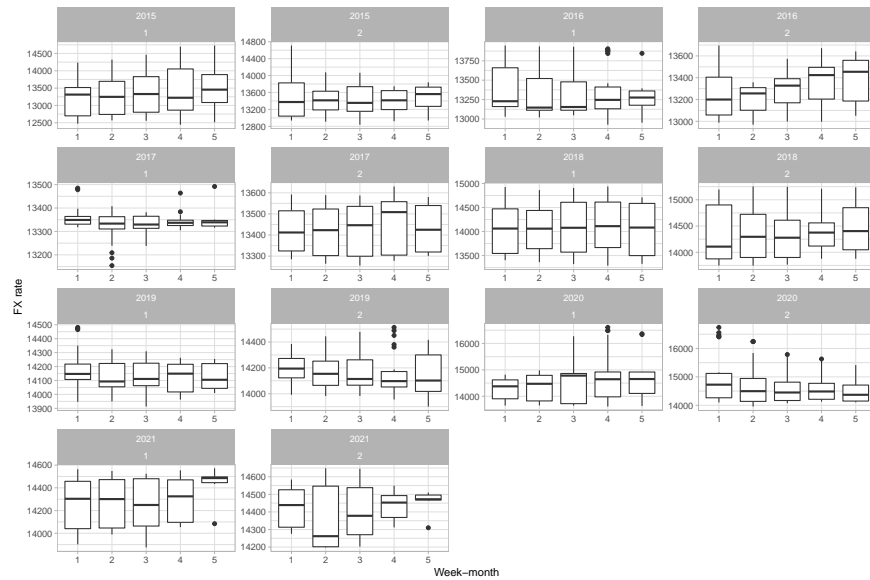
Figure 30: Probability distribution of exchange rate by semester and week in month

Figure 31: Time series of 10y-LCB yield and exchange rate (adjusted scale)
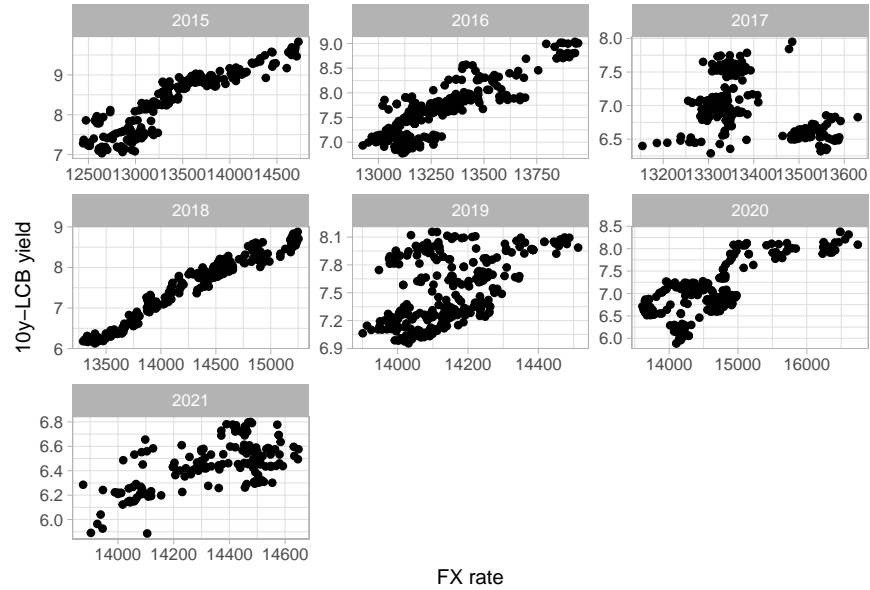
Figure 32: Relationship between exchange rate and 10y-LCB yield

4.6 System risk (primary dealers behavior)

Primary dealers system in Indonesia has been established since 2007. The system is expected to run several functions as shown in more developed economies. Arnone and 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.

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. They can bid both on behalf of their customers and for their own accounts. 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) 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 and Strebulaev 2004), which encourages them to bid aggressively and assign lower prices to the auctioned securities (Tchuindjo 2015), meaning higher demanded yields.

