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Title of Paper

Monthly and Sectoral Disaggregation of Indonesia's Gross Fixed Capital Formation

Abstract

Gross Fixed Capital Formation (GFCF) is one of the instruments driving the development and growth of the national economy. GFCF is a physical investment that shows the addition and reduction of fixed assets in a production unit. So far, GFCF data is available quarterly in accordance with the availability of GDP data. While now, more specific data, both temporal and sectoral, are necessity, where it will certainly be a reference in making more appropriate government policies in order to maintain and improve the investment climate, and in the business world it is useful as a direction for determining its policy. Therefore, the development of statistics with disaggregation methods is important to do in making data more specific. This study disaggregates Indonesian quarterly GFCF 2010/I to 2018/II into monthly GFCF by economic sector, and forecast for the next period. Temporal disaggregation is done for quarterly GFCF data into monthly GFCF using monthly production indices of large and medium manufacturing (industrial production indices) as the coincident indicator. Investment credits of commercial and rural banks combined with the Input-Output table are used for sectoral disaggregation. Modeling is done by simple linear regression and ARIMA for temporal disaggregation, and combined with Input-Output table for sectoral disaggregation. The results show that the monthly and sectoral disaggregation can be done and industrial production indices are suitable to be used as coincident indicator to describe monthly GFCF. Disaggregation will give rise to opportunities for statistical findings that can be a means of elaboration and recommendations for decision making.

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II. Introduction

Awareness of the importance of data has begun to be felt, mainly related to policies. This is because in making a policy certainly will not be separated from the role of data as the basis. Policies that are based on the accurate data will produce effective policies. In making a policy, the government can utilize the projection results, both strategic and influential policies in the long term and that are tactical and short term. Specific and directed policies are needed to support the resolution of the right problem. In order to make the policies produced are appropriate, more specific and certainly up-to-date data is needed.

One indicator to measure the economic performance of a country is Gross Domestic Product (GDP). GDP can be calculated through three approaches: production, expenditure, and income approaches. On the expenditure approach, GDP formed by total consumption, investment, and external activities that take place in a country or region. The GDP component according to expenditure explains the value of goods and services produced in an area to be used as final consumption, which is realized in the form of final household consumption expenditure, final consumption expenditure of Non-Profit Institutions Serving Households (NPISH), final government consumption expenditure, Gross Fixed Capital Formation (GFCF), and exports of goods and services.

Investment activity is one of the main factors that will affect the economic development of a country or region, through increasing production capacity. In the context of GDP, investment activities in physical form are reflected in the Gross Fixed Capital Formation (GFCF) component. The importance of investment related data, especially physical investment or GFCF, is because it is related to a good future prospect, because it can present description and warnings to the government. The contribution of GFCF to the formation of GDP which is quite high also shows the importance of investment. Therefore, GFCF, which is a reflection of physical investment, needs to obtain more specific data from the side of the series because the trend in investment is very important, seeing investment as an important factor driving economic growth.

The availability of specific and up-to-date Indonesia's GFCF data is still an obstacle. This can be seen from the value of Indonesia's GFCF available quarterly. While for policy making and analysis, more specific data is often needed, such as monthly is better than annually period. By looking more specifically, the expected results will be more accurate, and support investment-related planning, especially physical investment.

Based on the explanation above, the disaggregation of quarterly GFCF into monthly and sectoral GFCF is important to do. This is an innovation to obtain more accurate, specific, and up-to-date data. In this paper, disaggregation is conducted on Indonesia's quarterly GFCF data so that it will be obtained monthly Indonesia's GFCF, using variable that act as coincident indicator. The variable used as a coincident indicator for GFCF is the monthly production indices of large and medium manufacturing (industrial production indices).[1] The index is used because have high correlation and used to adjust the value of GDP (Guerrero, 2003). In addition, sectoral disaggregation is also carried out to see GFCF in each sector and to know which sectors are potential in forming GFCF. Investment credits of commercial and rural banks according to sectors and combined with Input-Output table are used for monthly GFCF sectoral disaggregation. Thus, the objectives of this study are to: (1) describe the movement pattern of Indonesia's quarterly GFCF and monthly production indices of large and medium manufacturing (industrial production indices); (2) disaggregate Indonesia's quarterly GFCF into monthly and sectoral GFCF using related variables; (3) forecast quarterly GFCF and monthly and sectoral GFCF in 2019.

III. Monthly and Sectoral Disaggregation of Indonesia’s Gross Fixed Capital Formation

A. Methodology of Monthly and Sectoral Disaggregation

1. Monthly Disaggregation

Disaggregation Method by Guerrero

Several methods have been proposed to obtain high frequency data (monthly) from low-frequency (quarterly) observations on important economic variables. Friedman (1962) suggested the use of related variables to estimate the series that were not observed from the series observed. But the research is not complete because it has not considered the consistency between the value of disaggregation results and actual values.

The method suggested by Chow and Lin (1971) and Denton (1971) may be the most frequently used method today. The method uses information from related variables while paying attention to the consistency of the value of disaggregation results and actual values. However, this method considers the autocorrelation structure of time series variables subjectively.

Solutions from Guerrero (1990) and Wei and Stram (1990) focus primarily on the use of appropriate autocorrelation structures. In his research, Guerrero presented a method by:

[1] Large and medium manufacturing industries are manufacturing industries that have workforce of more than or equal to 20 people.

(1) using related variables to obtain initial estimates, (2) using the appropriate autocorrelation structure (obtained from actual data), and (3) performing series disaggregation statistically optimal.

Statistical Time Series Model

Suppose $\{Z_t\}$ is a series that is not observed, with $t = 1, \ldots, mn$, $n \geq 1$ which show the total number of periods (quarterly) and $m \geq 2$ shows the intraperiod frequency (monthly, $m = 3$). Suppose $\{W_t\}$ is a non-stationary series which is possible from the initial estimation of unobserved data. The relationships formed are:

$$Z_t = W_t + S_t \qquad (1)$$

with S_t is the difference from unobserved data that is stationary with a zero average. The model is equipped with the following assumptions:

- Assumption 1

The Autoregressive and Moving Average (ARMA) model captures the dynamic structure of $\{S_t\}$, such as:

$$\phi_S(B)S_t = \theta_S(B)u_t \qquad (2)$$

with $\phi_S(B) = 1 - \phi_{S,1}B - \cdots - \phi_{S,p}B^p$ and $\theta_S(B) = 1 + \theta_{S,1}B + \cdots + \phi_{S,q}B^q$ is a polynomial in a backshift operator B. Unit roots from $\phi_S(x) = 0$ dan $\theta_S(x) = 0$ outside the circle unit, so that it is stationary and invertible. Other than that, $\{u_t\}$ Gaussian white noise with zero mean and variance σ_u^2.

- Assumption 2

The series of $\{W_t\}$ following the Autoregressive Integrated Moving Average (ARIMA) model, i.e.:

$$\phi_W(B)d(B)W_t = \theta_W(B)a_t \qquad (3)$$

with $d(B)$ is a differencing operator which make $\{d(B)W_t\}$ stationary. $\phi_W(B)$ and $\theta_W(B)$ are AR and MA polynomials with unit roots outside the unit circle. $\{a_t\}$ is white noise Gaussian with zero mean and variance σ_a^2 and does not correlate with $\{u_t\}$.
Model (3) can be written as:

$$S_t = \psi_S(B)u_t \qquad (4)$$

and $\psi_S(B) = a + \psi_{S,1}B + \psi_{S,2}B^2 + \cdots$ is the pure MA polynomial obtained from the relationship $\psi_S(B)\phi_S(B) = \theta_S(B)$ by equating the coefficient B. Equation (4) can be written as follows:

$$\mathbf{S} = \mathbf{\Psi}_S \mathbf{u} \quad (5)$$

with $\mathbf{S} = (S_1, \dots, S_{mn})'$ dan $\mathbf{u} = (u_1, \dots, u_{mn})'$. $\mathbf{\Psi}_S$ is a lower triangular matrix of mn × mn with a main diagonal of 1, the first sub diagonal is equal to $\psi_{S,1}$, the second sub diagonal is equal to $\psi_{S,2}$, etc. So that equation (5) is equivalent to equation (4), then $u_t = 0$ for $t \leq 0$.
Aggregated series $\{Y_1, \dots, Y_n\}$ can be written as:

$$Y_i = \sum_{j=1}^{m} c_j Z_{m(i-1)+j} \quad (6)$$

for $i = 1, \dots, n$, with c_j are constant defined by the type of aggregation. $C = I \otimes \mathbf{c}'$ where $\otimes$ is Kronecker product, $\mathbf{Y} = (Y_1, \dots, Y_n)'$, and $\mathbf{Z} = (Z_1, \dots, Z_{mn})'$, so it can be written as:

$$\mathbf{Y} = C\mathbf{Z} \quad (7)$$

Equation (1) when written in vector notation becomes:

$$\mathbf{Z} = \mathbf{W} + \mathbf{S} \quad (8)$$

with $\mathbf{W} = (W_1, \dots, W_{mn})'$. $\mathrm{E}(\mathbf{Z}|\mathbf{W}) = \mathbf{W}$, so $\mathbf{W}$ is the minimum Mean Squared Error Linear Estimator (MMSELE) of $\mathbf{Z}$ on condition $\mathbf{W}$. Equation (5) also shows that $\mathbf{\Sigma}_S = \sigma_u^2 \mathbf{\Psi}_S \mathbf{\Psi}_S'$. Therefore, the results obtained provide the optimal solution for direct disaggregation. Guerrero (2003) proposed that the MMSELE of $\mathbf{Z}$ with $\mathbf{W}$ and $\mathbf{Y}$ terms is as follows:

$$\hat{\mathbf{Z}} = \mathbf{W} + \hat{A}(\mathbf{Y} - C\mathbf{W}) \quad (9)$$

The MSE matrix is stated as follows:

$$\mathrm{MSE}(\hat{\mathbf{Z}}) = \sigma_u^2 (I_{mn} - \hat{A}C)\mathbf{\Psi}_S \mathbf{\Psi}_S' \quad (10)$$

with

$$\hat{A} = \mathbf{\Psi}_S \mathbf{\Psi}_S' C' (C \mathbf{\Psi}_S \mathbf{\Psi}_S' C')^{-1} \quad (11)$$

