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NOWCASTING REGIONAL ECONOMIC GROWTH IN INDONESIA

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ABSTRACT

This study aims to nowcast gross regional domestic product at the provincial level for Indonesia. The dynamic factor model and mixed data sampling were applied to three sets of variables; namely, macroeconomic, financial, and Google Trends. We find that both methods captured several economic expansions and contractions, including the recent downturn during the COVID-19 pandemic. By including the pandemic period, accuracy across the same set of variables and provinces was slightly reduced.

Keywords: Nowcasting DFM; MIDAS; GRDP.
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I. INTRODUCTION

The purpose of this study is to establish a nowcasting model of regional economic growth in Indonesia. Economic growth is a widely used indicator for monitoring and evaluating the economy, both at sectoral and regional levels. However, regional economic growth or Gross Regional Domestic Product (GRDP) growth is released with substantial delays, although up-to-date data on GRDP are required for regional planning. This is released five weeks after the end of the reference quarter. As a result, assessing regional economic activities becomes difficult for policymakers, especially during an unusual event like COVID-19 pandemic; for a survey of the COVID-19 literature, see Narayan (2021). To obtain an overview of current economic conditions, data nowcasting is performed by economists. According to Agostino *et al*. (2015), nowcasting is an act of monitoring economic conditions in real-time through high-frequency indicators, indicators with different frequencies, and those with various release times. Gil *et al*. (2019) used the terminology of very short-term forecasts to define nowcasting. Unlike national data, regional data typically have a narrower data range and lower quality due to the smaller number of samples and data sources. This issue made regional nowcasting difficult but there is still a need to offer timely information. In Indonesia, there was no nowcasting studies or components at the regional level until recently. Therefore, we attempt to answer the following research question: by using limited sets of variables at the regional level, can we perform nowcasting to obtain accurate estimation of regional economic growth?

Another challenge in nowcasting is the timeliness of high-frequency data from the official statistics. Google Trends is a database of Google search data that are available on a daily, weekly, and monthly basis. Another question is whether the quality by Google Trends data will create a more accurate estimation of regional economic growth? The reason behind this was the assumption that the internet search about economics could also capture the economic activity itself. Along with the Google Trend data, the accuracy with data from official statistics which was available on a monthly basis, that was openly accessible by anyone, and were relevant to economic activity will be compared. Thus, this study addresses these two research questions using monthly macroeconomic, financial, and Google Trends data at the regional level.

To build projections that can describe conditions in the present quarter, the nowcasting process requires monthly indicators and, as a result, we need econometric methodologies that can mix data from different frequencies. By disaggregating GDP into high-frequency series, Luthfiana and Nasrudin (2018) came up with a solution. Rather than disaggregating GDP, two nowcasting methodologies are used, namely the Dynamic Factor Model (DFM) with expectation-maximization algorithms by Bańbura and Reichlin (2010) and the unrestricted mixed data sampling (U-MIDAS) by Foroni *et al*. (2011). These nowcasting models are motivated by the fact that, unlike other econometric methods (e.g. Distributed Lag Model, Bridge Model), DFM and U-MIDAS can link the monthly data to quarterly GRDP growth. DFM's method can combine a large number of variables into a single factor. This ensures that variables can be used without being restricted by multicollinearity assumption. We also use U-MIDAS that has been recognized for nowcasting variables by mixing data frequencies.

According to results, both models can capture the direction and magnitude of current economic conditions using a limited set of variables. Also, the use of Google Trends data generated the best nowcasting accuracy compared to those from official statistics.

The contribution of this study are as follows: First, nowcasting studies based on Indonesia are still focused at the national level. At that level, Tarsidin *et al*. (2018) and Luciani *et al*. (2018) performed nowcasting studies, while Dewati *et al*. (2018) developed a nowcasting model in Sumatra, Java, and Eastern Indonesia. This study focuses on nowcasting at the regional level to provide the foundation for regional economic assessment. Second, this is the first study to map Google Trends topics and categories to the GRDP sector. The approach by Heikkinen (2019) and Woloszko (2020) was integrated to leverage Google Trends topics and categories to minimize the subjectivity of selecting the keywords in order to obtain Google Trends index. Furthermore, the final contribution is to provide useful nowcasting results due to the recent economic downturn. An appropriate approach is made to the data range by distinguishing the period prior to the COVID-19 pandemic from the period following the pandemic. By doing this, the models could still be beneficial to estimate the current economic condition despite economic contraction due to the pandemic.

II. DATA AND METHODOLOGY

A. Data

The dataset includes monthly variables and quarterly GRDP growth over the period 2012Q2 to 2020Q4 for 13 Indonesian provinces. The monthly variables consist of farmer exchange rate, exports value, imports value, demand deposit, saving deposit, time deposit, loans for working capital, loans for investment, loans for consumption, credit to micro, small, and medium enterprise, and Google Trends variables. Due to the availability of data, our study employed seven provinces out of 34 provinces in Indonesia. According to the National Standardization Agency, the provinces' name abbreviations are North Sumatra (SU), West Sumatra (SB), Riau (RI), Jambi (JA), Lampung (LA), Bangka Belitung Islands (BB), Riau Islands (KR), Central Java (JT), Banten (BT), Bali (BA), East Java (JI), West Kalimantan (KB), and South Kalimantan (KS). There are several provinces with zero search volume indices (SVI) during the first few years of the data range considered in this study and this is a limitation of the Google Trends data because of lower search intensities. Due to this limitation, the nowcasting process can only be done in 7 provinces. An appropriate approach was made to the recent economic downturn by dividing the data range into two sub-samples, namely a pre-pandemic (2012Q2-2019Q4) and a period that includes pandemic (2012Q2-2020Q4). To establish an appropriate approach to the COVID-19 pandemic where economic growth is decreased drastically, the two types of periods are used. This situation will affect the nowcasting performance, therefore, evaluating the benefit of the nowcasting model in that period is necessary.

Moreover, our datset can be categorized into three categories namely, macroeconomic, financial, and Google Trend. More specifically, there are three macroeconomic variables, nine financial variables, and twelve Google Trends variables. Google Trends data is collected by the application of a scraping data method using the RStudio package called gtrendsR. This transformation is needed to induce stationarity and to adjust the type of data. Table 1 provides the summary of variables used in this study.

Table 1.
Summary of Variables Used in the Model

This table describes the variables used in this study. These variables are divided into three categories. The first set includes macroeconomic variables from Badan Pusat Statistik (BPS), the official statistic agency Indonesia. The second set is financial variables from Bank Indonesia, the central bank in Indonesia. The third set is Google Trends. DFM block also refers to the name of sets of variables. Variable block abbreviation: FIN for Financial, MACRO for Macroeconomics, GT for Google Trends. The transformation that we apply is also reported.

