Nowcasting Indonesia's GDP Growth Using Dynamic Factor Model: Are Fiscal Data Useful?

Ardiana Alifatussaadah[1], Anindya Diva Primariesty[2], Agus Mohamad Soleh[3], Andriansyah[4].
{ardianaalifatus@gmail.com[1], divaprimariesty@gmail.com[2], agusms@apps.ipb.ac.id[3], andriansyah@fiskal.kemenkeu.go.id[4]}

Department of Statistics, IPB University, Bogor, 16680,Indonesia[1],
Department of Statistics, IPB University, Bogor, 16680,Indonesia[2],
Department of Statistics, IPB University, Bogor, 16680,Indonesia[3],
Fiscal Policy Agency, Ministry of Finance, Indonesia[4].

Abstract. Since introduced by Giannone *et. al.*, GDP nowcasting models have been used in many countries, including Indonesia. Variables to select usually include housing and construction, income, manufacturing, labor, surveys, international trade, retails and consumptions. Interestingly, fiscal variables are excluded even though government expenditure is an integral part of the basic GDP identity. By employing the previous journal of quarter-to-quarter real GDP growth nowcasting technique by Bok *et. al.*, this paper is aimed at testing the usefulness of inclusion of fiscal variables, in addition to 61 non-fiscal variables, in nowcasting Indonesia GDP. The results show, even though based on the fact that fiscal data have low correlation coefficients to GDP, the inclusion of fiscal data may help to produce a better early estimate of GDP growth based on a better RMSEP value.

Keywords: Dynamic Factor Model,Indonesian GDP, Nowcasting.

1 Introduction

Macroeconomic indicators explain economic changes that affect societies, companies, and markets. One of the macroeconomic indicators is GDP (Gross Domestic Product), i.e. the value of all final goods and services produced by a country within a certain period of time. GDP is very important to be monitored in real time because it is used as a reference for decision making whether the economy contracts or develops, and to keep the economy from threats such as recession or inflation. However, GDP data in Indonesia is released by Statistics Indonesia (BPS) with 5 weeks delays after the end of each quarter, so we need a model that can be used to predict the real time current quarter GDP.

[2] Bok, *et. al* said that new methodologies in time-series econometrics developed over the past two decades have made possible the construction of automated platforms for monitoring macroeconomic conditions in real time. [5] Giannone, *et. al*built the first formal and internally consistent statistical framework of this kind by combining models for big data and filtering techniques. Because of the emphasis on the present, they dubbed it “nowcasting," a term originally used in meteorology for forecasting the weather in the present and in the next

ICSA 2019, August 02-03, Bogor, Indonesia

DOI 10.4108/eai.2-8-2019.2290478

few hours. So, in this paper we use nowcasting to predict the current situation of GDP data in Indonesia.

GDP in Indonesia has many indicators and variables which certainly affect the results of the predictions. Therefore, in this paper, we focused on selecting variables that found in fiscal and non-fiscal data to construct the best model. [12] Maintaining sustainable fiscal policy has been increasingly important in the scope of economists and policymakers, therefore we concern with fiscal data. [4] Ehrhart and Llorca said the main objective of fiscal sustainability is to provide a country with the macroeconomic stability to maintain both its budget deficit and public debt within sustainable limits. We produced the prediction by employing a Dynamic Factor Model (DFM) and selected the best model by comparing the Root Mean Square Error Prediction (RMSEP) value of each model with different variable. [8] [11] Nowcasting GDP in Indonesia using dynamic factor models has been performed by Luciani *et. al.* and Tarsidin *et. al*. Nowcasting has beenproven to be effective for economic assessments in Indonesia and the dynamic factor model that has been proven to be the best model than any other models such as auto regressions and bridge equations. So, in this paper we built nowcasting GDP in Indonesia using dynamic factor models.

The purpose of this paper is to build the best model by selecting the variable of Indonesian GDP by comparing the RMSEP with nowcasting using dynamic factor model and to utilize the benefits of fiscal data.

2Materials

In this section we described the indicators that are used for this research. The data for estimation used in this research was for the period from April 2011 to March 2019 with the pseudo out-of-sample testing used from April 2018 to March 2019 data. The reference series were Indonesia’s GDP in quarter-on-quarter (q-o-q) growth rate, while the component series were various representative indicators. We divided the indicators into two sub categories: fiscal data and non-fiscal data. Not all data for the indicators was available from 2011-2019. Therefore, the data was ragged data with differing availability across the period.