Aggregated Difference Model

The aggregate difference or difference in the quarterly series is used to estimate the value of $\mathbf{\Psi}_S$. The aggregate difference is stated by:

The aggregate difference or difference in the quarterly series is used to estimate the value. The aggregate difference is stated by:

$$\mathbf{D} = C\mathbf{S} = C\mathbf{Z} - C\mathbf{W} = \mathbf{Y} - C\mathbf{W} \quad (12)$$

The aggregate series $\{D_i\}$ is assumed to follow the ARMA model i.e.

$$\phi_D(L)D_i = \theta_D(L)\varepsilon_i \quad (13)$$

for $i = 1, \dots, n$, with $\phi_D(L) = 1 - \phi_{D1}L - \cdots - \phi_{DP}L^P$ and $\theta_D(L) = 1 + \theta_{D1}L + \cdots + \theta_{DQ}L^Q$ is the polynomial in the backshift L operator in the variable aggregate. When the aggregate series $\{D_i\}$ follows the seasonal ARMA model, seasonal lengths are indicated by E/m, and seasonal AR and MA polynomials are expressed as $\Phi_D\left(L^{E/m}\right) = 1 - \Phi_1 L^{E/m} - \cdots - \Phi_P L^{PE/m}$ and $\Theta_D\left(L^{E/m}\right) = 1 + \Theta_1 L^{E/m} + \cdots + \Theta_Q L^{QE/m}$To obtain the disaggregate series model, the procedure performed is as follows. First, choose the seasonal AR and MA polynomials as follows:

$$\Phi_S(B^E) = 1 - \Phi_1 B^E - \cdots - \Phi_P B^{PE} \quad (14)$$

and

$$\Theta_S(B^E) = 1 + \Theta_1 B^E + \cdots + \Theta_Q B^{QE} \quad (15)$$

with the same parameter values as the aggregate series model. Secondly, do the summarization of the aggregate series and disaggregate with:

$$FD_i = \Phi_D\left(L^{E/m}\right)\Theta_D\left(L^{E/m}\right)^{-1}D_i \quad (16)$$

and

$$FS_t = \Phi_S(B^E)\Theta_S(B^E)^{-1}S_t \quad (17)$$

Then apply the procedures for non-Muslim series to obtain the following models:

$$\phi_S(B)FS_t = \theta_S(B)u_t \quad (18)$$

Multiplicative Disaggregated Difference Model

The complete model for the disaggregate difference series is stated as follows:

$$\phi_S(B)\Phi_S(B^E)S_t = \Theta_S(B^E)\theta_S(B)u_t \quad (19)$$

The matrix $\mathrm{MSE}(\hat{\mathbf{Z}})$ of equation (10) will produce different variances for disaggregate values $\{\hat{Z}_t\}$ because the elements in the diagonal $\mathbf{\Psi}_S\mathbf{\Psi}_S'$ are different, partly because the initial conditions $u_t = 0$ are imposed for $t \leq 0$. Adjustments to improve this non-stationary situation are done by replacing diagonal elements with theoretical variances on the model. For example, if the model $(1 - \Phi B^E)S_t = (1 + \theta_1 B + \cdots + \theta_q B^q)u_t$, with $0 \leq q \leq E$, the variance is stated as follows:

$$\mathrm{Var}(S_t) = \left(1 + \theta_1^2 + \cdots + \theta_q^2\right)\sigma_u^2/(1 - \Phi^2) \quad (20)$$

Estimating Preliminary Series

In practice, the preliminary series can be estimated from variables related to Z. The variables associated with Z are denoted by $X_1, \dots, X_G$ with $G \geq 1$. Therefore, the equation become:

$$W_t = \beta_1 X_{1t} + \cdots + \beta_G X_{Gt} \quad (21)$$

for $t = 1, \dots, mn$, with the coefficients $\beta_1, \dots, \beta_G$ estimated from the data. The linear regression model formed is as follows:

$$Z_t = \beta_1 X_{1t} + \cdots + \beta_G X_{Gt} + \varepsilon_t \quad (22)$$

for $t = 1, \dots, mn$. The models for aggregate variables are as follows:

$$Y_i = \beta_1 X_{1i}^a + \cdots + \beta_G X_{Gi}^a + \varepsilon_i^a \quad (23)$$

for $i = 1, \dots, n$, with $X_1^a, \dots, X_G^a$ dan ε^a linked to $X_1, \dots, X_G$ and ε, likely Y, linked to Z. So that it is obtained:

$$X_{gi}^a = \sum_{j=1}^{m} c_j X_{g,m(i-1)+j} \quad (24)$$

for $g = 1, \dots, G$, and the same thing happens with ε_i^a as a function of ε_t.. The parameter β can be estimated from equation (23) with OLS and the estimation coefficients are included in equation (21) to estimate the initial series.

To get baseline estimates, criteria can be used to select the X_g variable, as follows:

1. The relationship between related variable to variable to be disaggregated can be interpreted adequately in the economic sphere;
2. Fulfill Friedman's assumption (1962) that the related variable has a high intraperiod correlation with Z;
3. Series $\{X_{gt}\}$ is long enough to include data from $t = 1, \dots, mn$ and subsequent observations or $t > mn$;
4. Observed with the latest;
5. The measurement method does not change from time to time.

Data Aggregation by Wei & Stram

Wei and Stram (1990) developed a generalized least squares procedure for performing time series disaggregation. The Guerrero disaggregation technique is a development of the techniques of Wei and Stram disaggregation. Suppose $\mathbf{z} = (z_1, z_2, \dots, z_{mn})'$ is a series vector disaggregated by length mn and $h_t = (1 - B)^d z_t$ so that $\mathbf{h} = (h_{d+1}, h_{d+2}, \dots, h_{mn})'$ is a series vector disaggregated after differencing so that it is stationary with the autocovariance V_h matrix. Suppose the observed data (aggregate) is expressed as $\mathbf{Y} = (Y_1, Y_2, \dots, Y_n)'$ and vector $\mathbf{U} = (U_{d+1}, U_{d+2}, \dots, U_n)'$are series after differencing is $U_t = (1 - L)^d Y_T$ with V_U autocovariance matrix. The autocovariance of U_t and h_t are denoted by $\gamma_U(k)$ and $\gamma_h(k)$ for $k = 0, 1, 2, \dots$ .The relationship of the two autocovariance is stated as follows:

$$\gamma_U(k) = (1 + B + \cdots + B^{m-1})^{2(d+1)} \gamma_h(mk + (m-1)(d+1)) \quad (25)$$

where:

$\gamma_U(k)$: autocovariance of the observed series / aggregate (U_t) lag k;

$\gamma_h(mk + (m-1)(d+1))$: autocovariance from the series that are not observed / disaggregated after differencing (h_t) with lag to $(mk + (m-1)(d+1))$;

B : backshift operator;

m : intra period frequency or number of periods between observed periods;

d : differencing order;

k : periods.

So $\gamma_U(k)$ is a linear combination of autocovariance $\gamma_h(j)$ from $j = mk - (m-1)(d+1)$ to $j = mk + (m-1)(d+1)$. For any $k > [(d+1) - (d+1)/m]$ with $[z]$ denoting the largest integer less than or equal to z, it can be stated as follows:

$$\begin{pmatrix} \gamma_U(0) \\ \gamma_U(1) \\ \vdots \\ \gamma_U(k) \end{pmatrix} = \boldsymbol{A} \begin{pmatrix} \gamma_h(-(m-1)(d+1)) \\ \vdots \\ \gamma_h(0) \\ \vdots \\ \gamma_h(mk + (m-1)(d+1)) \end{pmatrix} \quad (26)$$

where $\boldsymbol{A}$ is a matrix containing the value c_i which is the coefficient of B^i in the polynomial $(1 + B + \cdots + B^{m-1})^{2(d+1)}$For any positive integer i, because $\gamma_h(-i) = \gamma_h(i)$, $\gamma_h(-i)$ can be omitted from equation (26) by adding the coefficient of $\gamma_h(-i)$ to the coefficient $\gamma_h(i)$.. Finally, the one-to-one relationship between autocovariance $\gamma_U(k)$ dan $\gamma_h(k)$can be known, and hence, the disaggregate model and autocovariance can be derived from the aggregate model that was previously known.