Thus, our analysis will be based on an assumption that primary dealers' strategic behavior in the auctions can affect sovereign bonds yield. To check this assumption, we use dummy variables of "auction days" that 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, we define auction days as days started from T-3 until T+1. Here, we exclude the day of settlement (T+2) since bonds is usually distributed by the Central Bank in the morning of the settlement day. In addition, we only include 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.

In order to check if the yield difference of these two periods is really significant or not, we create new variable "difference" that is calculated by subtracting yield of the last with the first day for each period. The summary table of the yield difference (showing only first 10 rows) can be seen in table 1.

Table 1: The yield's difference between auction and non-auction days

auction_day	date_from	date_to	domestic_10y_from	domestic_10y_to	difference
1	2015-01-02	2015-01-07	7.86	8.12	0.26
0	2015-01-08	2015-01-14	8.07	7.83	-0.24
1	2015-01-15	2015-01-21	7.79	7.40	-0.39
0	2015-01-22	2015-02-10	7.37	7.20	-0.17
1	2015-02-11	2015-02-17	7.41	7.39	-0.02
0	2015-02-18	2015-02-25	7.20	7.14	-0.05
1	2015-02-26	2015-03-04	7.10	7.29	0.18
0	2015-03-05	2015-03-25	7.40	7.34	-0.07
1	2015-03-26	2015-04-01	7.38	7.52	0.14
0	2015-04-02	2015-05-05	7.51	8.08	0.58

After the calculation, we visualize the difference of yield in each period as shown in figure 33. 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 last day in the period are lower than the first day. In other words, 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.

In addition, using boxplot to visualize the difference as seen in figure 34, the median difference between auction and non-auction days are also quite similar.
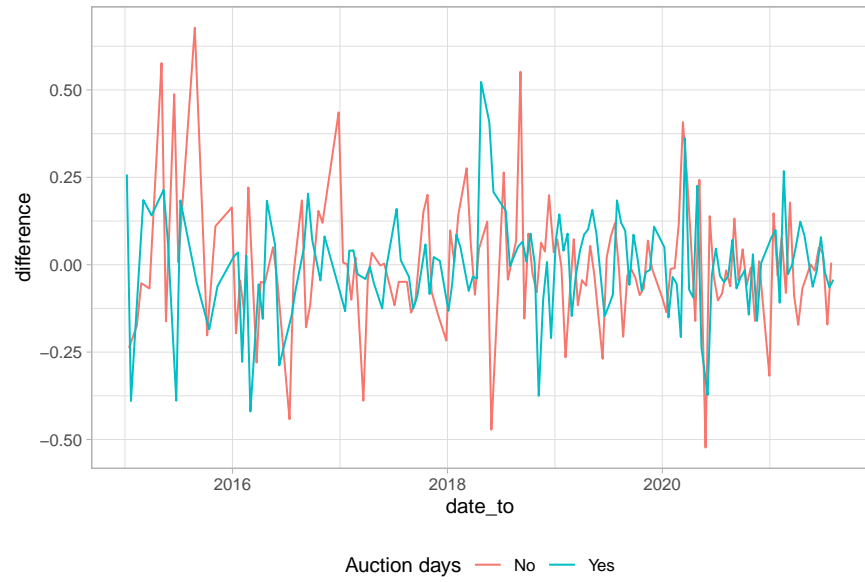
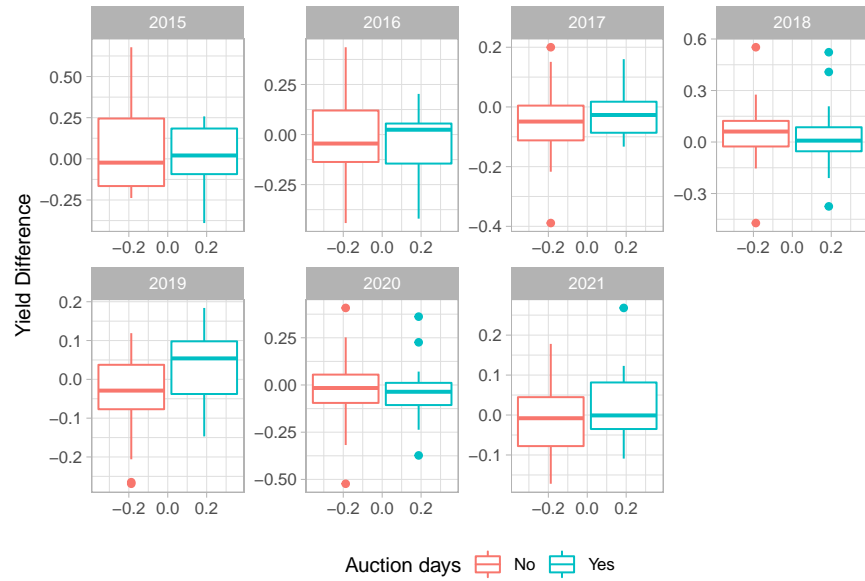Figure 33: The yield difference in auction and non-auction days