There are 72 variables used in this study including the Indonesian GDP variable, 61 non-fiscal variables and 10 fiscal variables. From the 61 of non-fiscal variables, there are 59 variables used starting from April 2011, while commercial & rural bank loans start from June 2016 and manufacturing purchasing managers' index (PMI) starts from July 2014. Variable sources were obtained from CEIC, Bloomberg and Haver and collected by Fiscal Policy Agency, Ministry of Finance.

From the 10 fiscal variables above, domestic VAT, import VAT, palm oil price and Brent prince the data starting from April 2011, whereas coal Newcastle starting from January 2013 and the remaining 5 variables starting from January 2012. Variable sources were obtained from CEIC and the State Budget (APBN).

3Methods

3.1 Dynamic Factor Model (DFM)

Dynamic factor model has been proven to be the best model than any other models such as the ARIMA and bridge equation for nowcasting current GDP. [7] Factor models are based on the idea that macroeconomic fluctuations are the result of a few macroeconomic shocks that affect *the whole* economy and a number of sectoral/regional shocks that affect *a part of* the economy. Therefore, each variable in the dataset can be decomposed into a common part and an idiosyncratic part, where the common part is assumed to be characterized by a small number of common factors ($\mathbf{f}_t$) that capture the co-movement in the data. [3] assumed that the observed, stationary growth signals of k monthly indicators are generated by a factor model:

$$x_{it}= \lambda_i f_t+ \xi_{it} \tag{1}$$

with:

x_{it}: ith indicator growth signal at time t.
λ_i: ith indicator loading on common factor.
f_t: common factor at time t.
ξ_{it}: specific or idiosyncratic component of ith indicator at time t.

The vector of common factors evolve over time as a VAR(p)processdrivenbythecommonshocks$\mathbf{u}_t \sim N(0,\mathbf{I}_r)$,whileeachidiosyncratic component follows an independent AR(1) model driven by the idiosyncratic shocks e_{it}. The loadings $\lambda_i$measure the sensitivity of the growth signal of each indicator forchanges in the factor. [1] Dynamic Factor Model was subsequently developed further by Aruoba. The equation (1) involved estimating the representative parameters of the state space using the principal components. DFM proved very successful in real-time forecasting, and when used for this task, they work as follows: suppose that we are at day d, and that at date d, it is available a given vintage of data: X^d. Further, suppose that on the basis of X^d we have constructed our prediction:

$$\hat{x}_{it}^{d}= \hat{\lambda}_i \hat{f}_t^{d}+ \hat{e}_t \tag{2}$$

Now, suppose that at day d + 1 a new data is released (e.g. exports). Based on this new piece of information we can check if our stand about the business cycle is still correct or if we need to revise it, which is what the DFM does automatically. More specifically, at day d + 1 we have now a new vintage of data: X^{d+1}. Given this new vintage we can update our estimate of the factors, $\hat{f}_t^{d+1}$, and hence update our predictions [7]:

$$\hat{x}_{it}^{d+1}= \hat{\lambda}_i \hat{f}_t^{d+1}+ \hat{e}_t \tag{3}$$

3.2 Variable Selection Process

Before we go to the nowcasting process, we need to select the best variables firstly by check the correlation among variables. The candidate variables were subsequently whittled down using several criteria in order to observe the correlation with the reference series (based on the coefficient of correlation). Several indicators were thus selected for use in the estimations. Indicators with a correlation coefficient value of 0.70 or more were selected for the evaluation stage.Pearson's correlation coefficient r is the mostly used non-parametric measure of association for two random variables. [10] Samuel said the quantity r, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The linear correlation coefficient is sometimes referred to as the Pearson product moment correlation coefficient in honor of its developer Karl Pearson. The value of r is such that $-1 \leq r \leq +1$. The + and – signs are used for positive linear correlations and negative linear correlations, respectively.

3.3 Model Evaluation

To choose the best model, we compare the Root Mean Square Error of Prediction (RMSEP) of each model. The RMSEP are calculated for the data set as:

$$\mathrm{RMSEP} = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}} \qquad (4)$$

Where N is the number of objects in the prediction set. $\hat{y}_i$ and y_i are the predicted and the experimental property of the *i*th object, respectively [6].