Disaggregation of the ARIMA Model

Assuming that there is no periodic pattern of m that shows no seasonal pattern, and the aggregate series follows the ARIMA (p, d, r) model with $r \leq p + d + 1$, the steps to reduce the disaggregate model are as follows:

Factoring the AR polynomial from the aggregate model, namely:

$$\alpha_p(L) = \prod_{i=1}^{p}(1 - r_i L) \tag{27}$$

If some real roots of $\alpha_p(B) = 0$ are negative, and m is even, disaggregation cannot be done. Otherwise, the AR polynomial of the disaggregate model will be:

$$\phi_p(B) = \prod_{i=1}^{p}\left(1 - r^{1/m}B\right) = 1 - \phi_1 B - \cdots - \phi_p B^p \tag{28}$$

Assuming that the MA order of the disaggregate model is $q = p + d + 1$. $\gamma_h(k)$ can be obtained from $\gamma_U(k)$ which is known for $k = 0, \ldots, p + d + 1$ based on equation (26).

Calculate the value of the MA parameter ϕ_j through its relation to autocovariance $\gamma_h(k)$ and the AR parameter that has been obtained in step (a). The solution is usually obtained from nonlinear equations and only those that meet the invertibility requirements are maintained.

Disaggregation of the Seasonal ARIMA Model

Suppose the series disaggregate $\{z_t\}$ follows a multiplicative seasonal ARIMA model denoted by ARIMA (p, d, q) × (P, D, Q) s, written by Box and Jenkins (2008) as:

$$\phi_p(B)\Phi_P(B^s)(1 - B)^d(1 - B^s)^D z_t = \theta_q(B)\Theta_Q(B^s)e_t \tag{29}$$

If the number of m periods divides the seasonal period s, Wei and Stram (1990) shows that the corresponding aggregate model will follow the multiplicative seasonal ARIMA model or ARIMA (p, d, q) × (P, D, Q) $_{s/m}$ as follows:

$$\phi_p(L)\Phi_P\left(L^{s/m}\right)(1 - L)^d\left(1 - L^{s/m}\right)^D Y_t = \theta_q(L)\Theta_Q(L^{s/m})A_T \tag{30}$$

The parameter values of the seasonal AR and MA polynomials of the disaggregate and aggregate models did not change. Steps to disaggregate the aggregate data that follows the seasonal ARIMA model are as follows:

Choose the AR and MA seasonal polynomials, namely:

$$\Phi_p(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps} \tag{31}$$

and

$$\Theta_Q(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Qs} \tag{32}$$

with seasonal parameter values that are the same as the aggregate model.

Defines de-seasonalised stationary series or series that have eliminated seasonal effects for aggregate series and disaggregates, namely:

$$f_t = \Phi_p(B^s)\Theta_Q(B^s)^{-1}(1-B^s)^D(1-B)^d z_t \tag{33}$$

and

$$F_T = \Phi_p\left(L^{s/m}\right)\Theta_Q\left(L^{s/m}\right)^{-1}\left(1-L^{s/m}\right)^D(1-L)^d Y_T \tag{34}$$

The relationship is shown as follows:

$$F_T = (1 + B + \cdots + B^{m-1})^{d+1} f_{mT} \tag{35}$$

The relationship between autocovariance $\gamma_f(k)$ of $\{f_t\}$ and $\gamma_F(k)$ of $\{F_T\}$ is identical to the relationship between $\gamma_h(k)$ of $\{h_t\}$ and $\gamma_U(k)$ of $\{U_T\}$.. If the number of m periods divides the seasonal period s, the model (29) implies the model (30) and the parameter values of the seasonal AR and MA polynomials of the disaggregate and aggregate models do not change.

2. Sectoral Disaggregation

In carrying out sectoral disaggregation, it is necessary to have initial weighting as value dividers for each sector. These values are obtained from the proportion of each sector from the input-output table. In this sectoral disaggregation, it will be made into three major sectors with the largest proportion, and the remainder going into the other sector.

In monthly disaggregation, a vector $\boldsymbol{Z}_t$ of size (t x 1) has been obtained. With the initial weighting of the input-output table ($\boldsymbol{W}_{IO}$), the $\boldsymbol{W}_{it}$ sectoral PMTB matrix will be obtained as follows:

$$\boldsymbol{Z}_{t_{(\boldsymbol{t}\times\boldsymbol{1})}}.\boldsymbol{W}_{IO_{(1\times i)}} = \boldsymbol{W}_{it_{(\boldsymbol{t}\times\boldsymbol{i})}} \tag{36}$$

where

$i =$ number of sectors (1, 2, 3, …).

By getting the $\boldsymbol{W}_{it}$ matrix as the preliminary value, then adjustments will be made to disaggregation by using another auxiliary variable. Adjustments are made because the weight has not accommodated the intersectoral interactions that occur. This will be similar to the equation (1) so that the value of $\boldsymbol{S}_{it}$ will be obtained when the equation of each i sector is as follows:

$$\widehat{\boldsymbol{W}}_{it_{(\boldsymbol{t}\times\boldsymbol{1})}} = \boldsymbol{X}_{it}\boldsymbol{\beta} \tag{37}$$

After regressing each sector i with the auxiliary variable, the difference value $\boldsymbol{e}_{it}$ will be obtained from each sector. Obtained difference value will cause disaggregation value to be not the same as the aggregate value of $\boldsymbol{Z}_t$. The sum of this difference or the sum of $\boldsymbol{e}_{it}$ is a matrix $\boldsymbol{e}_t$ of size (1 x t). It will be distributed to each sector using distribution matrix. The distribution matrix is defined by Sax and Steiner (2013):

$$\boldsymbol{A}_{(i\times 1)} = \boldsymbol{\Sigma}_{(i\times i)} C'_{(i\times 1)} \left(C_{(1\times i)} \boldsymbol{\Sigma}_{(i\times i)} C'_{(i\times 1)} \right)^{-1} \tag{38}$$

where

$\boldsymbol{\Sigma}$ = Leontief matrix to shows the relationship between sectors.

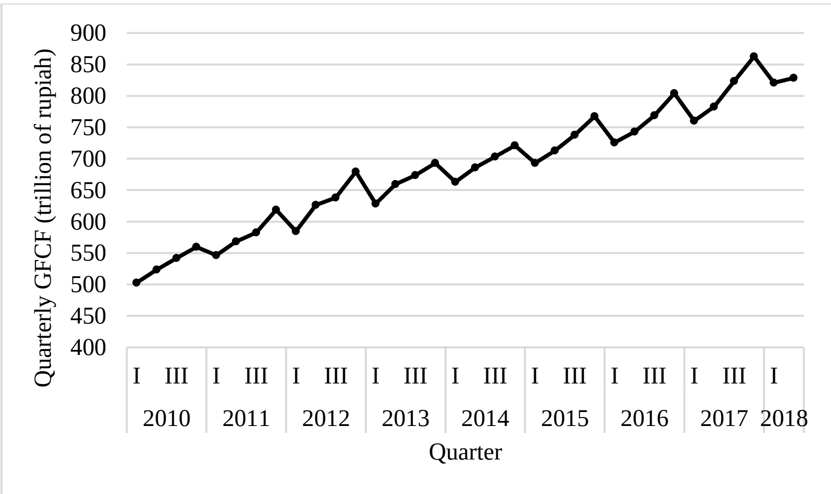
The monthly and sectoral disaggregated series are obtained from the equation

$$\hat{\mathbf{Z}} = \mathbf{W} + \hat{\boldsymbol{A}} \boldsymbol{e}_t \tag{39}$$

The different between temporal and sectoral disaggregation is in the vector C'. In temporal disaggregation, the C' is the proportion of disaggregate value from the aggregate, but in sectoral disaggregation is a same proportion of vector that consist of value 1. It will make the same value of aggregate with distribute residuals.

B. The Movement Pattern of Indonesia's Quarterly GFCF and Monthly Industrial Production Indices

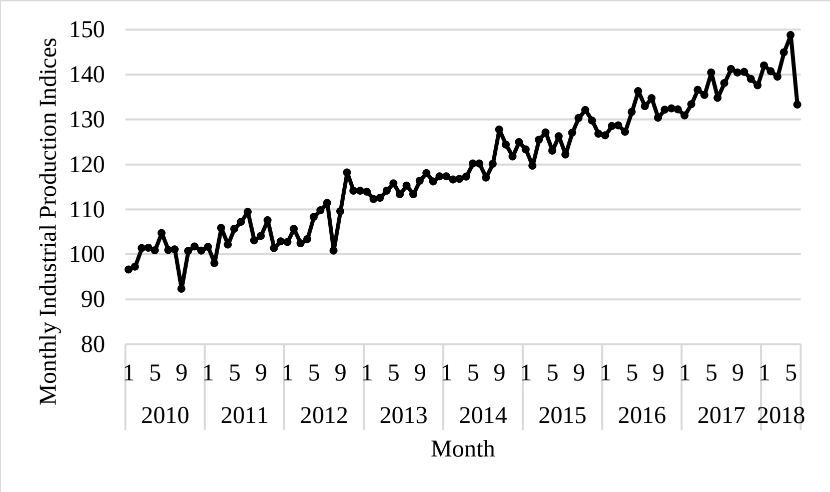
Gross Fixed Capital Formation (GFCF) is one of the instruments driving national economic growth. GFCF can explain the fixed assets used in the production process. GFCF shows an overview of various goods and services used as physical investments.



Source: BPS

Figure 1. Indonesia's quarterly Gross Fixed Capital Formation (GFCF) on the basis of constant prices in 2010-quarter II 2018

Data of Indonesia's quarterly GFCF shows a seasonal pattern in each year. From the first quarter to the fourth quarter there was an increase in each quarter, and then a decline in the first quarter of the next year. The seasonal pattern that occurs is an important indication both in conducting analysis and forecasting.