Transformation (1) is the difference q-to-q to the difference year-on-year: $(Y_t\text{-}Y_{t\text{-}4})\text{-}(Y_{t\text{-}1}\text{-}Y_{t\text{-}5})$

Transformation (2) is the difference month-to-month: $Y_t\text{-}Y_{t\text{-}1}$

Transformation (3) is growth year-on-year: $\frac{Y_t - Y_{t-12}}{Y_{t-12}}$

Transformation (4) is the year-on-year difference of the natural logarithm: $ln\ Y_t$ - $lnY_{t\text{-}12}$

Variable	Name	DFM Block	Data Source	Lag release	Unit	Transformation
GRDP Growth	PDRB	-	BPS	6 weeks	%	1
Farmer Exchange Rate	FER	MACRO	BPS	3 days	Index	2
Exports	EKS	MACRO	BPS	5 weeks	Million US$	3
Imports	IMP	MACRO	BPS	5 weeks	Million US$	3
Demand Deposit	GIR	FIN	BI	5 weeks	Million Rp	4
Saving Deposit	TAB	FIN	BI	5 weeks	Million Rp	4
Time Deposit	SIM	FIN	BI	5 weeks	Million Rp	4
Working Capital	MOD	FIN	BI	5 weeks	Million Rp	4
Investment	INV	FIN	BI	5 weeks	Million Rp	4
Consumption	KON	FIN	BI	5 weeks	Million Rp	4
Micro	MIK	FIN	BI	5 weeks	Million Rp	4
Small	KEC	FIN	BI	5 weeks	Million Rp	4
Medium	MEN	FIN	BI	5 weeks	Million Rp	4
Google Trends	GT (A-I)	GT	Google Trends	Real time	Index	3

Stock and Watson (1989) constructed a GDP index coincident based on characteristics that follow the core concept of calculating GDP. These include the supply, demand, and income side of the equation. By considering the availability of regional variables in Indonesia, three macroeconomic variables, namely export, import, and Farmer Exchange Rate are used as the proxies for supply, demand, and income component of GDP. The supply-side is represented by export, while the demand-side is represented by import. Based on expenditure approaches, export and import are the components of GRDP. According to Badan Pusat Statistik (2020), Farmer Exchange Rate is used as a measure of purchasing power of farmers in rural areas. Although Farmer Exchange Rate has never been utilized in Indonesian nowcasting studies, this study uses it to portray the income side because purchasing power can describe income, especially in rural areas.

In several nowcasting studies, financial variables have proven efficient in capturing economic movements. According to Glocker and Wegmueller (2020), banking indicators contain information about liquidity in the financial sector. Bhadury *et al*. (2020) also formed a financial block in DFM due to its ability to increase accuracy in nowcasting GDP growth. However, the financial variable is more useful in capturing future conditions (leading indicator) and the recovery period in economic activity. According to Narayan (2019), financial sectors, specifically financial technology, have a significant and positive impact on economic growth in Indonesia. Financial variables from Bank Indonesia is also used in this analysis, which includes private deposits, loans, and credit to micro, small, and medium enterprise. Private deposit is divided into demand, saving, and time deposit. Furthermore, loan is divided by the purpose: working capital, investment, and consumption, while credit to the enterprise is divided by the size of the enterprise: micro, small, and medium.

One of the most notable big data sources provided by Google is Google Trends data. This data is defined as an index based on a search ratio and Woloszko (2020) explained the index using the following formula:

$$SVI_{ct} = \frac{SV_{ct}}{SVT_t} * C_c \tag{1}$$

SVI refers to search volume indices, *SV* represents search volume, *SVT* indicatestotal search volume, *c* represents the category or topic, and *t* is time. Therefore, *SVI* is the ratio of searches for a particular category and time to the total searches for that time. To ensure the index result is at a maximum value of 100, the ratio is multiplied by the constant $C_c = \left(\frac{SV_{ct}}{SVT_t}\right)^{-1}$. The index value of 100 indicates that the search was most popular at that time and location.

As proposed by Heikkinen (2019) and Woloszko (2020), a combination of topics and categories was fitted to GRDP sectors based on the production approach. To combine the subsectors into the GRDP sectors, the first component of the principal component analysis is used. Table 2 reports the concordance between Google Trends topics and categories and GRDP sectors.

Table 2.
Google Trends Topics and Categories

This table shows the concordance result of Google Trends topics and categories to GRDP sectors based on the production approach. The first column is the industry or sector of GRDP based on the production approach. The second column is the Google Trends topic/category that is fitted to GRDP sectors. The first component of principal component analysis (PCA) is used to compress subsectors into a sector, e.g. food production, agriculture, animal product & services, forestry are compressed to sector A (agriculture, forestry, and fishing).

Industry	**Google Trends Topic/Category**
(1)	**(2)**
A. AGRICULTURE, FORESTRY, AND FISHING	
Food Crops	Food Production
Plantation Crops	Agriculture
Livestock	Animal Product & Services
Forestry	Forestry

Table 2.
Google Trends Topics and Categories

Industry	Google Trends Topic/Category
(1)	(2)
B. MINING AND QUARRYING	
Crude Petroleum, Natural Gas	Oil & Gas
Coal, Lignite, Iron Ore, and Other Mining	Metals & Mining
C. MANUFACTURING INDUSTRY	
Manufacture of Food and Products and Beverages	Food & Drink
Manufacture of Textiles, and Wearing Apparel	Textiles & Nonwovens
Manufacture of Wood	Wood
Manufacture of Paper and Paper Products	Paper
Manufacture of Chemicals	Chemical Industry
Manufacture of Cement	Cement
Manufacture of Transport Equipment, Machinery, and Equipment	Automotive Industry
D. ELECTRICITY AND GAS	
Electricity	Electricity
Manufacture of Gas	Gasoline
Manufacture of Clean Water	Water Filters & Purifiers
E. CONSTRUCTION	
F. WHOLESALE AND RETAIL TRADE	
Wholesale and Retail Trade	Retail Trade
Hotel	Hotel & Accommodation
Restaurants	Restaurants
G. ACCOMMODATION AND COMMUNICATION	
Railways Transport	Rail Transportation
Land Transport	Urban Transportation
Sea Transport	Maritime Transportation
Air Transport	Aviation, Airport Parking &
Communication	Internet & Telecom
H. FINANCIAL, REAL ESTATE, AND BUSINESS ACTIVITIES	
Bank	Banking
Financial Institutions Non-Bank	Financial Markets
Financial Supporting Service	Business Finance
Real Estate	Real Estate
Business Activities	Business Service
I. SERVICES	
Public Administration and Defence	State & Local Government
Other Public Administration Service	Government Contracting & Procurement
Social Society	Social Services
Entertainment and Recreation	Entertainment & Industry
Individual and Household	Housing & Development

B. Methodology

In this study, we follow the DFM approach proposed by Bańbura and Reichlin (2010) using maximum likelihood estimation in an expectation-maximization algorithm. They state the model by the following specification:

$$x_t = \Lambda f_t + \varepsilon_t \tag{2}$$

$x_t=(x_{1t},x_{2t},\ldots,x_{nt})'$ is a set of stationary and standardized monthly variables for $t=1,\ldots,T$. The vector of common factors with order $r\times1$ is expressed as f_t where we set a fixed number of factors, $r=2$. The vector of idiosyncratic components is expressed as ε_t. The loading matrix of the factors that explained the contribution of the variable to the common factor is expressed as Λ. The common factors, f_t, are assumed to follow the VAR process with order 2 as follows:

$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p+} u_t\,, \qquad u_t \sim i.i.d.N(0,Q) \tag{3}$$

A_1,A_2 is the coefficient matrix of $AR(p)$. Idiosyncratic components, $\varepsilon_{i,t}$, are assumed to follow the $AR(2)$ process as follows:

$$\varepsilon_{i,t} = \alpha_{i1}\varepsilon_{i,t-1} + \alpha_{i2}\varepsilon_{i,t-1} + e_{i,t}, \qquad e_{it} \sim i.i.d.N(0,\sigma_i^2) \tag{4}$$

$E\left[e_{i,t}e_{j,s}\right] = 0$ for $i\neq j$. The index s represents the *lag* in the model where $s=1,\ldots,q$.