Figure 34: Boxplot of yield difference by year

5 Model

In conducting analysis on determining factors for the 10y-LCB yield, we will use dynamic regression model (DRM) to explain relation between our response and its predictors. There are two main advantages of using this type of model. First, it supports the use of regular linear regression model. Second, it enables us to combine the regression with ARIMA model that will handle timeseries dynamics (Hyndman, Rob and Athanasopoulos, n.d.). Thus, our DRM will consist of a linear regression model and an ARIMA model.

Before constructing the DRM, we will apply some preliminary testing as a standard procedure for implementing linear regression with time series variables. First, we will check multicolinearity between the predictors fitted in the linear regression model. Second, as ARIMA model requires all variables to be stationary except if they are cointegrated (Hyndman, Rob and Athanasopoulos, n.d.), we will check whether our response and predictors are cointegrated.

The last step is to fit DRM and analyze performance of the model by forecasting the yield based on the DRM and comparing the prediction with the real yield.

5.1 Multicolinearity test

For conducting multicolinearity test, we build a linear model with the LCB yield as a response and remaining variables as predictors. Then, we calculate Variance Inflation Factor (VIF) of all predictors. The result can be seen table 2.

Table 2: Statistic result of multicolinearity test

variable	VIF
ust_10y	2.08
vix	3.48
cds_5y	7.39
rate	2.30
foreign	8.90
exchange_mid	3.55
auction_day	1.02

From the result we see that 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 we can use the upper threshold for multicolinearity indication as suggested by Jongh et al. (2015). Thus, we can use all variables in our model since there is no presence of multicolinearity.

5.2 Cointegration test

Cointegration test is an important preliminary check before analysing time series of regression model especially in economics and finance, since many variables used in these fields are usually non-stationary, and regressing non-stationary time series could potentially produce spurious results (2003). At the same time, if we try to use difference for all non-stationary predictors (detrending), this approach will erase all long run effect of these variables with only short run dynamics remains (2003). As a result, the explanatory power of the model will be weakened.

The concept of cointegration can be described as follows: while individual variable is simply non-stationary, their long-run combination with other variables could potentially be stationary (2003). Hence, we will check if all of our time series used in this study are actually cointegrated.

Table 3: Table of unitroot test

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

For this purpose, we will use Johansen procedure[6] (Johansen 1991) since this testing method enable us to use combination of more than two time series. As a requirement for the test, we must ensure that all time series are 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, we see that 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, we will use a single differenced version of this variable (diff_foreign) so as to make its integration order I(1) in the cointegration testing. No seasonal difference is needed for all variables. Full result of the KPSS test can be seen in table 3[7].

The Johansen procedure is conducted using trace statistic method that produce eigenvalues (λ), rank of the matrix as shown in table 5 and eigenvector associated with the highest eigenvalue as shown in table 6. The first hypothesis, r=0, tests for the presence of cointegration between all seven variables included. It is clear that since the test statistic exceeds the 1% level significantly (868.11) we have 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, we can conclude that in order to form linear combination that poses cointegration we need at least 4 combination of the variables. Using all combination (7 variables) can perfectly make these time series cointegrated.

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[6]The Johansen procedure is conducted in R using library urca (Pfaff, B. 2008)

[7]ndiff = regular difference needed, nsdiff = seasonal difference needed

Table 4: Eigenvalues of variable's linear combination

lambda1	lambda2	lambda3	lambda4	lambda5	lambda6	lambda7
0.289	0.056	0.02	0.016	0.006	0.005	0.001

Table 5: The rank of matrix

	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

Summing up cointegration values from multiplication of eigenvector in table 6 with its corresponding variable, we can visualize the stationary of the linear combination of all time series as shown in figure 35.