Source: BPS

Figure 2. Indonesia's monthly production indices of large and medium manufacturing (industrial production indices) in 2010-II quarter 2018

One indicator to see the development of GFCF is the monthly production indices of large and medium manufacturing (industrial production indices) which acts as a coincident indicator.[2] Temporal disaggregation methods are used to disaggregate time series data with low frequency into series with higher frequency. Temporal disaggregation is carried out using a series indicator, that is industrial production indices.

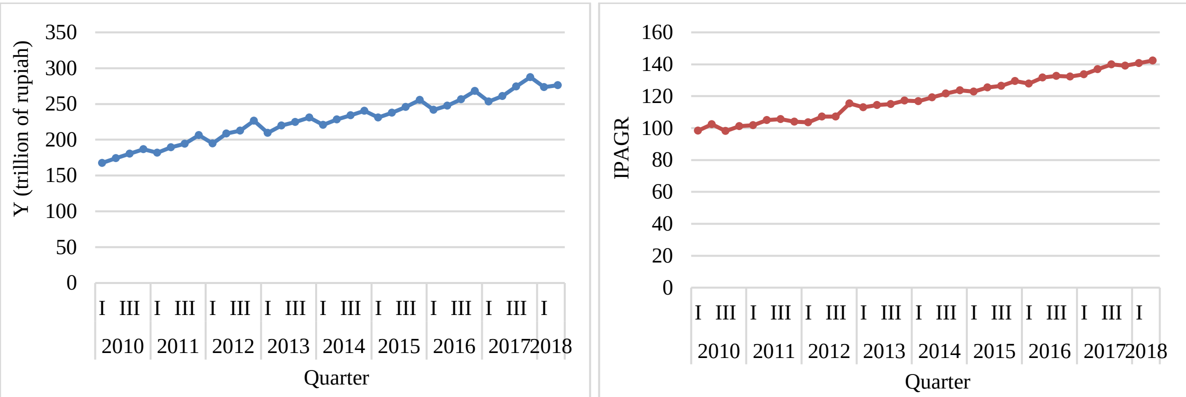


Figure 3. The average of monthly GFCF per quarter (Y) and the average of monthly industrial production indices per quarter (IPAGR) in 2010-quarter II 2018

From the graph above, it can be seen both patterns simultaneously. The pattern that moves together shows that the industrial production indices is a coincident indicator of GFCF.

[2] The coincident indicator is the current indicator that moves in conjunction with the reference series.

Industrial production indices data available in monthly periods or having high frequencies that can be related variables used in monthly GFCF disaggregation. The production index numbers are presented according to the 2 digits Klasifikasi Baku Lapangan Usaha Indonesia (KBLI), that follows "International Standard Industrial Classification of All Economic Activities (ISIC)" Revised 4 of 2015 (Appendix 5).

C. Monthly and Sectoral Disaggregation of Indonesia's GFCF

Monthly Disaggregation

The preliminary estimation of aggregate GFCF obtained from simple linear regression with the dependent variable is the average of monthly GFCF per quarter (Y) and the independent variable is the average of monthly industrial production indices per quarter (IPAGR).

Table 1. The estimation results of the preliminary model of aggregate GFCF

Variable	Coefficient	Standard error	t-stat	p-value t
(1)	(2)	(3)	(4)	(5)
Intercept	-44397.54	11020.43	-4,029	0.0003
IPAGR	2283.28	91.87	24,852	0.0000
Summary of statistics				
Adjusted R-squared		0.9492	DW	1.3825
F-stat		617.6	p-value F	0.0000

After the estimation of preliminary model is obtained, a classical assumption is performed because it uses the OLS method. Testing of autocorrelation using the Durbin-Watson test shows the results of the DW statistic = 1.3825 with p-value = 0.02. It means that there is intertemporal residual autocorrelation so that the non-autocorrelation assumption is violated. To overcome the problem of autocorrelation that occurs, a Cochrane-Orcutt procedure is performed. The Cochrane-Orcutt procedure estimates the value of ρ for transformation on the dependent and independent variables. The ρ value obtained through the Cochrane-Orcutt procedure is 0.2659. After the value of ρ is obtained, a transformation is performed on the variable and a simple linear regression is performed again.

Table 2. The estimation results of the preliminary model of aggregate GFCF after transformed

Variable	Coefficient	Standard error	t-stat	p-value t
(1)	(2)	(3)	(4)	(5)

Intercept	-25410.8	10536.4	-2.412	0.022
IPAGR	2205.9	118.6	18.601	0.0000
Summary of statistics				
Adjusted R-squared		0.9151	DW	1.99
F-stat		346	p-value F	0.0000

After the estimation of preliminary model after the transformation is obtained, classical assumptions are tested. Testing of non-autocorrelated assumptions using the DW test produces DW statistics = 1.99 with p-value = 0.4157. This means that there is no intertemporal residual autocorrelation so that non-autocorrelation assumption is fulfilled. Testing the assumption of normality is done through the Jarque-Bera test. The test results obtained was Jarque-Bera = 0.9085 with p-value = 0.6349. This means that the residuals are normally distributed so that the assumption of normality is fulfilled. The homoscedasticity assumption test is carried out by the Glejser test. Testing is done by regression between residuals and independent variables. The test results show that the independent variables have p-value = 0.956. This means that the assumption of homoscedasticity is fulfilled which means that the residual has a constant variance. Because all assumptions have been fulfilled, then the parameter estimates obtained from the regression variable transformations are returned to the original form. The new parameter estimation and will be used in the next step is: $\beta_0 = \frac{\beta_0'}{1-\hat{\rho}} = -34617.2$ and $\beta_1 = \beta_1' = 2205.9$.

The next step is using the parameter estimates of aggregate preliminary model to estimate the disaggregate preliminary model. Monthly preliminary GFCF data for the period January 2010 to June 2018 are obtained through equations

$$W_t = -34617.2 + 2205.9 IP_t \qquad (40)$$

After the preliminary monthly GFCF estimation (W) is obtained, the next step is to calculate S. The step begins with calculating the aggregate difference (D), which is the difference between the average of monthly GFCF quarterly (Y) and the average of preliminary monthly GFCF per quarter (YAGR), obtained by calculating the average of W for each quarter. This is expressed by $D_i = Y_i - YAGR_i$ for i is the period from the first quarter of 2010 to the second quarter of 2018. After D series is obtained, identification of the appropriate ARMA model is carried out. Seasonal effects allow the right model to be seasonal ARMA. From the tentative model, the best model is chosen with the smallest AIC value.

Table 3. Comparison of D series models

Model	AIC
(1)	(2)
ARMA(1,0)^4	691.56
ARMA (2,0)^4	693.13
ARMA (3,0)^4	694.93

The best model for D series is ARMA (1,0)^4. Estimated results from the model are stated by

$$\begin{gathered}(1-0.6448\,L^4)D_i=\hat{\varepsilon}_i\\ (s.e\;0.1497)\end{gathered} \tag{41}$$

To check the model's adequacy, use Portmanteau test with Ljung-Box test by Ljung and Box (1978). The Ljung-Box statistic results show that $Q'(6) = 7.54$ with p-value = 0.2736. The p-value is more than α so it is concluded that there is no reason to doubt the model's adequacy. To obtain the disaggregate model, the seasonal AR polynomial is defined as follows

$$\widehat{\Phi}(B)=1-0.6448\,B^{12} \tag{42}$$

The deseasonalized series is obtained from D using the equation:

$$FD_i=D_i-0.6448\,D_{i-4} \tag{43}$$

For the seasonal AR and MA polynomials from the disaggregate difference series, obtained by analyzing the autocorrelation of the FD series. The result does not show autocorrelation that is significantly different from zero. Selected polynomial order chosen was taken by Wei and Stram (1990) with p = 0 and q = p + 1 = 1. The relationship between the aggregate difference series and the disaggregate difference is stated by

$$FD_i=\frac{1}{3}(1+B+B^2)FS_{3i} \tag{44}$$

with the autocovariances of the aggregate series and disaggregates are

$$\gamma_{FD}(0)=\frac{1}{9}(1+B+B^2)^2\gamma_{FS}(2) \tag{45}$$

$$\gamma_{FD}(0)=\frac{1}{9}[\gamma_{FS}(-2)+2\gamma_{FS}(-1)+3\gamma_{FS}(0)+2\gamma_{FS}(1)+\gamma_{FS}(2)] \tag{46}$$

and

$$\gamma_{FD}(1) = \frac{1}{9}(1 + B + B^2)^2 \gamma_{FS}(5) \quad (47)$$

$$\gamma_{FD}(1) = \frac{1}{9}[\gamma_{FS}(1) + 2\gamma_{FS}(2) + 3\gamma_{FS}(3) + 2\gamma_{FS}(4) + \gamma_{FS}(5)] \quad (48)$$

The valid assumption is $\gamma_{FD}(k) = 0 = \gamma_{FS}(k)$ for $k \neq 0, \pm 1$. So that the system equation above can be written in the form of a matrix

$$\begin{pmatrix} \gamma_{FD}(0) \\ \gamma_{FD}(1) \end{pmatrix} = \begin{pmatrix} 3/9 & 4/9 \\ 0 & 1/9 \end{pmatrix} \begin{pmatrix} \gamma_{FS}(0) \\ \gamma_{FS}(1) \end{pmatrix} \quad (49)$$

Autocovariance value is obtained $\hat{\gamma}_{FD}(0)$=27536263 and $\hat{\gamma}_{FD}(1) = \hat{\gamma}_{FD}(0)\hat{\rho}_{FD}(1)$ =9267511. So that the system of the equation above can be solved into

$$\begin{pmatrix} \gamma_{FS}(0) \\ \gamma_{FS}(1) \end{pmatrix} = \begin{pmatrix} 3 & -12 \\ 0 & 9 \end{pmatrix} \begin{pmatrix} 27536263 \\ 9267511 \end{pmatrix} = \begin{pmatrix} -28601337 \\ 83407596 \end{pmatrix} \quad (50)$$

The results obtained are not acceptable because it will produce the first autocorrelation estimation of the series FS_t denoted by $\hat{\rho}_{FS}(1) = \frac{\hat{\gamma}_{FS}(1)}{\hat{\gamma}_{FS}(0)} = -2.9162$. This result is not significant because the absolute value of the first autocorrelation MA (1) should not be more than 0.5.