4Results and Discussion

The following section explores the results of the variable selection process, data management as well as estimations and predictions of nowcasting using the Dynamic Factor Model (DFM).

4.1 Variable Selection

There is a wide set potentially monthly and quarterly series that could help to extract information of Indonesia’s GDP. As mentioned in the *Materials* section, there are many variables that are predicted to influence changes in Indonesia's GDP. Since the variables in the information set are numerous, estimating full models with all variables would limit the degrees of freedom and also the models would perform poorly in forecasting because of the large uncertainty in the parameters estimation [5]. Therefore we plan to construct a new data set, in addition to improving the performance of the analysis results, it is also to improve the efficiency of data usage. We construct our new data set using two approaches, that is statistically and economically judgment.

Starting from the set of numerous variables (1 variable Indonesian GDP and 71 Indonesian GDP indicator variables), we construct our dataset as follows:

1. Exclude variables that had too view observations or could not retrieved. In this case, variable Commercial & Rural Banks: Loans that we only could retrieve starting from June 2016, Production Index: Crude Oil that we only could retrieve starting from April 2011 until March 2017 and Manufacturing purchasing managers' index (PMI) we only could retrieve starting from July 2014. Those three variables have more than 1/3 missing values. The time series with more than 1/3 missing values, i.e. NAs, are deleted and the remaining are modified such that the missings and outliers are replaced by an approximated value, i.e. the median. So we deleted 3 variables of Indonesia’s GDP and left 68 variables.
2. The candidate indicators variables were subsequently whittled down using several criteria in order to observe the correlation with the reference series (based on the

coefficient of correlation). Several indicators were thus selected for use in the estimations. Indicators with a correlation coefficient value of 0.70 or more were selected for the evaluation stage. Table 1 presents the coefficients of correlation of several candidate indicators in terms of level.

Table 1. Coefficients of correlation of several indicators of non-fiscal data with GDP

No.	Coefficient Correlation	No.	Coefficient Correlation	No.	Coefficient Correlation	No.	Coefficient Correlation
X1	0.9404	X16	0.3963	X31	0.9837	X47	-0.6223
X2	0.9937	X17	0.9783	X32	0.9663	X49	-0.6509
X3	0.2488	X18	0.9824	X33	0.9564	X50	-0.6130
X4	0.9630	X19	0.9700	X34	0.9485	X52	0.9378
X5	-0.0265	X20	0.9762	X35	-0.7614	X53	0.0369
X6	0.5435	X21	0.4378	X36	0.4113	X54	0.3516
X7	0.1947	X22	0.4313	X37	0.3831	X55	0.9551
X8	0.6864	X23	0.3649	X38	0.9777	X56	0.5416
X9	0.9865	X24	0.2902	X39	0.9706	X57	0.7234
X10	0.9922	X25	0.8047	X40	0.9813	X58	0.0478
X11	-0.0523	X26	0.9103	X41	0.9748	X59	-0.7096
X12	0.9822	X27	0.8847	X42	0.1628	X60	-0.5862
X13	-0.1055	X28	0.1909	X44	0.9269	X61	0.0110
X14	-0.1218	X29	-0.4306	X45	0.9762		
X15	0.2907	X30	0.9785	X46	0.9019		

Based on the results of the correlation coefficient on each GDP indicator shown in Table 1, of the 58 non-fiscal variables available in this research, it is known that 29 variables have correlation coefficient values of more than 0.70 and 29 other variables have correlation coefficient values less than 0.70. So that we will use 29 non-fiscal variables that have a correlation value of more than 0.70 for the estimation process. We also examine the correlation of fiscal variables shown below.

Table 2. Coefficients of correlation of several indicators fiscal data with GDP

No.	Coefficient Correlation	No.	Coefficient Correlation
X62	0.57541	X67	0.43232
X63	0.33465	X68	0.33235
X64	0.16368	X69	-0.7774
X65	-0.1139	X70	0.10983
X66	0.13318	X71	-0.8364

As we can see from the fact that the correlation coefficient in Table 2 is only palm oil and Brent which have a correlation value of more than 0.7, we should be consistent with not using the other 8 variables. However, with consideration to find out whether fiscal data has an effect on Indonesia's GDP, we will still use the 10 fiscal variables even though there are variables whose correlation values are less than 0.7.