Table 6: Component of eigenvector for 10y-LCB yield

	lcb_yield
lcb_yield	1.000
ust_yield	0.222
vix	0.122
dif_foreign	1.584
cds	-0.008
exchange rate	-0.001
policy rate	-0.599

$Cointegration\_values = 1 * lcb\_10y + 0.222 * ust\_10y + 0.122 * vix + 1.584 * d\_foreign - 0.008 * cds\_5y - 0.001 * exchange - 0.599 * pol\_rate$
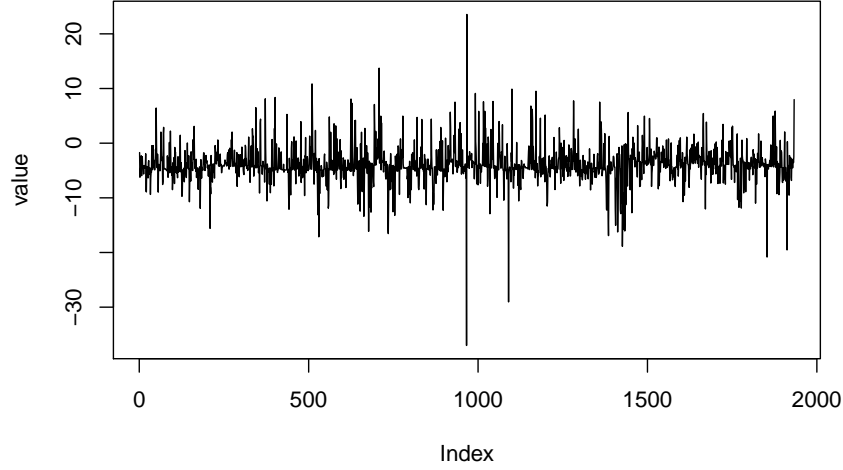
Figure 35: Stationarity of cointegrated variables

From the figure, we see that long-run effect of all combined variables seems not significantly different from zero (white noise) hence we can conclude that they are all cointegrated based on this visualization.

5.3 Dynamic regression model (DRM)

Regarding the result from the previous section, we can write down the general equation of the relation between all variables in a dynamic regression model 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 represent each predictor and η_t is an ARIMA error.

Summary statistic of the data is shown in table 7.

Table 7:

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

5.3.1 Full and smaller DRM

Using all predictors in the model (full DRM), we can see the model's statistics as shown in table 11. From the table, all predictors are significant on 5% level except for vix, dif_foreign, auction_day1 as well as seasonal AR(1). 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.

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Regarding the result, we will consider to build a smaller model consisting only significant variables (removing vix, dif_foreign, auction_day1) and no seasonal AR. Then, we will use the second-order Akaike Information Criterion (AICc) from these two models to check which model is better, indicated by a lower value of the AICc.

Table 8: Model estimation for 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 + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6593
Smaller model	ARIMA(lcb_10y ~ ust_10y + cds_5y + exchange_rate + pol_rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6596

From table 8, we see that the smaller model looks slightly better than the full model AICc (-6596 vs -6594) but is preferred since it can explain the LCB yield with 3 less variables.

5.3.2 DRM with lagged predictors

It is reasonable to think that some significant predictors in the regression model may have delayed impact on the LCB yield. This is particularly possible for predictors that have daily changed values such as 10y-UST yield, 5y-CDS, and exchange rate. Thus, in this section, we will add some lagged versions of these predictors into the smaller model, and later compare the AICc value of the model to the smaller model without lags.

The dynamic regression model with lagged effects can be written as follow:

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

where x_i represent each predictor and η_t is an ARIMA process.

For this purpose, we will select appropriate number of lags for each predictor 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 version, lag-2 and lag-3 versions. We also restrict the data for the models as it is important to ensure that the models use same fitting period when comparing number of lags (Hyndman, Rob and Athanasopoulos, n.d.).

Table 9: 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

The result of comparing AICc for each different predeictors can be seen in table 9. For 10y-UST yield, lag-1 can moderately reduce AICc (5274) hence 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/no lag) can produce the best AICc (5547) compared to its lag versions.

Based on the result, we then build a new model 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 full model-no lags and the smaller model-no lags are shown in table 10. As we can see the smaller model with lagged predictors can significantly reduce the AICc from -6594 (of the full model) to as low as -6676.