The results obtained above can be explained because there is a hidden period, namely order $m = 3$ in the FS_t series. So, the MA polynomial is assumed to have order $q = 3$, which has implications for pada $\gamma_{FD}(k) = 0$ for $k \neq 0, \pm 1$ and $\gamma_{FS}(k) = 0$ for $k \neq 0, \pm 3$. The system of the equation above becomes

$$\begin{pmatrix} \gamma_{FD}(0) \\ \gamma_{FD}(1) \end{pmatrix} = \begin{pmatrix} 3/9 & 0 \\ 0 & 3/9 \end{pmatrix} \begin{pmatrix} \gamma_{FS}(0) \\ \gamma_{FS}(3) \end{pmatrix} \quad (51)$$

With solution

$$\begin{pmatrix} \gamma_{FS}(0) \\ \gamma_{FS}(3) \end{pmatrix} = \begin{pmatrix} 3 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} 27536263 \\ 9267511 \end{pmatrix} = \begin{pmatrix} 82608790 \\ 27802532 \end{pmatrix} \quad (52)$$

The autocorrelation estimation of the FS_t series is denoted by $\hat{\rho}_{FS}(3) = 0.3365$ has met the requirements. The autocovariance obtained allows to estimate the parameter MA (3) of $FS_t = (1 + \theta_3 B^3)u_t$. Theoretical autocovariance for the model are $\gamma_{FS}(0) = (1 + \theta_3^2)\sigma_u^2$ and $\gamma_{FS}(0) = \theta_3 \sigma_u^2$, so the estimator $\hat{\theta}_3$ is obtained by solving the equation

$$\hat{\gamma}_{FS}(3) - \hat{\gamma}_{FS}(0)\hat{\theta}_3 + \hat{\gamma}_{FS}(3)\hat{\theta}_3^2 = 0 \quad (53)$$

So that it is obtained:

$$\hat{\theta}_3 = \frac{\hat{\gamma}_{FS}(0) \pm \sqrt{\hat{\gamma}_{FS}^2(0) - 4\hat{\gamma}_{FS}(3)}}{2\hat{\gamma}_{FS}(3)} = \frac{\hat{\gamma}_{FS}(0)}{2\hat{\gamma}_{FS}(3)} \pm \sqrt{\left\{\frac{\hat{\gamma}_{FS}(0)}{2\hat{\gamma}_{FS}(3)}\right\}^2 - 1} \quad (54)$$

The estimator $\hat{\theta}_3$ obtained is $\hat{\theta}_{31} = 0.3869$ and $\hat{\theta}_{32} = 2.5843$. Estimator $\hat{\theta}_{31} = 0.3869$ was chosen to meet the invertible model. Thus, the model estimate for S_t series is

$$(1 - 0.6448\, B^{12})S_t = (1 + 0.3869\, B^3)\hat{e}_t \quad (55)$$

In estimating $\mathbf{Z} = \mathbf{W} + \mathbf{S}$ series, it is done through $\hat{\mathbf{Z}} = \mathbf{W} + \hat{A}(\mathbf{Y} - C\mathbf{W})$ or $\hat{\mathbf{Z}} = \mathbf{W} + \hat{A}\mathbf{D}$. $\hat{A}$ is the distribution matrix calculated by

$$\hat{A} = \mathbf{\Psi}_S \mathbf{\Psi}_S' C'(C\mathbf{\Psi}_S \mathbf{\Psi}_S' C')^{-1} \quad (56)$$

$\mathbf{\Psi}_S$ is the lower triangular matrix sized $mn \times mn$ with the main diagonal being 1, the first sub diagonal is $\psi_{S,1}$, the second subdiagonal is $\psi_{S,2}$, and so on. To calculate the weight of pure MA obtained by
$\psi_{3+12(j+1)} = \Phi^{j-1}\theta$ for $j = 1,2, \ldots$; $\psi_{12j} = \Phi^j$ for $j = 0,1, \ldots$; and $\psi_j = 0$ for others.
While the matrix $C = I \otimes \mathbf{c}'$ with $\mathbf{c}'$ corresponds to the type of disaggregation, where in this case $\mathbf{c}' = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix}$.

To correct the non-constant variance, a modification is made on $\mathbf{\Psi}_S \mathbf{\Psi}_S'$ so that the value $\mathrm{Var}(S_t)/\sigma_u^2 = (1 + \theta^2)/(1 - \Phi^2) = (1 + 0.3869^2)/(1 - 0.6448^2) = 1.9679$. Next can be calculated series $\{S_t\}$ and series $\{Z_t\}$.

The assumption that $\{W_t\}$ is the preliminary estimate of $\{Z_t\}$ can be validated empirically with a compatibility test, where the statistic $K = 32.3688$. This value is compared with the statistic $\chi_{34}^2 = 48{,}6024$. The results show a failure to reject H_0 so it can be concluded that the preliminary series and disaggregated series are compatible and support compatibility assumptions between the preliminary series and disaggregated series.

The results of the monthly Indonesia's GFCF disaggregation and the accuracy are as follows:

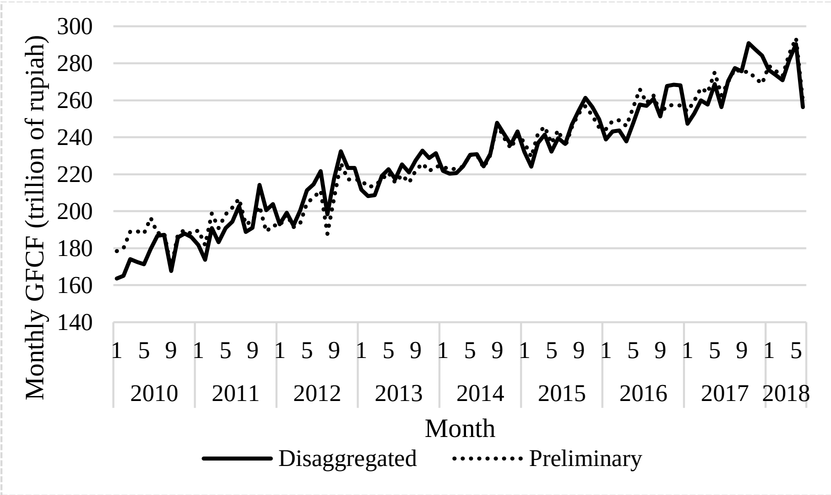


Figure 4. Indonesia's monthly gross fixed capital formation (GFCF), 2010-quarter II 2018

The accuracy of model estimates of the preliminary series and the disaggregated series obtained are:

Table 4. Accuracy of model estimates of the preliminary series and disaggregated series of monthly GFCF

Preliminary Series		Disaggregated Series	
Series (1)	MAPE (%) (2)	Series (3)	MAPE (%) (4)
In sample	2.2445	In sample	2,1906
Out sample		Out sample	
Quarter III	3.3890	Quarter III	0,0951
Quarter IV	6.2621	Quarter IV	0,5349
Quarter III & IV	4.8255	Quarter III & IV	0,3150

Sectoral Disaggregation

After the monthly GFCF disaggregation results are obtained, sectoral disaggregation is then carried out on monthly GFCF data. The sectors used are three sectors with the largest proportion, they are agriculture, manufacture, construction, and the remainder going into the other sector. The principle is the same as monthly disaggregation. Dividers to obtain the proportion of each sector from the input-output table.

Table 5. Proportion of GFCF in each sector

Sector	Share (%)
(1)	(2)
Agriculture	0.0504
Manufacture	0.1317
Construction	0.7302

Others	0.0876

The next step is to calculate the preliminary series of each sector using simple linear regression with the independent variable is investment credits of commercial and rural banks for each sector. The data is obtained from Bank Indonesia.