Bańbura and Reichlin (2010) handle the mixed frequency issue by transforming the quarterly growth of GRDP using Mariano and Murasawa (2003) approximation. We notated y_t^Q as quarterly growth of GRDP and y_t as an unobserved monthly growth rate of GRDP where $y_t=\Delta Y_t^M$. Mariano and Murasawa (2003) linked y_t with y_t^Q by assigning the value of the quarterly variable to the third month of the respective quarter, which is denoted by Y_t^Q,t=3,6,9,…. The quarterly level of GRDP can be expressed as the sum of its unobserved monthly level, Y_t^M:

$$Y_t^Q = Y_t^M + Y_{t-1}^M + Y_{t-2}^M \tag{5}$$

y_t is assumed to have the same factor model as the monthly variables as follows:

$$y_t = \Lambda_Q f_t + \varepsilon_t^Q \tag{6}$$

$$\varepsilon_t^Q = \alpha_{Q\varepsilon_{t-1}}^Q + e_t^Q \tag{7}$$

To link y_t with the observed GRDP data, Mariano and Murasawa (2003) constructed a partially observed monthly series and use the following approximation:

$$
\begin{aligned}
y_t^Q &= Y_t^Q - Y_{t-3}^Q \\
&\approx (Y_t^M + Y_{t-1}^M + Y_{t-2}^M) - \left(Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M\right) \\
&= (Y_t^M - Y_{t-3}^M) + (Y_{t-1}^M - Y_{t-4}^M) + \left(Y_{t-2}^M - Y_{t-5}^M\right) \\
&= (y_t + y_{t-1} + y_{t-2}) + (y_{t-1} + y_{t-2} + y_{t-3}) + (y_{t-2} + y_{t-3} + y_{t-4}) \\
&= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4}
\end{aligned}
\tag{8}
$$

The MIDAS variant used in this study is unrestricted MIDAS (U-MIDAS). In this context, unrestricted means that the polynomial lag function of the high frequency variable is not included. U-MIDAS is built with a simple linear polynomial lag and can be estimated using Ordinary Least Squares (OLS) method. Foroni *et al*. (2015) stated that U-MIDAS can be well applied to data with small frequency differences, such as monthly and quarterly. Leboeuf and Morel (2014) specified the U-MIDAS model as follows:

$$
Y_t^{(Q)} = \beta_1 + \lambda_1 Y_{t-1}^{(Q)} + \cdots + \lambda_p Y_{t-p}^{(Q)} + \sum_{j=1}^{3} \gamma_{1,j} X_t^{(M_j)} + \cdots + \sum_{j=1}^{3} \gamma_{q,j} X_{t-q}^{(M_j)} + u_t \tag{9}
$$

where $Y_t^{(Q)}$ is a reference variable with quarterly frequency, $X_t^{(M_j)}$ is a monthly variable.

The stationary test is done using Augmented Dickey-Fuller (ADF) test. ADF test is also used to check the robustness of the model by testing the residual of the fitted model. Gujarati (2004) states that the white noise assumption has an average of zero, constant variance, and is not autocorrelated. Residuals that meet the stationarity condition have also satisfied the white noise assumption.

III. MAIN FINDINGS

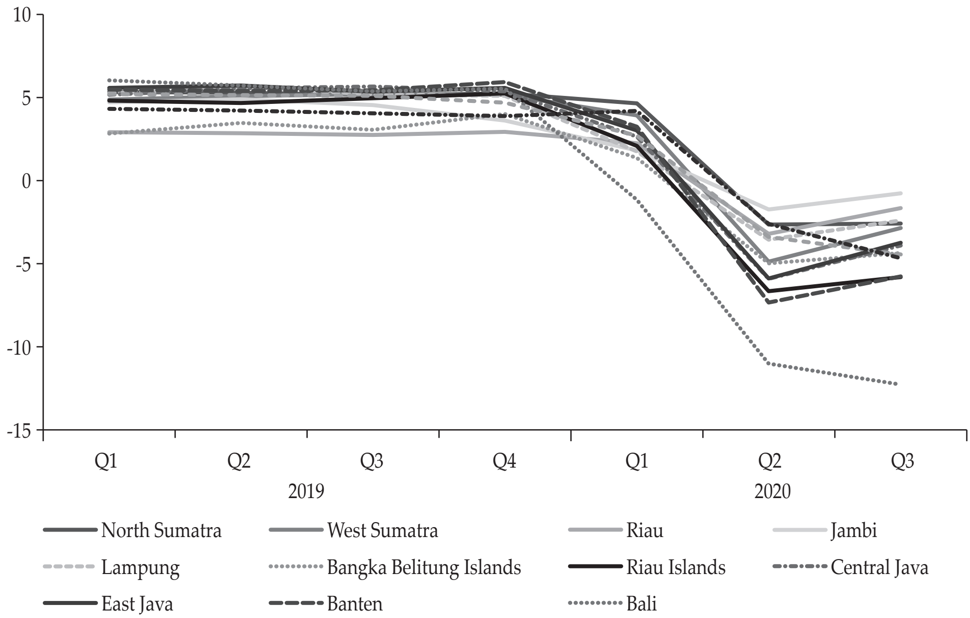
The discussion on main findings of this study is divided into five subsections. In the first subsection, the GRDP growth rate movement is discussed, and in the second subsection, the correlation variables are examined. The third subsection discusses nowcasting GDP at the national level, while the fourth and fifth subsections examine nowcasting GRDP using DFM and MIDAS, respectively.

A. GRDP Growth Movement

Every region's economic growth follows a different pattern. However, the recent economic downturn due to the COVID-19 pandemic affected all provinces. Figure 1 shows that in the second quarter of 2020, all provinces saw a significant contraction. To prevent the spread of the virus, the government imposed social restrictions in various provinces at the beginning of the pandemic. This resulted in a major decline in business performance and income levels. Firms were restraining their spendings, while households were limiting their consumption. Bali experienced the deepest contraction in that period with a contraction rate of -11.06%. In the third and fourth quarters of 2020, this value fell to -12%.

Figure 1.
Quarterly Growth of GRDP in 13 Provinces in Indonesia

This figure depicts the quarterly year-on-year growth of GRDP over the period 2019Q1-2020Q3 to show the period before the COVID-19 pandemic the beginning of the COVID-19 pandemic period that directly affects economic grwoth.



B. Correlation of Economic Growth with Variables Used

Based on the correlation analysis of economic growth and 3-month-average of all variables, Farmer Exchange Rate in Riau Islands had the strongest correlation (0.76) with GRDP growth. In general, the correlation coefficients are relatively low. The highest correlation value in West Kalimantan is 0.23. This means that none of the variables in West Kalimantan has the correlation value that is exceeding 0.23. Although the correlation between variables is small, nowcasting is still feasible. According to Giannone *et al*. (2008), any information from variables that are deemed unnecessary should not be discarded. Each variable may potentially affect the current-quarter estimates and precision.

Farmer Exchange Rate in Bali and Riau Islands has the strongest link with GRDP increase. This indicates that these variables can accurately describe economic activity, especially in terms of income. The export variable has the highest correlation among other monthly variables in West Kalimantan and South Kalimantan. However, the financial variables have the highest correlation in Riau, East Java, West Sumatra, Jambi, and Bangka Belitung Islands. In Lampung, Banten, and Central Java, the Google Trends variable from the concordance sector of electricity, gas, and clean water sector indicates a high correlation.

Table 3.
Correlation Coefficient

This table reports the Pearson correlation coefficient between quarterly GRDP growth and all monthly variables. The monthly variables used are transformed into 3-months-average.