Table 10: 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 + pdq(2, 1, 0) + PDQ(0, 0, 0))	-6593
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

6 Analysis

6.1 Model interpretation

Table 11: 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

As seen in table 11, all variables including their lags version are significant on 5% level except for AR(2)[8] that is only significant on 10% level. We can also see that the biggest 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. However, we also notice that the exchange rate is also a quite powerful factor in determining the yield since a moderate increase in the exchange rate, i.e. 1000 USD/IDR, will make the yield increase about 40bps (0.4%) on average.

Interpretation from each significant coefficient can be written as follow[9]:

1. for 1% increase in lag-1 LCB yield[10], the LCB yield will increase about 12bps (on average)

2. for 1% increase in 10y-UST yield, the LCB yield will increase about 14bps (on average)

3. for 1% increase in lag-1 10y-UST yield, the LCB yield will increase about 20bps (on average)

4. for 10 points increase in 5y-CDS, the LCB yield will increase about 4bps (on average)

5. for 10 points increase in lag-1 5y-CDS, the LCB yield will increase about 2bps (on average)

6. for 1000 USD/IDR increase in exchange rate, the LCB yield will increase about 40bps (on average)

7. for 1% increase in policy rate, the LCB yield will decrease about 7bps (on average)

6.2 Model Performance

6.2.1 Residual Check

In this section we will check if residuals from the DRM is resembling white noise. This is important 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 (O'Hara-Wild, Hyndman, and Wang 2021) to show the innovation residuals. From the residuals plot as seen in figure 36[11], we can see that residuals of the estimated ARIMA errors (2,1,0)(0,0,0) seems not significantly different from a white

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[8]Lag-2 of the LCB yield

[9]The effect of each predictor on the response is assuming other factors are hold constant

[10]Shown as AR(1)

[11]Residuals from year 2015 are not shown in the figure since policy rate variable in the model is only available from 2016

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.
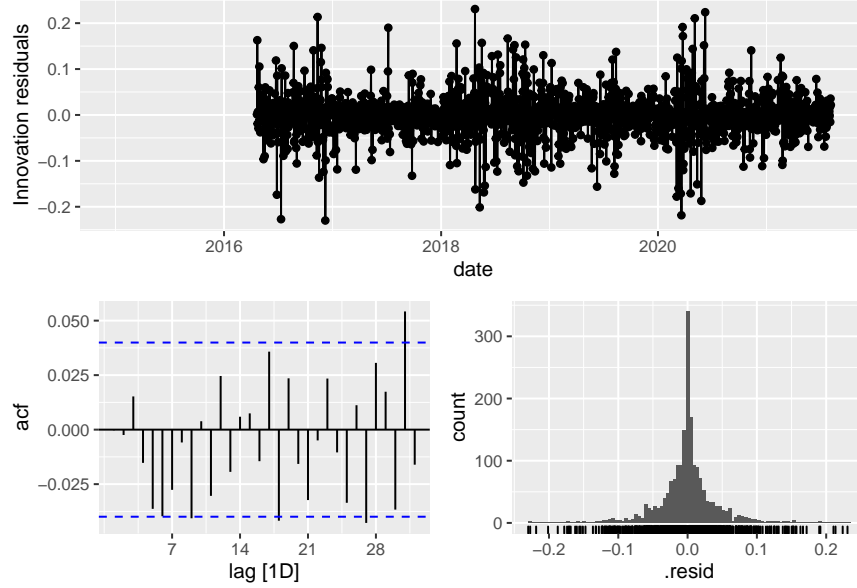

Figure 36: Innovation residuals of the model. All plots indicate residuals are not different from zero

We complement the visualization check with a formal test using Ljung-Box test. From the test result, we can confirm that the residuals are similar to white noise since the pvalue produced (with lag = 21) is large (0.24).

Table 12: Ljung-Box test on innovation residuals

lb_stat	lb_pvalue
25.12276	0.24

6.2.2 Prediction using the best model

In this section we will evaluate performance of the best model (the smaller model with lags) by making prediction on the real 5y-LCB yield. The prediction will be based on the fitted model of training data. For this purpose, we separate data into training and testing. The training data contains all observations up to 31 December 2020, while the testing data contains all observations from 1 January 2021 until 8 August 2021.