After the preliminary series of each sector obtained, the next step is to calculate the difference between the monthly GFCF value and the sum of the preliminary series of GFCF in each sector. This difference will be distributed to each sector using the distribution matrix. The equation for the distribution matrix is as follows:

$$A = \Sigma C'(C\Sigma C')^{-1} \quad (57)$$

In calculating the distribution matrix in sectoral disaggregation, it is done by utilizing the inter-sector linkages obtained from the input-output table. The Σ matrix is calculated using the Leontief matrix. While the $C = (1 \quad 1 \quad 1 \quad 1 \quad 1)$ matrix is used because the aggregate series is the sum of the disaggregated series.

$$\Sigma = \begin{pmatrix} 1,0804 & 0,2285 & 0,1282 & 0,0613 \\ 0,1585 & 1,5021 & 0,7026 & 0,2861 \\ 0,0226 & 0,0156 & 1,0176 & 0,0279 \\ 0,0976 & 0,4232 & 0,4525 & 1,3611 \end{pmatrix} \quad (58)$$

$$A = \begin{pmatrix} 0,1981 \\ 0,3502 \\ 0,1432 \\ 0,3085 \end{pmatrix} \quad (59)$$

The Indonesia's monthly and sectoral GFCF disaggregation results and the accuracy are as follows:

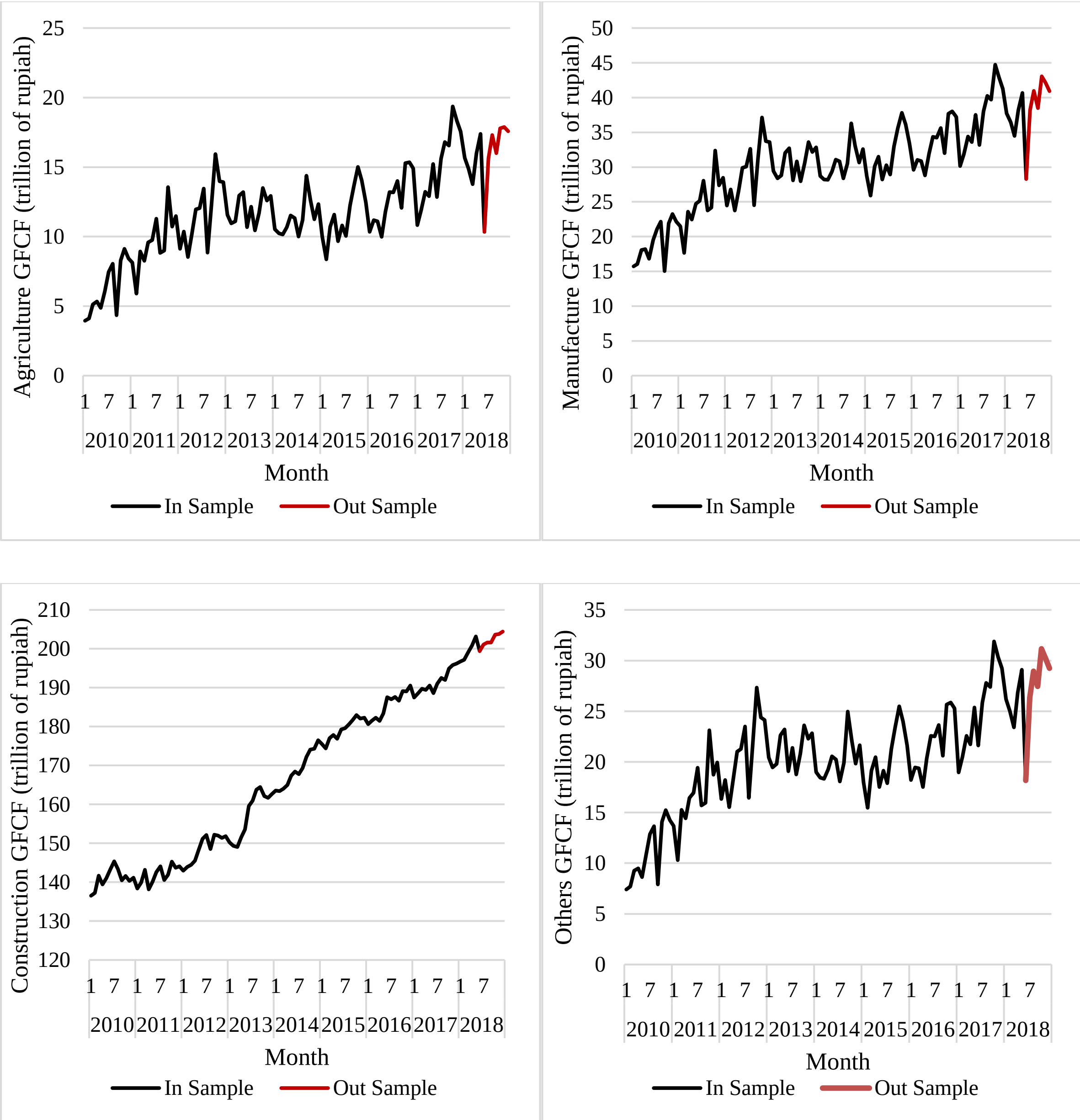


Figure 5. Indonesia's monthly and sectoral GFCF, 2010-quarter II 2018

The accuracy of the estimated models obtained are:

Table 6. Accuracy of Indonesia's monthly and sectoral model estimates

Series (1)	MAPE (%) (2)
In sample	
Agriculture	8.5762
Manufacture	5.9511
Construction	0.7048
Others	7.9839
Out sample	
Quarter III	3.0955

Quarter IV	3.5528
Quarter III & IV	3.3241

D. Forecasting Quarterly GFCF and Monthly and Sectoral GFCF

Disaggregation has been completed and the next step is to forecast for the 2019 period. Forecasting for the monthly preliminary series and disaggregated series are shown in the following graph:

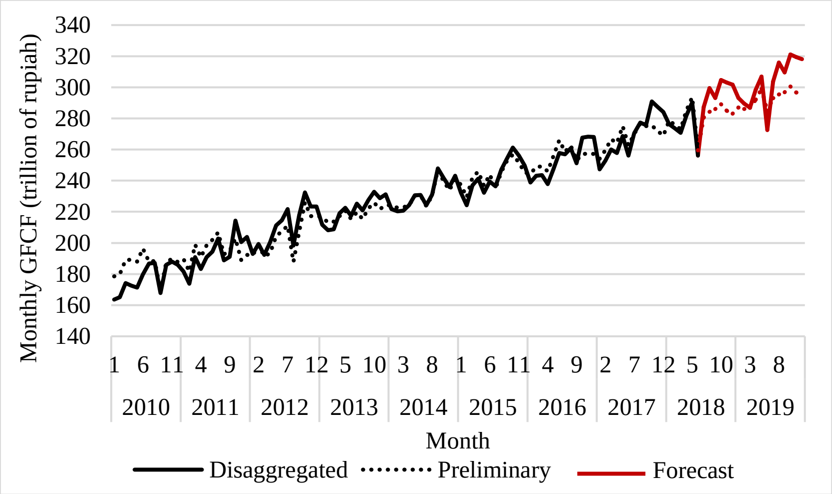


Figure 6. Indonesia's monthly GFCF and its forecast, 2010-2019

Re-checking is done by Ljung-Box test to find out whether the model is adequate. The Ljung-Box statistic results show that for preliminary series $Q'(20) = 15.22$ with p-value = 0.7635 and for disaggregated series $Q'(20) = 16.29$ with p-value = 0.6987. Both the preliminary series and the disaggregated series have p-value more than α, so it is concluded that there are no reasons to doubt model's adequacy. Quarterly GFCF forecast in 2019 is shown in the following graph.

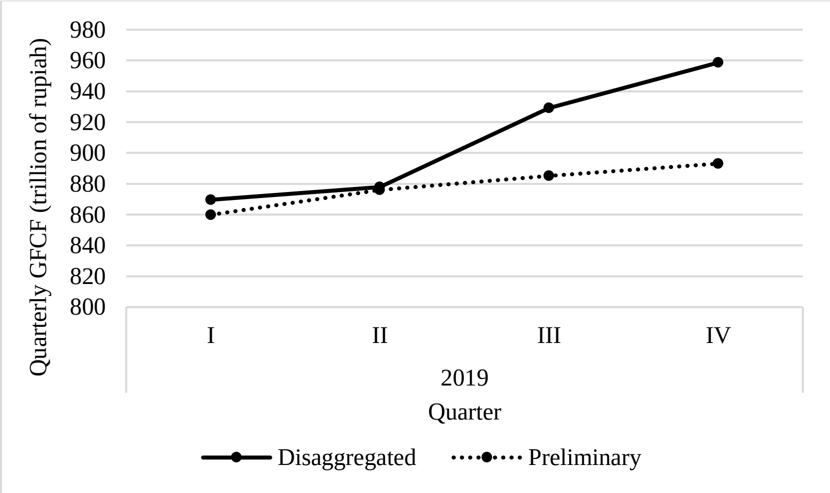


Figure 7. Indonesia's quarterly GFCF and its forecast, 2010-2019

The forecasting result show that there is an increase of GFCF from quarter I-quarter IV 2019. This result is consistent with the pattern of quarterly GFCF in previous periods.

In addition, forecasting is also done on sectoral data. The model for each sector is also checked by the Ljung-Box test to find out whether the model is adequate. The Ljung-Box statistic results for each sector are shown in the table below.

Table 7. The Ljung-Box statistic results for each sector

Sector	$Q'(20)$	p-value
(1)	(2)	(3)
Agriculture	16.29	0.6987
Manufacture	16.83	0.6637
Construction	27.53	0.1210
Others	15.36	0.7557

The Ljung-Box statistic for all sectors indicate a failure to reject H_0 so that the model for each sector is adequate. Monthly and sectoral GFCF forecasting is shown in the following graph.