Variable	SU	RI	LA	BT	JT	JI	BA	SB	JA	KR	BB	KB	KS
FER	0.198	0.025	0.463	0.293	0.185	0.375	0.741*	0.587	0.509	0.760*	0.520	0.171	0.610
EKS	0.379	0.366	0.486	0.041	0.255	0.062	0.575	0.499	0.499	0.607	0.441	0.234*	0.735*
IMP	0.457	0.287	0.628	0.475	0.441	0.127	0.378	0.555	0.239	0.576	0.250	0.037	0.634
GIR	0.378	0.223	0.455	0.469	0.415	0.550	0.110	0.595	0.624	0.402	0.275	0.169	0.633
TAB	0.621*	0.263	0.513	0.558	0.447	0.563	0.500	0.627	0.673	0.675	0.497	0.145	0.489
SIM	0.530	0.356	0.481	0.540	0.323	0.509	0.490	0.648*	0.690	0.702	0.562	0.179	0.597
MOD	0.454	0.311	0.560	0.523	0.367	0.432	0.409	0.597	0.700*	0.510	0.564*	0.183	0.554
INV	0.602	0.310	0.675	0.436	0.506	0.517	0.490	0.629	0.659	0.673	0.447	0.169	0.686
KON	0.578	0.259	0.468	0.511	0.337	0.454	0.450	0.633	0.698	0.719	0.540	0.142	0.599
MIK	0.528	0.217	0.572	0.527	0.389	0.570*	0.494	0.616	0.646	0.690	0.520	0.170	0.451
KEC	0.479	0.273	0.510	0.510	0.442	0.564	0.476	0.575	0.673	0.710	0.536	0.216	0.589
MEN	0.365	0.511*	0.521	0.464	0.343	0.420	0.396	0.214	0.628	0.419	0.493	0.085	0.645
GT_A	0.223	0.311	0.566	0.636	0.539	0.299	0.450						
GT_B	0.264	0.297	0.626	0.587	0.573	0.335	0.514						
GT_C	0.456	0.326	0.628	0.574	0.555	0.478	0.477						
GT_D	0.220	0.348	0.681*	0.662*	0.617*	0.422	0.485						
GT_E	0.119	0.252	0.484	0.456	0.434	0.200	0.394						
GT_F	0.187	0.167	0.484	0.420	0.343	0.236	0.139						
GT_G	0.048	0.202	0.434	0.293	0.304	0.013	0.136						
GT_H	0.358	0.308	0.618	0.550	0.539	0.394	0.407						
GT_I	0.078	0.279	0.497	0.525	0.497	0.185	0.317						

*variable with the highest correlation amongst a province

C. Nowcasting Indonesia's GDP Growth

To analyze the consistency of variables used for nowcasting at the regional and national levels, the nowcasting model is compared using different sets of variables. At the national level, we use the variables that are commonly used in the national level nowcasting studies: export, import, narrow money, broad money, index of the manufacturing industry, index of general wholesale prices, and foreign tourists. Table 4 shows that the Root Mean Squared Error (RMSE) values are similar for each set of variables. The national level variables in nowcasting studies produce the lowest accuracy. This shows that while nowcasting at the national level can use the same variables as nowcasting at the regional level, the outcomes will be worse.

Gil *et al*. (2019) mention that using the same variables in nowcasting models at the regional and national levels will produce similar accuracy. However, the results at the national level are smoother and more accurate and this is because of the various data problems at the regional level. By taking into account the result at the national level, the use of these variables at the regional level is possible once the results at the national level are accurate.

Table 4.
RMSE of Nowcasting at National Level-by Sets of Variables

Regional level variables are the sets of variables that we will be used at our study at the regional level. National level variables are the commonly used variables at the national level nowcasting studies. These variables are only available at the national level, except export and import. M1 is narrow money, M2 is broad money, IBS is index of the manufacturing industry, IHPB is index of general wholesale prices, foreign tourists are all foreign visitor directly arrived in Indonesia. FIN+MACRO covers all the variables from macroeconomics and financial categories. FIN refers to financial variables, MACRO represnets Macroeconomics variables, and GT represents Google Trend variables.

Set of Variables	**Regional Level Variables**					**National Level Variables**
Estimation Method	DFM		MIDAS			DFM
Sets Variable	FIN+ MACRO	GT	FIN	MACRO	GT	Export, Import, M1, M2, IBS, IHPB, Foreign Tourists, Rice Price, Coal Price
RMSE	1.0586	1.5049	1.1977	0.1016	0.8647	1.0737

D. Nowcasting Regional Economic Growth using DFM

Figure 2 presents results of nowcasting with financial, macroeconomic, and Google Trend variables. This figure shows that the nowcasting model can capture the economic downturn in the COVID-19 pandemic. In the first quarter of 2020, a low magnitude along with the economic shock was demonstrated by the nowcasting results. However, in the fourth quarter of 2020, economic movements in the seven provinces began to experience expansion and a rebound economic pattern was also shown in the nowcasting models.

Figure 2.
DFM Nowcasting Results in 7 Provinces-by Sets of Variables

This figure shows the year-on-year growth rate of GRDP (black line) compared to DFM nowcast using financial and macroeconomic variables (blue line), and google trends variables (red line) in 7 Indonesian provinces.

A. North Sumatera

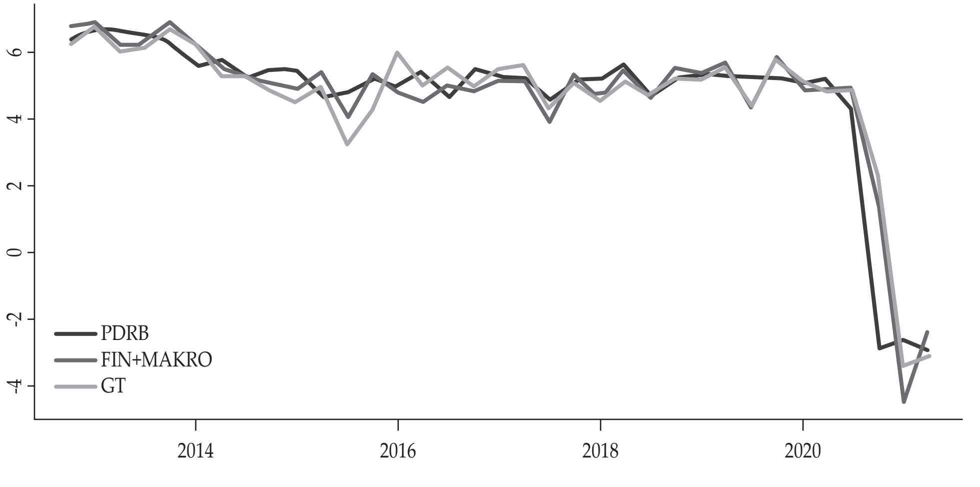
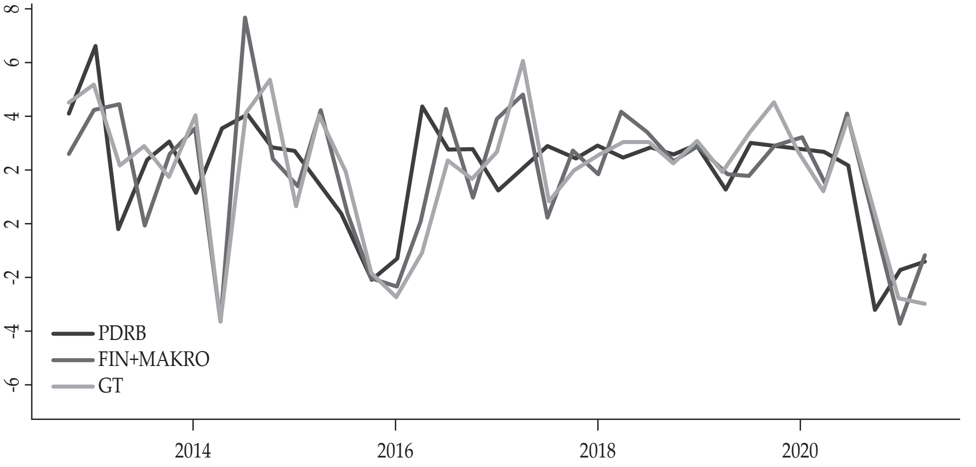