Since our purpose is to predict the real 10y- LCB yield, we will use real data of the predictors instead of forecasting each of these exogenous variables. The prediction is using library Forecast in R (R. J. Hyndman and Khandakar 2008) and the result can be seen in figure 37.
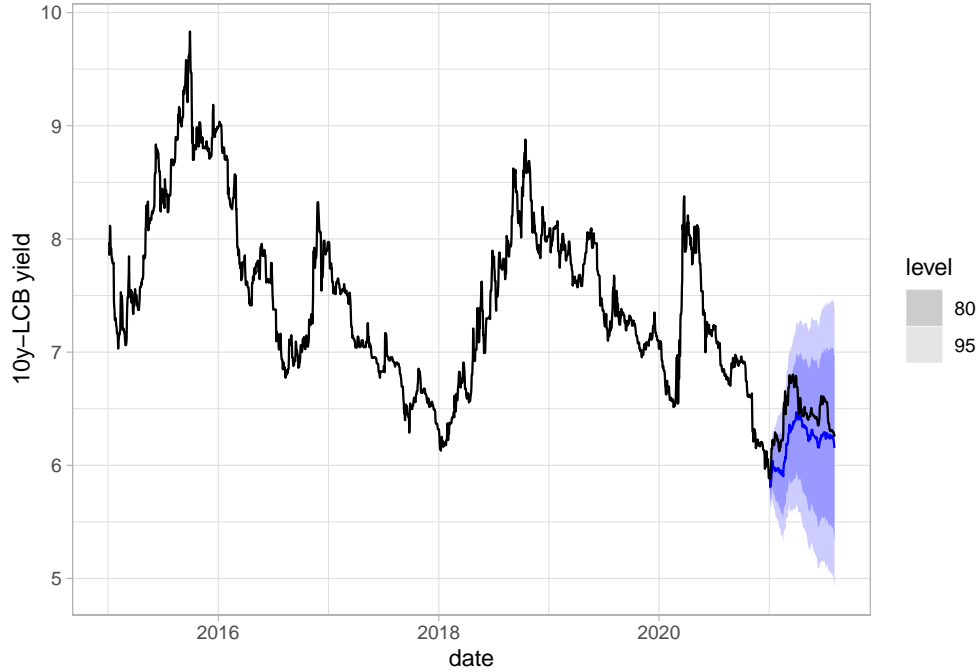
Figure 37: Performance of model in predicting real 10y-LCB yield (blue line is the prediction)

From the plot, the DRM seems to nicely capture the LCB yield's dynamics (trend and volatility) quite 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 time series (5 years long) and at the same time our forecast horizon is quite long (7 months) hence more uncertainty is associated with the prediction.

Table 13: 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_mid + rate + pdq(2, 1, 0) + PDQ(0, 0, 0))	0.26	1.78

From table 13, the DRM seems to have very low prediction error indicated by small score of RMSE and MASE that are 0.26 and 1.78 consecutively.

7   Conclusion and limitation

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 dynamic regression model (DRM), several predictors are not significant enough on 5% level which are VIX, foreign ownership (in difference version), as well as auction/non-auction days. Thus, in the second model these insignificant variables are excluded to make 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 version 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 lagged predictors significantly reduce the AICc score. In addition, during evaluation of model performance, the model also nicely predict 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 that consist of lag-1 of the LCB yield, 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 best model is the lag-2 LCB yield.

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. However, we also notice that the exchange rate is also considerably a quite powerful factor in determining the yield since a moderate increase in the exchange rate, i.e. 1000 USD/IDR, will make the yield increase about 40bps (0.4%) on average.

From the result, we suggest that finding appropriate level of foreign exchange rate and maintaining its stability can directly impact the level and the stability of the LCB yield. Adjusting policy rate to its optimum level may also reduce the LCB yield as suggested by our best model, possibly because more capital inflow will enter Indonesia's financial market that in turn will help to stabilize the exchange rate as explained by Gadanecz et al. (2018).

There are several limitation from this study. First, the range of most time series 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, largely due to a mandatory purchase regulation aimed to reduce and stabilize the LCB yield during pandemic. 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, the abrupt changes in policy may also cause our foreign ownership predictor to be insignificant.

Lastly, this study only include 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 limitation 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.

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