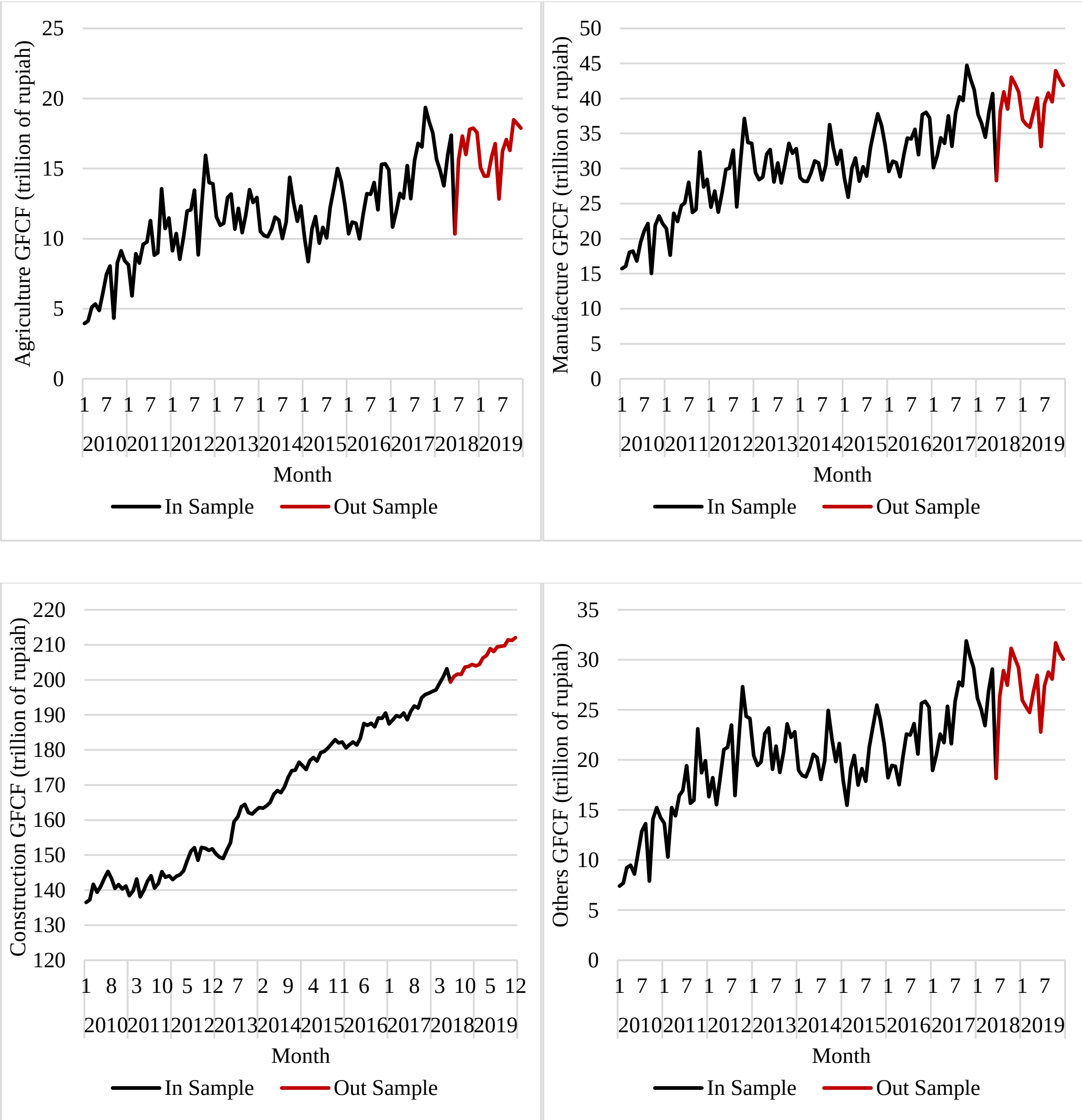


Figure 8. Indonesia's monthly and sectoral GFCF and its forecast, 2010-2019

IV. Conclusion

From the analysis that has been done, it can be concluded that disaggregation is able to provide a more detailed picture of aggregate data both in terms of temporal and sectoral. From temporal disaggregation, it was found that the industrial production indices was able to become a coincident indicator for Gross Fixed Capital Formation. On the sectoral side, investment credits and Leontief IO matrices are able to be used to disaggregate by creating unique patterns from each sector.

The more detailed picture of the movement of Gross Fixed Capital Formation, both temporally and sectorally, can be used in policy formulation. In addition, the temporal and sectoral variations provided are able to make forecasting better because it gets more specific characteristics both from monthly data and data from each sector. The variations obtained are also useful for early warnings for certain times in certain sectors.

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VI. Appendix

Appendix 1. Indonesia's GFCF (in billion of Rupiah at 2010 prices)

Year	Quarter	GFCF	Y	IPAGR	YAGR	D
(1)	(2)	(3)	(4)	(5)	(6)	(7)
2010	I	502873.55	167624.52	98.41	182474.62	-14850.10
	II	523471.69	174490.56	102.35	191165.94	-16675.38
	III	541676.74	180558.91	98.12	181834.90	-1275.99
	IV	559818.69	186606.23	101.11	188415.89	-1809.66
2011	I	546295.29	182098.43	101.86	190077.69	-7979.26
	II	568551.72	189517.24	105.02	197041.03	-7523.79
	III	582733.97	194244.66	105.56	198232.23	-3987.57
	IV	618778.12	206259.37	103.94	194673.35	11586.02
2012	I	584460.64	194820.21	103.62	193952.75	867.46
	II	626152.32	208717.44	107.16	201769.05	6948.39
	III	637811.69	212603.90	107.27	202004.35	10599.55
	IV	679304.13	226434.71	115.47	220107.59	6327.12
2013	I	628573.64	209524.55	112.93	214504.55	-4980.01
	II	659187.45	219729.15	114.41	217769.31	1959.84
	III	673791.17	224597.06	115.00	219070.81	5526.25
	IV	692822.78	230940.93	117.20	223923.83	7017.10
2014	I	662774.26	220924.75	116.91	223267.91	-2343.15
	II	685670.41	228556.80	119.21	228351.89	204.91
	III	703109.97	234369.99	121.64	233706.29	663.70
	IV	720916.13	240305.38	123.68	238211.75	2093.63
2015	I	693216.77	231072.26	122.82	236312.90	-5240.64
	II	713107.13	237702.38	125.47	242153.68	-4451.30
	III	737766.63	245922.21	126.51	244451.40	1470.81
	IV	767265.46	255755.15	129.56	251181.46	4573.69
2016	I	725586.64	241862.21	127.89	247492.97	-5630.76
	II	742915.46	247638.49	131.76	256024.99	-8386.50
	III	769037.14	256345.71	132.67	258051.04	-1705.33
	IV	804047.38	268015.79	132.28	257179.61	10836.18
2017	I	760190.65	253396.88	133.59	260075.67	-6678.79
	II	782584.93	260861.64	136.88	267324.36	-6462.72
	III	823498.00	274499.33	139.91	274020.90	478.43
	IV	862473.94	287491.31	139.06	272139.56	15351.75
2018	I	820597.64	273532.55	140.75	275857.11	-2324.57
	II	828429.20	276143.07	142.35	279394.66	-3251.59

Appendix 2. Result of the monthly disaggregation of Indonesia's GFCF (2010-quarter II 2018)

Year	Month	Industrial Production	Preliminary Series (W)	Disaggregated Series (Z)	Year	Industrial Production	Preliminary Series (W)	Disaggregated Series (Z)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010	1	96.59	178452.50	163602.39	2011	101.66	189636.50	181657.25
	2	97.28	179974.58	165124.48		98.06	181695.20	173715.94
	3	101.37	188996.79	174146.68		105.86	198901.36	190922.10
	4	101.44	189151.20	172475.82		102.19	190805.64	183281.84
	5	100.90	187960.00	171284.63		105.63	198394.00	190870.20
	6	104.72	196386.61	179711.24		107.23	201923.47	194399.67
	7	100.93	188026.18	186750.19		109.45	206820.61	202833.03
	8	101.12	188445.31	187169.32		103.10	192813.02	188825.45
	9	92.32	169033.22	167757.23		104.12	195063.06	191075.49
	10	100.77	187673.23	185863.57		107.59	202717.60	214303.62
	11	101.72	189768.86	187959.19		101.35	188952.67	200538.69
	12	100.83	187805.59	185995.93		102.89	192349.78	203935.81
2012	1	102.76	192063.01	192930.48	2013	113.91	216659.00	211678.99
	2	105.63	198394.00	199261.46		112.31	213129.53	208149.52
	3	102.46	191401.24	192268.70		112.58	213725.13	208745.12
	4	103.38	193430.68	200379.07		114.12	217122.24	219137.67
	5	108.31	204305.86	211254.25		115.78	220784.07	222632.73
	6	109.79	207570.62	214519.01		113.34	215401.63	217417.05
	7	111.41	211144.21	221743.75		115.28	219681.11	225228.87
	8	100.78	187695.29	198294.84		113.37	215467.81	220951.04
	9	109.61	207173.55	217773.10		116.36	222063.50	227611.26
	10	118.17	226056.21	232383.34		118.05	225791.50	232808.60
	11	114.13	217144.30	223471.43		116.20	221710.55	228727.66
	12	114.12	217122.24	223449.37		117.36	224269.42	231286.52
2014	1	117.32	224173.40	221830.25	2015	123.33	237432.02	232191.38
	2	116.60	222602.03	220258.88		119.67	229361.85	224121.21
	3	116.80	223028.28	220685.13		125.46	242144.82	236904.18
	4	117.25	224025.82	224266.57		127.11	245784.04	241355.84
	5	120.16	230449.01	230582.24		123.03	236783.16	232285.63
	6	120.22	230580.85	230821.60		126.26	243893.85	239465.65
	7	117.05	223582.11	224259.68		122.21	234972.30	236452.05
	8	120.13	230374.54	231010.50		127.01	245554.48	247007.40
	9	127.74	247162.22	247839.79		130.31	252827.43	254307.18
	10	124.37	239723.25	241816.87		132.07	256721.46	261295.16
	11	121.73	233911.88	236005.50		129.77	251642.44	256216.13
	12	124.94	241000.13	243093.75		126.84	245180.48	249754.17
2016	1	126.50	244427.24	238796.49	2017	130.86	254049.32	247370.53
	2	128.50	248843.35	243212.60		133.35	259533.24	252854.45
	3	128.67	249208.31	243577.55		136.57	266644.46	259965.67
	4	127.28	246142.17	237770.57		135.43	264136.45	257683.34
	5	131.69	255881.22	247464.92		140.43	275150.64	268668.70
	6	136.30	266051.57	257679.97		134.78	262685.99	256232.88
	7	132.93	258610.96	256902.88		138.09	269997.16	270479.31
	8	134.72	262567.20	260867.39		141.22	276900.60	277371.59
	9	130.37	252974.95	251266.87		140.43	275164.95	275647.10
	10	132.15	256903.59	267739.77		140.60	275538.00	290889.75
	11	132.42	257485.86	268322.04		139.00	272001.21	287352.96
	12	132.27	257149.38	267985.57		137.58	268879.48	284231.23
2018	1	142.00	278613.33	276288.76				
	2	140.75	275856.96	273532.39				
	3	139.50	273101.06	270776.49				
	4	144.95	285137.54	281892.15				
	5	148.79	293591.73	290327.74				
	6	133.31	259454.70	256209.31				