Figure 2.
DFM Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

B. Riau



C. Lampung

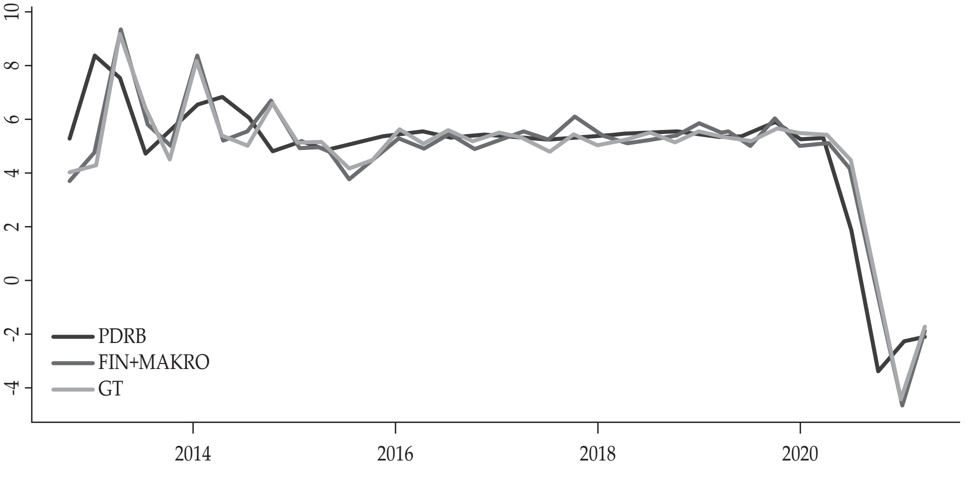
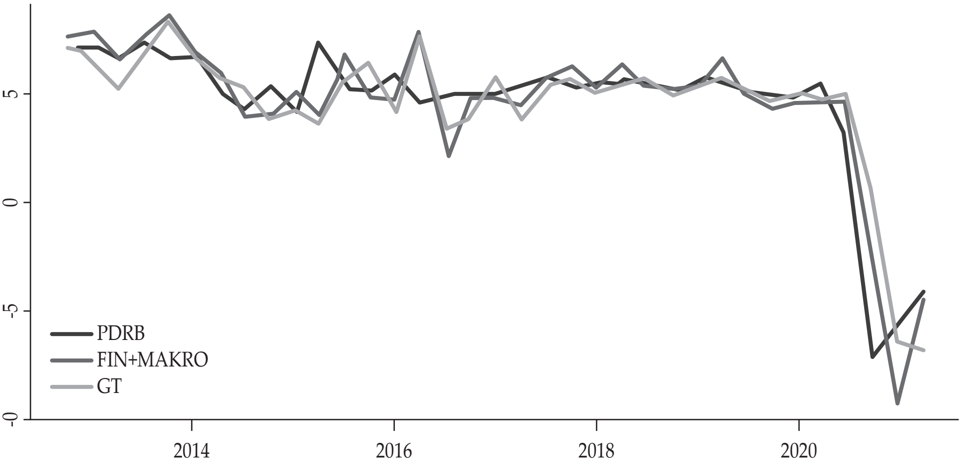


Figure 2.
DFM Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

D. Banten



E. Central Java

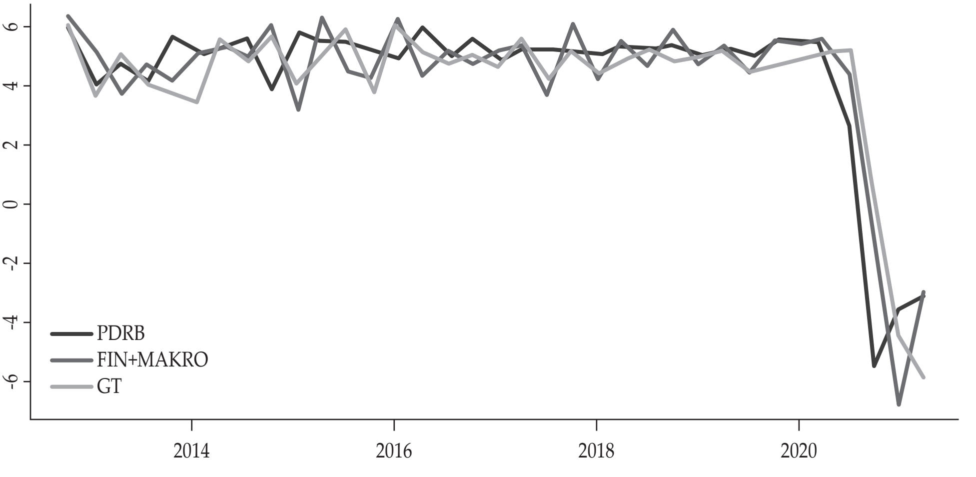
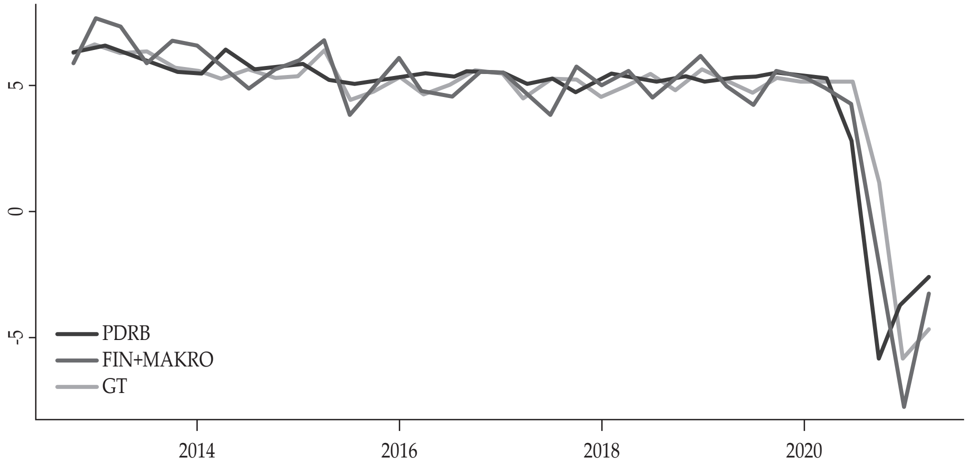


Figure 2.
DFM Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

F. East Java



G. Bali

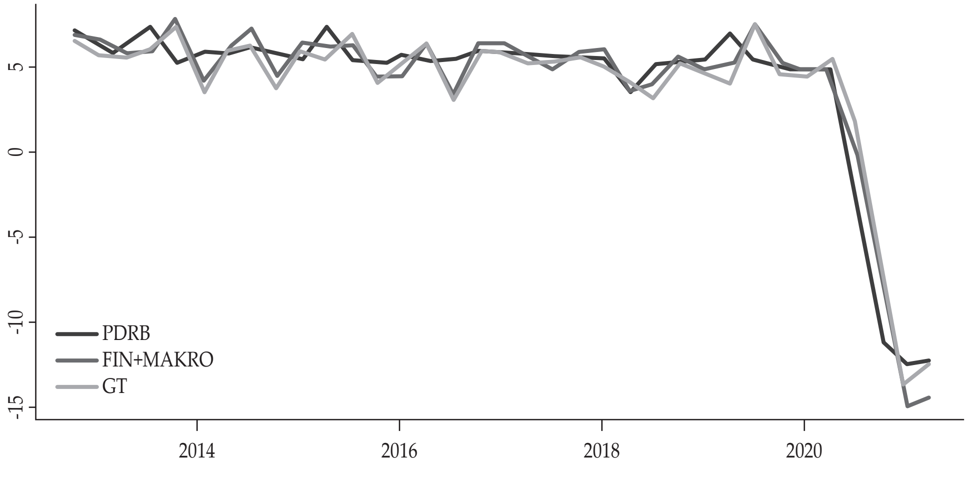
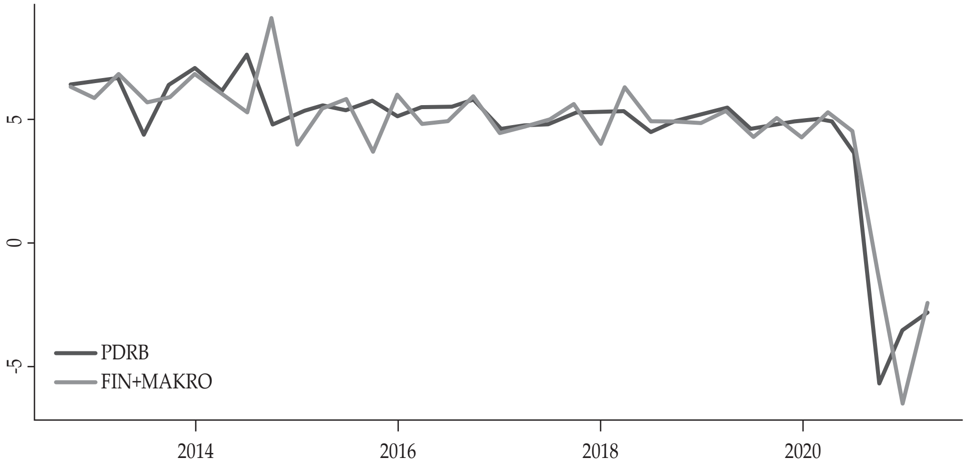