By following strategy above, it ends with 39 indicator variables that correspond to the initial criteria for variable trimming with a statistical and economic judgment. For the purpose of knowing how the fiscal variables affect the GDP variable, we will form 3 sets of data to analyze and compare from the 39 variables. We form these indicators into three data sets to compare. The first data set is all of non-fiscal variables with a correlation coefficient of more than 0.70 without fiscal variables. The second data set is a combination of all non-fiscal variables that have a correlation coefficient of more than 0.70 with all of fiscal variables. The third data set is all of 10 fiscal variables. And also we will compare those three data sets with one data set that contains all of variables exclude variables with more than 1/3 missing values.

4.2 Nowcasting estimation using DFM

As we know, GDP can affect the whole economy sectors. But the GDP itself is released late which is around 5 weeks after the end of quarter. While changes in the value of GDP are crucial in terms of policy making in the economic sector. So that GDP is very crucial to always be predicted. Changes in GDP values in Indonesia are certainly influenced by many factors. The numerous factors that affect the GDP can be decomposed into several parts. Therefore, using DFM, a set of factors that have proximity will be made into a limited of factors, making analysis more efficient. In addition, the application of nowcasting can be used so that the value of GDP can always be predicted while still not released. DFM proved very successful in real-time forecasting [7]. In the next section we will use nowcasting analysis using DFM to build a prediction model of Indonesian GDP with available variables as shown before. The resulting model can be used to produce real-time predictions of Indonesian GDP growth.

4.3 Comparison against statistical benchmark and between data sets

The selection of the best model is based on the smallest value of Root Mean Square Error for prediction (RMSEP). Based on the results of pseudo out-of- sample testing, the model with the smallest RMSEP will be considered for selection. The RMSEP value is obtained from the pseudo out-of-sample of the period the second quarter of 2016 to the first quarter of 2017, the second quarter of 2017 to the first quarter of 2018 and the second quarter of 2018 to the first quarter of 2019. In order to obtain a more stable RMSEP estimator, the average value of the RMSEP will be carried out for the last 3 periods. Note that the frequency of observations between variables is different so that the transformation is performed first into q-o-q. In addition to using DFM analysis, we also try to compare with analysis of Autoregressive Integrated Moving Average (ARIMA). [9] ARIMA model is derived by general modification of an autoregressive moving average (ARMA) model. This model type is classified as ARIMA(p,d,q), where p denotes the autoregressive parts of the data set, d refers to integrated parts of the data set and q denotes moving average parts of the data set and p,d,q are all nonnegative integers. ARIMA models are generally used to analyze time series data for better understanding and forecasting. So the results of ARIMA RMSEP are obtained as follows:

Table 3. RMSEP of ARIMA(1,0,1)

Period	2016-2107	2017-2018	2018-2019	Average
RMSEP	2.8711	2.4822	2.5624	2.6386

By using ARIMA, the average RMSEP of the last three period is 2.6386 with the comparison of the last three period RMSEP values is not so significant. These result will be compared with DFM analysis. The following is the result of a comparison of the RMSEP values using DFM with four data sets. In addition, the number of factors to be compared, we will use 2 to 4 factors. The lag of VAR values that are compared are 1 and 2 in the VAR model governing the evolution over time of the factors. The following table is the result of a comparison of the RMSEP values:

Table 4. Comparison of RMSEP values based on each data set

No.	Total variables	Criteria	Number of factor	VAR(1)	VAR(2)
1.	29	Non fiscal data with correlation coefficient >0.70	2	2.6214	2.0823
			3	2.4617	2.0926
			4	2.3613	2.1769
2.	10	Fiscal data	2	2.3780	2.3724
			3	2.1708	2.2263
			4	2.1982	2.2185
3.	39	Non fiscal data with correlation coefficient >0.70 with fiscal data	2	2.4557	1.8799
			3	2.2181	1.8384
			4	1.9237	1.9656
4.	68	All variables exclude variables with more than 1/3 missing	2	2.7941	2.4970
			3	2.0841	1.4294
			4	1.6678	1.4258