Appendix 3. Result of the monthly and sectoral disaggregation of Indonesia's GFCF (2010-quarter II 2018)

Year	Month	Agriculture	Manufacture	Construction	Others
(1)	(2)	(3)	(4)	(5)	(6)
2010	1	3950.47	15731.44	136514.49	7406.00
	2	4113.26	16053.98	137254.76	7702.48
	3	5129.68	18077.21	141679.23	9260.57
	4	5334.94	18216.24	139435.79	9488.86
	5	4881.08	16796.83	140988.32	8618.39
	6	6066.64	19501.05	143302.06	10841.49
	7	7464.61	21068.82	145334.68	12882.08
	8	8044.64	22167.15	143306.70	13650.83
	9	4338.24	15036.32	140466.96	7915.72
	10	8286.44	21898.80	141603.39	14074.93
	11	9129.87	23242.51	140342.55	15244.25
	12	8424.95	22155.28	141159.02	14256.68
2011	1	8126.82	21464.59	138390.36	13675.48
	2	5911.22	17655.31	139840.13	10309.28
	3	8925.79	23596.87	143148.13	15251.32
	4	8267.87	22459.43	138113.49	14441.05
	5	9590.08	24712.98	140117.64	16449.51
	6	9757.58	25130.47	142571.54	16940.09
	7	11295.80	28030.03	144093.94	19413.26
	8	8821.92	23750.80	140555.18	15697.55
	9	8995.50	24179.08	141931.68	15969.23
	10	13562.38	32372.43	145253.49	23115.32
	11	10728.13	27370.60	143704.83	18735.13
	12	11473.73	28457.17	144073.31	19931.59
2012	1	9126.16	24484.02	142978.94	16341.36
	2	10369.29	26778.98	143897.96	18215.23
	3	8525.41	23763.13	144443.81	15536.35
	4	10137.62	26569.70	145518.37	18153.39
	5	11967.29	29896.90	148368.33	21021.73
	6	12054.72	30066.20	151114.84	21283.24
	7	13459.46	32644.47	152142.13	23497.69
	8	8840.56	24522.70	148481.99	16449.59
	9	12429.63	31106.02	152221.26	22016.19
	10	15943.51	37145.54	151958.94	27335.34
	11	13990.48	33711.71	151393.02	24376.21
	12	13911.25	33591.53	151808.90	24137.69
2013	1	11567.11	29425.01	150263.83	20423.04
	2	10960.98	28399.44	149336.43	19452.68
	3	11103.15	28789.73	149053.57	19798.67
	4	12940.78	32037.08	151522.65	22637.15
	5	13193.12	32701.35	153543.78	23194.48
	6	10670.64	28096.54	159578.14	19071.73
	7	12153.53	30802.93	160897.45	21374.96
	8	10438.43	27972.76	163794.30	18745.54
	9	11683.11	30621.35	164489.91	20816.89
	10	13503.20	33591.03	162118.08	23596.29
	11	12587.01	32166.66	161700.30	22273.68
	12	12934.27	32829.01	162691.98	22831.26
2014	1	10523.48	28718.20	163586.02	19002.55
	2	10229.09	28205.69	163373.26	18450.85

Appendix 3. Continued

Year	Month	Agriculture	Manufacture	Construction	Others
(1)	(2)	(3)	(4)	(5)	(6)
	3	10145.65	28185.02	164032.69	18321.77
	4	10685.32	29329.86	164999.81	19251.58
	5	11529.70	31082.66	167415.75	20554.12
	6	11329.92	30817.07	168439.24	20235.37
	7	10010.87	28380.70	167802.28	18065.83
	8	11210.69	30508.91	169371.32	19919.57
	9	14380.49	36281.48	172224.89	24952.93
	10	12601.00	33074.48	174072.05	22069.34
	11	11243.58	30652.45	174274.83	19834.64
	12	12330.70	32583.79	176526.32	21652.94
2015	1	10005.33	28700.69	175503.09	17982.28
	2	8369.85	25901.47	174379.94	15469.94
	3	10704.05	30086.61	176985.37	19128.15
	4	11581.57	31507.52	177816.47	20450.28
	5	9672.47	28224.32	176879.29	17509.55
	6	10813.26	30263.21	179269.02	19120.17
	7	10043.91	28933.89	179594.39	17879.86
	8	12229.09	32986.87	180519.30	21272.14
	9	13627.64	35559.71	181710.84	23408.99
	10	15002.11	37822.54	182977.98	25492.53
	11	14037.81	36135.47	182045.29	23997.56
	12	12460.76	33397.11	182283.42	21612.89
2016	1	10343.61	29605.93	180630.89	18216.05
	2	11173.95	31037.22	181550.25	19451.18
	3	11092.48	30858.48	182264.87	19361.72
	4	9988.71	28818.35	181438.66	17524.85
	5	11794.83	31952.65	183375.26	20342.18
	6	13200.25	34340.84	187559.88	22579.01
	7	13171.85	34211.29	187014.69	22505.05
	8	14000.24	35597.39	187630.72	23639.05
	9	12060.10	31983.67	186613.05	20610.05
	10	15290.38	37675.47	189121.65	25652.27
	11	15338.86	38035.09	189075.23	25872.85
	12	14914.77	37227.87	190557.47	25285.46
2017	1	10829.20	30129.34	187452.66	18959.32
	2	11896.61	31871.60	188586.01	20500.23
	3	13224.63	34398.78	189759.66	22582.61
	4	12899.07	33584.49	189463.05	21736.73
	5	15215.14	37529.11	190548.09	25376.36
	6	12852.84	33160.32	188596.27	21623.45
	7	15596.37	38011.10	191027.11	25844.74
	8	16808.87	40230.82	192547.11	27784.79
	9	16557.24	39688.67	191999.31	27401.88
	10	19361.65	44731.07	194908.08	31888.95
	11	18324.77	42879.74	195804.93	30343.52
	12	17556.58	41257.96	196187.33	29229.35
2018	1	15657.92	37731.82	196717.51	26181.50
	2	14877.42	36479.70	197143.87	25031.40
	3	13770.68	34467.20	199117.70	23420.92
	4	15970.75	38197.38	200879.27	26844.75
	5	17382.02	40681.00	203176.50	29088.23
	6	10349.96	28287.56	199402.58	18169.20

Appendix 4. Forecasting result for Indonesia's GFCF

Year	Month	Forecast	Quarter	Forecast
(1)	(2)	(3)	(4)	(5)
2018	7	287321.6		
	8	299486.7		
	9	293149.2	III	879957.5
	10	304690.0		
	11	303034.5		
	12	301693.6	IV	909418.1
2019	1	293164.1		
	2	289531.1		
	3	286934.1	I	869629.3
	4	298458.1		
	5	306873.2		
	6	272570.2	II	877901.5
	7	303669.1		
	8	315914.9		
	9	309593.0	III	929177
	10	321100.0		
	11	319433.2		
	12	318106.1	IV	958639.3

Appendix 5. 2 digits KBLI and the description

No.	KBLI	Description
(1)	(2)	(3)
1	10	Manufacture of food products
2	11	Manufacture of beverages
3	12	Manufacture of tobacco products
4	13	Manufacture of textiles
5	14	Manufacture of wearing apparels
6	15	Manufacture of leather and related products and footwear
7	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, bamboo, rattan and the like
8	17	Manufacture of paper and paper products
9	18	Printing and reproduction of recorded media
10	20	Manufacture of chemicals and chemical products
11	21	Manufacture of pharmaceuticals, medicinal chemical and botanical products
12	22	Manufacture of rubber and plastic products
13	23	Manufacture of other nonmetallic mineral products
14	24	Manufacture of basic metals
15	25	Manufacture of fabricated metal products, excepts machinery and equipment
16	26	Manufacture of computers, electronic and optical products
17	27	Manufacture of electrical equipment
18	28	Manufacture of machinery and equipment n.e.c
19	29	Manufacture of motor vehicles, trailers and semi-trailers
20	30	Manufacture of other transport equipment
21	31	Manufacture of furniture
22	32	Other manufacturing
23	33	Repair and installation of machinery and equipment