Figure 3 depicts nowcasting in six provinces without the Google Trend variables. Overall, the decline in the economic movement since the COVID-19 pandemic can be captured using nowcasting with financial and macroeconomic variables. This is demonstrated by the low magnitude since the second quarter of 2020. In the second quarter, the negative values are obtained in Riau Islands and Bangka Belitung Islands, while in the third quarter they are found negative in all provinces.

Figure 3.
DFM Nowcasting Results in 6 Provinces-by Sets of Variables

This figure shows the year-on-year growth rate of GRDP (black line) compared to DFM nowcast using financial and macroeconomic variables (blue line) in 6 Indonesian provinces.

A. West Sumatra



B. Jambi

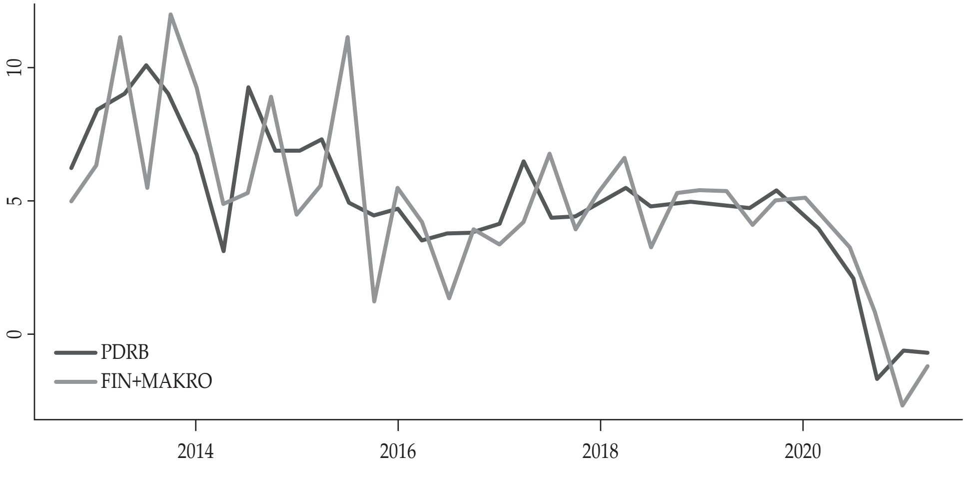
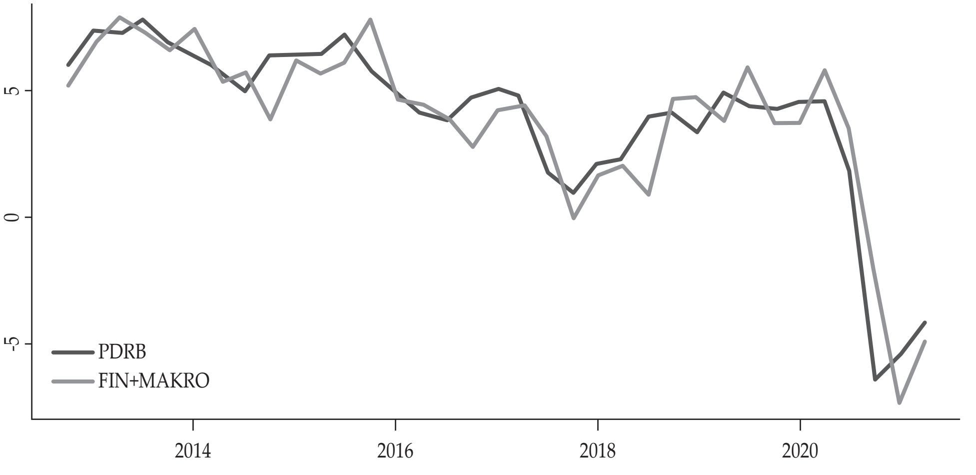


Figure 3.
DFM Nowcasting Results in 6 Provinces-by Sets of Variables (Continued)

C. Riau Islands



D. Bangka Belitung Islands

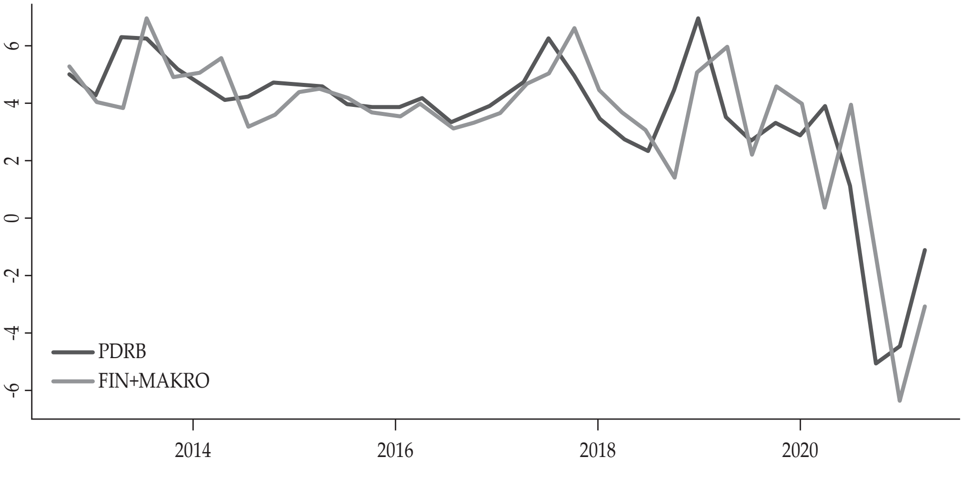
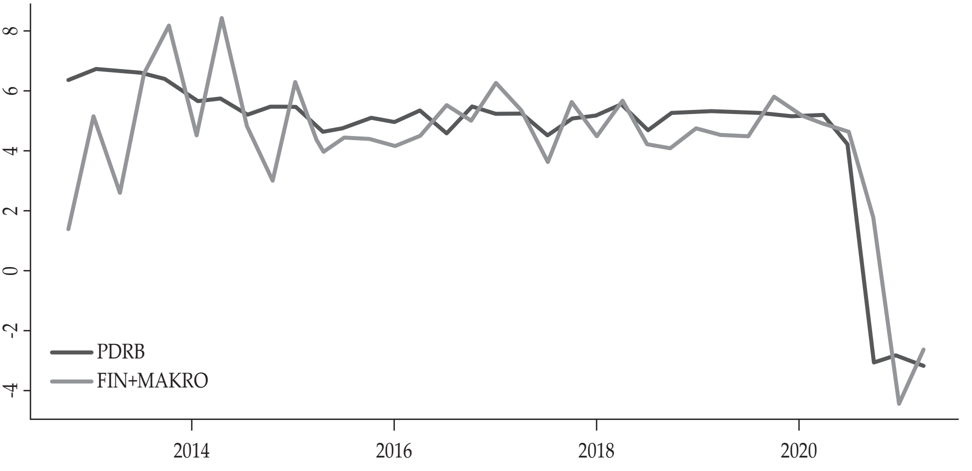