Based on the average of RMSEP value in Table 3 which is 2.6386, it is known that using the ARIMA method the RMSEP value obtained is no better than using DFM. By using DFM, we can find a much smaller RMSEP value. Based on the results of the comparison of the RMSEP values in Table 4, it is known that the smallest RMSEP value is in the data set number four. The criteria is all variables exclude variable with more than 1/3 missing with the value of RMSEP 1.4258 using 2 lag of VAR of and 4 factors. But for the aim of this research to select best variable that can use to build model in the future that have the most efficient predictors that is not too numerous or too small, we decided to choose the third criteria as a best result to predict nowcasting of GDP. Third criteria is a data set of variable with correlation value more than 0.70 with additional fiscal data. Where the value of RMSEP is 1.8384 using number of factor of 3 and VAR lag of 2.

5Conclussion

Related to the importance of knowing the current condition of GDP in relation to determining policies in Indonesia, in this paper we have carried out an analysis of nowcasting using dynamic factor model. The aim of this analysis is to find best model so that it can use to predict the GDP growth in Indonesia.

The smallest RMSEP on the criteria of data set all variables exclude variable with more than 1/3 missing with the value of RMSEP is 1.4258 using the VAR lag of and 4 common factors. But, for the aim of this research to select best variable that can use to build model in the future that have the most efficient predictors that is not too numerous or too small, we decided to choose the third criteria as a best result to predict nowcasting of GDP. The best selected model is with additional fiscal variables to the data of non-fiscal with coefficient correlation more than 0.70. Even based on the coefficient correlation fiscal data has a small number of correlation to GDP, but the addition of fiscal data on the model can improve the goodness of the model.

References

[1] Aruoba, S. B., Diebold, F. X., Nalewaik, J., Schorfheide, F., & Song, D. (2016). Improving GDP measurement: A measurement-error perspective. *Journal of Econometrics*, *191*(2), 384–397. https://doi.org/10.1016/j.jeconom.2015.12.009

[2] Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., & Tambalotti, A. (2018). Macroeconomic Nowcasting and Forecasting with Big Data. *Annual Review of Economics*, *10*(1), 615–643. https://doi.org/10.1146/annurev-economics-080217-053214

[3] Cuevas, Á., & Quilis, E. M. (2012). A factor analysis for the Spanish economy. *SERIEs*, *3*(3), 311–338. https://doi.org/10.1007/s13209-011-0060-9

[4] Erhart, C., & Llorca, M. (2008). The sustainability of fiscal policy: Evidence from a panel of six South-Mediterranean countries. *Applied Economics Letter*, *15(10)*, 797–803. https://doi.org/10.1080/13504850600749156

[5] Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, *55*(4), 665–676. https://doi.org/10.1016/j.jmoneco.2008.05.010

[6] Jin, L., Fernández Pierna, J. A., Xu, Q., Wahl, F., De Noord, O. E., Saby, C. A., & Massart, D. L. (2003). Delaunay triangulation method for multivariate calibration. *Analytica Chimica Acta*, *488*(1), 1–14. https://doi.org/10.1016/S0003-2670(03)00629-9

[7] Luciani, M., Pundit, M., Ramayandi, A., & Veronese, G. (2015). *Nowcasting Indonesia | ADB Economics Working Paper No. 471 - December 2015*. (471). Retrieved from http://dx.doi.org/10.17016/FEDS.2015.100.

[8] Luciani, M., Pundit, M., Ramayandi, A., & Veronese, G. (2018). Nowcasting Indonesia. *Empirical Economics*, *55*(2), 597–619. https://doi.org/10.1007/s00181-017-1288-4

[9] Mondal, P., Shit, L., Goswami, S. (2014). Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices. *International Journal of Computer Science, Engineering and Applications (IJCSEA)* Vol.4, No.2

[10] Samuel M, Okey L.E. 2015. The Relevance and Significant of Correlation in Social Science Research. *European Centre for Research Training and Development UK.*

[11] Tarsidin, ., Idham, ., & Rakhman, R. N. (2018). Nowcasting Household Consumption and Investment in Indonesia. *Buletin Ekonomi Moneter Dan Perbankan*, *20*(3), 375–403. https://doi.org/10.21098/bemp.v20i3.858

[12] Thuy, N. T. (n.d.). *Fiscal Sustainability in Some ASEAN Countries : Evidence from a Panel Data Analysis*. 1–40.