Figure 3.
DFM Nowcasting Results in 6 Provinces-by Sets of Variables (Continued)

E. West Kalimantan



F. South Kalimantan

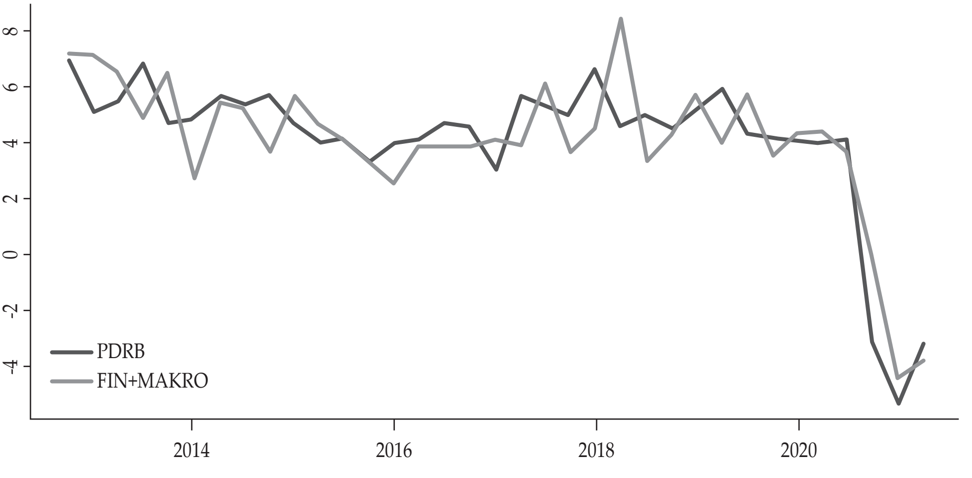


Table 5 presents the DFM performance for 13 Indonesian provinces. The nowcasting results are compared with the univariate model, *AR*(2), and the forecasting results across provinces. Our findings suggest that DFM's performance relative to *AR*(2) is better in the data range that includes economic shocks. Therefore, this implies that economic shock is better captured with econometric models that include more information than using univariate models. Assuming the comparison is made without considering the ratio of the two models, the results reveal that both DFM and *AR*(2), produce smaller RMSE in data before the pandemic. This indicates that the models perform better without including the economic shock period.

The results of GRDP forecasting in the North Sumatra, West Sumatra, Jambi, Riau Islands, Central Java, Banten, Bali, East Java, and South Kalimantan indicates that adding more observations for GRDP forecasting in 2019Q4 does not significantly increase the forecasting accuracy between the forecasting periods. In this case, the difference between the forecasted periods is merely 0.013 point. For example, the RMSE of Riau remains at 1.03, in backcasting, nowcasting, and forecasting. This may indicate that the variables used are not exposed to significant shocks. Also, this condition occurs in several provinces experiencing economic shocks, namely Riau Islands and South Kalimantan.

Table 5.
DFM RMSE of Nowcasting Using Financial and Macro Sets of Variables-by Methodologies and Provinces

This table reports the accuracy measurement using Root Mean Squared Error (RMSE). The notation -2, -1, 0, 1, 2 states the number of months before the release of the quarterly GRDP value. Backcasting is conducted in months (-2) and (-1). Nowcasting is conducted in the month (0). Forecasting is conducted in months (1) and (2). 2019Q4 refers to the nowcast of the fourth quarter of 2019, period prior to the COVID-19 pandemic. 2020Q4 refers to the nowcast of the fourth quarter of 2020, period that includes COVID-19 pandemic. Order 2 for AR is chosen based on the use of lag order in DFM so that the forecast includes the same amount of lag. FIN+MACRO includes macroeconomics and financial variables.

Province	*AR*(2)	FIN+MACRO					Relative to *AR*(2)				
		-2	-1	0	1	2	-2	-1	0	1	2
Panel A: 2019Q4											
SU	0.4545	0.3809	0.3208	0.3247	0.3255	0.3248	0.8382	0.7058	0.7144	0.7163	0.7147
SB	2.7956	1.0419	1.0319	1.0279	1.0234	1.0258	0.9700	0.9607	0.9570	0.9528	0.9550
RI	1.2916	2.3490	2.3720	2.3739	2.3570	2.3706	0.8403	0.8485	0.8491	0.8431	0.8480
JA	1.2577	2.2381	2.2353	2.2349	2.2341	2.2440	0.8567	0.8556	0.8555	0.8552	0.8589
LA	1.4237	1.4391	1.4450	1.4362	1.4307	1.4408	1.1142	1.1188	1.1120	1.1077	1.1155
BB	1.3052	1.2404	1.4403	1.4497	1.4539	1.4078	0.6920	0.8035	0.8088	0.8111	0.7854
KR	0.5317	1.1680	1.1851	1.1831	1.1866	1.1765	1.1324	1.1490	1.1471	1.1505	1.1407
JT	1.0741	1.0412	1.0351	1.0358	1.0346	1.0378	0.8278	0.8230	0.8236	0.8226	0.8252
BT	2.6125	1.1986	1.2103	1.2035	1.1972	1.1974	0.8419	0.8501	0.8453	0.8409	0.8410
BA	1.7924	1.1509	1.1613	1.1795	1.1773	1.1857	0.8818	0.8898	0.9037	0.9020	0.9084
JI	1.0314	0.3998	0.3995	0.3994	0.3994	0.4078	0.7520	0.7513	0.7511	0.7512	0.7669
KB	2.7152	2.4343	2.4324	2.4625	2.4626	2.4654	0.8965	0.8958	0.9069	0.9070	0.9080
KS	1.2595	1.3295	1.3309	1.3318	1.3293	1.3413	1.0555	1.0567	1.0574	1.0554	1.0649
Panel B: 2020Q4											
SU	1.26	0.6676	0.6849	0.6892	0.6901	0.6932	0.5299	0.5436	0.5470	0.5477	0.5502
SB	1.892	1.3118	1.3261	1.3011	1.3063	1.3050	0.6933	0.7009	0.6876	0.6904	0.6897
RI	2.836	2.3277	2.3229	2.3179	2.3174	2.3501	0.8207	0.8190	0.8173	0.8171	0.8286
JA	2.629	2.1275	2.1731	2.1737	2.1766	2.2270	0.8093	0.8267	0.8269	0.8280	0.8471
LA	1.715	1.0363	1.0383	1.0422	1.0423	0.9978	0.6044	0.6056	0.6079	0.6079	0.5820
BB	1.941	1.4029	1.4949	1.4867	1.4871	1.5540	0.7229	0.7703	0.7661	0.7663	0.8008
KR	2.352	1.4893	1.4877	1.4824	1.4759	1.5427	0.6332	0.6325	0.6303	0.6275	0.6559
JT	2.033	1.3819	1.3749	1.3854	1.3869	1.3555	0.6798	0.6763	0.6815	0.6822	0.6668
BT	2.299	1.5795	1.5767	1.5738	1.5692	1.7140	0.6872	0.6859	0.6847	0.6827	0.7457
BA	2.255	1.2523	1.2653	1.2521	1.2115	1.3184	0.5553	0.5611	0.5552	0.5373	0.5847
JI	1.711	1.1675	1.1966	1.1906	1.1845	1.5350	0.6823	0.6993	0.6958	0.6923	0.8971
KB	2.94	2.4322	2.4724	2.4586	2.4742	2.4791	0.8272	0.8409	0.8362	0.8415	0.8431
KS	1.798	1.3654	1.3666	1.3675	1.3805	1.4014	0.7595	0.7602	0.7606	0.7679	0.7795

For further examination, we compare the nowcasting results of Google Trend variables andfinancial and macroeconomic variables by the econometric methods: the DFM and *AR*(2). Table 6 shows that the RMSE obtained using the Google Trend variables differs for each province. In general, all estimates before the pandemic show a smaller RMSE across provinces. This means that the model works better with the absence of economic shock. One of the reasons behind this is that this model does not distinguish between the treatment of non-linearity in the data. Woloszko's (2020) revealed similar findings for a period that include economic shock due to the global economic crisis in 2008 indicating that forecasting results have worsened.