Appendix

Data Description of Non fiscal Data

Code	Variable	Freq	Unit
Y	Gross Domestic Product Current Prize (GDPCP)	Q	Percent
X1	Consumption Expenditure	Q	Percent
X2	Private Consumption Expenditure	Q	Percent
X3	Government Expenditure	Q	Percent
X4	Gross Fixed Capital Formation	Q	Percent
X5	Change in Stocks	Q	Percent
X6	Export of Goods and Services	Q	Percent
X7	Import of Goods and Services	Q	Percent
X8	Agriculture	Q	IDR bn
X9	Industry	Q	IDR bn
X10	Services	Q	IDR bn
X11	Current Account	Q	USD mn
X12	External Debt	Q	USD mn
X13	Foreign direct investment	Q	USD mn
X14	Consumer tendency index	Q	
X15	Production Capacity Utilization: Manufacturing Industry	Q	Percent
X16	Business Tendency Index	Q	Point
X17	Consumer Price Index (CPI): overall	M	2012 = 100
X18	Consumer Price Index (CPI): core	M	2012 = 100
X19	Consumer Price Index (CPI): food	M	2012 = 100
X20	Wholesale price index	M	2010 = 100
X21	Government Bond 1Y	M	Percent
X22	Government Bond 3Y	M	Percent
X23	Government Bond 5Y	M	Percent
X24	Government Bond 10Y	M	Percent
X25	Jakarta Stock Exchange: Index Share Price; eop	M	2010 = 100
X26	Exchange Rate: end of period	M	IDR/USD
X27	Exchange Rate: period average	M	IDR/USD
X28	Interbank Rate	M	Percent
X29	Interest Rate: Central Bank policy rate: end of period	M	Percent
X30	Money Supply M1	M	IDR bn
X31	Money Supply M2	M	IDR bn

Code	Variable	Freq	Unit
X32	Reserve money	M	IDR tn
X33	Currency in circulation	M	IDR tn
X34	Net foreign assets	M	IDR tn
X35	Net domestic assets	M	IDR tn
X36	International reserves	M	USD bn
X37	Commercial & Rural Banks: Private Deposits (PD)	M	IDR bn
X38	Commercial Banks: Credit	M	IDR bn
X39	Commercial Banks: Credit: Investments	M	IDR bn
X40	Comm Banks: Credit: Consumption	M	IDR bn
X41	Comm Banks: Credit: Working Capital	M	IDR bn
X42	Commercial & Rural Banks: Loans Approval	M	IDR bn
X43	Commercial & Rural Banks: Loans	M	IDR bn
X44	Number of Electronic Card: Credit Card	M	Unit
X45	Number of Electronic Card: ATM and Debit Card	M	Unit
X46	Tourist Arrivals	M	Person
X47	Gold Reserves	M	USD bn
X48	Production Index: Crude Oil	M	2010 = 100
X49	Exports; fob	M	USD mn
X50	Imports; cif	M	USD mn
X51	Manufacturing purchasing managers' index (PMI)	M	Index
X52	Industrial Production Index: Manufacturing	M	2010 = 100
X53	Car sales	M	Unit
X54	Consumer confidence index	M	
X55	Retail Sales Index	M	2010 = 100
X56	Consumption: Cement: Domestic	M	Ton th
X57	Consumption: Cement: Export	M	Ton th
X58	Imports: Consumption Goods	M	USD mn
X59	Imports: Capital Goods	M	USD mn
X60	Imports: Raw materials and auxiliary goods	M	USD mn
X61	DV_PMI_M	M	

Note: Q=quarterly, M=monthly, IDR=Indonesian Rupiah, USD=United State Dollar, mn=millions, bn=billions, tn=trillions

Data Description of fiscal Data

Code	Variable	Freq	Unit
X62	Personal Expenditure	M	IDR tn
X63	Materials Expenditure	M	IDR tn
X64	Capital Expenditure	M	IDR tn
X65	Social Spending	M	IDR tn
X66	Other Spending	M	IDR tn
X67	Domestic VAT	M	IDR tho
X68	Import VAT	M	IDR tho
X69	Palm Oil	M	USD/metric ton
X70	Coal Newcastle	M	USD/metric ton
X71	Brent	M	USD/barrel

Note: M=monthly, IDR=Indonesian Rupiah, USD=United State Dollar, tho=thousands, tn=trillions