In the sample period up to 2019Q4 which excludes economic shock due to the COVID-19 pandemic, forecasting with the Google Trend variables produces better projections in all provinces, except in the case of Riau, Lampung, and East Java than those financial and macroeconomic variables. While comparing with the univariate model, our results suggest that North Sumatra, Banten, and Bali outperformed the *AR* model, while Riau, Lampung, Central Java, and East Java have higher accuracy using the *AR* model. This means that the Google Trend variables has been able to provide meaningful information in cases where the RMSE of those provinces is only slightly different from others, except in Riau. This demonstrates that, in the presence of stable economic conditions, the Google Trend variables can be effectively used to explain the direction of economic movement.

Table 6.
DFM RMSE of Nowcasting Using Google Trends Set of Variabels-by Methodologies and Provinces

This table reports the accuracy measurement of DFM using root mean squared error (RMSE). The result based on Google Trend variables is compared to FIN+MACRO variables. FIN+MACRO includes all macroeconomics and financial variables. FIN refers to financial variables, MACRO represnets Macroeconomics variables, and GT represents Google Trend variables.

Province	2019Q4			2020Q4		
	GT	Relative to FIN+MACRO	Relative to *AR*(2)	GT	Relative to FIN+MACRO	Relative to *AR*(2)
SU	0.1339	0.2945	0.3517	1.0688	1.1846	0.8484
RI	4.7698	1.7062	2.0181	5.1350	2.2108	1.8106
LA	1.3311	1.0306	1.2821	1.7085	1.4280	0.9965
JT	1.2496	0.9936	1.2101	3.2775	2.3719	1.6122
BT	0.5517	0.3875	0.4763	2.1523	1.4409	0.9364
BA	0.1957	0.1499	0.1650	2.0710	1.5540	0.9184
JI	1.0699	2.0123	2.6991	2.8971	2.3911	1.6931

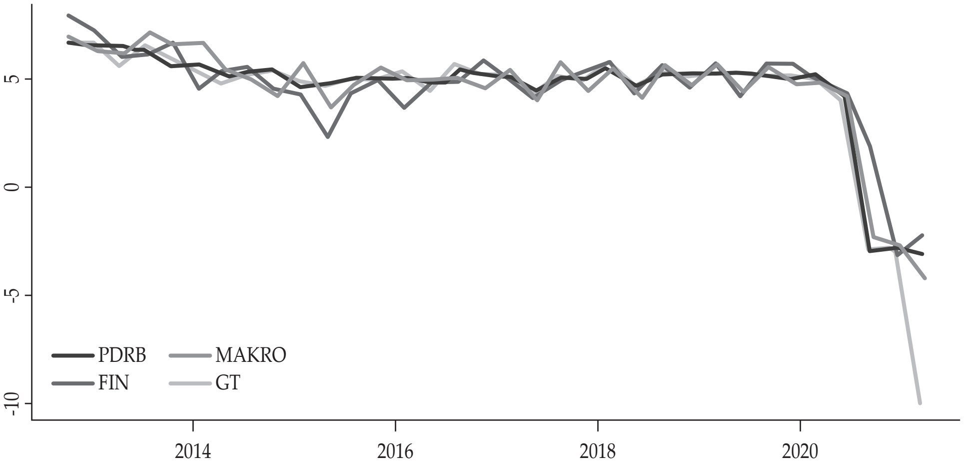
E. Nowcasting Regional Economic Growth Using MIDAS

In general, MIDAS nowcasting models based on financial, macroeconomic, Google Trend variables, shown in Figure 4 reveal the direction of economic decline since the pandemic. Some models in several provinces can well depict the fall in economic growth that reached negative values in all provinces in the second quarter of 2020. Furthermore, economic rebound movements can be captured by nowcasting in the fourth quarter of 2020 as expansion begins. Lampung has shown the best nowcasting result in the fourth quarter of 2020. This captured economic rebound movements due to expanding economic conditions. Visually, the nowcasting movement using DFM was smoother than the MIDAS.

Figure 4.
MIDAS Nowcasting Results in 7 Provinces-by Sets of Variables

This figure shows the year-on-year growth rate of GRDP (black line) compared to MIDAS nowcast using financial variables (blue line), macroeconomic (green line), and google trends variables (red line) in 7 Indonesian provinces.

A. North Sumatra



B. Riau

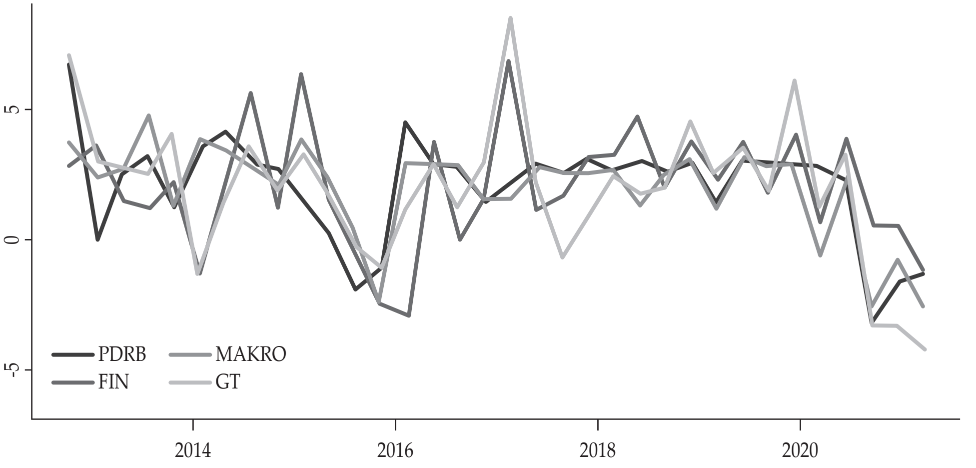
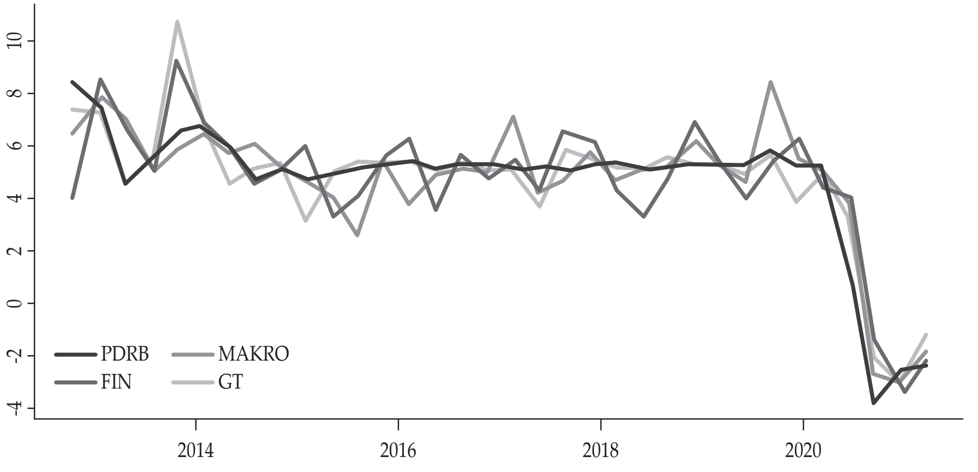


Figure 4.
MIDAS Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

C. Lampung



D. Banten

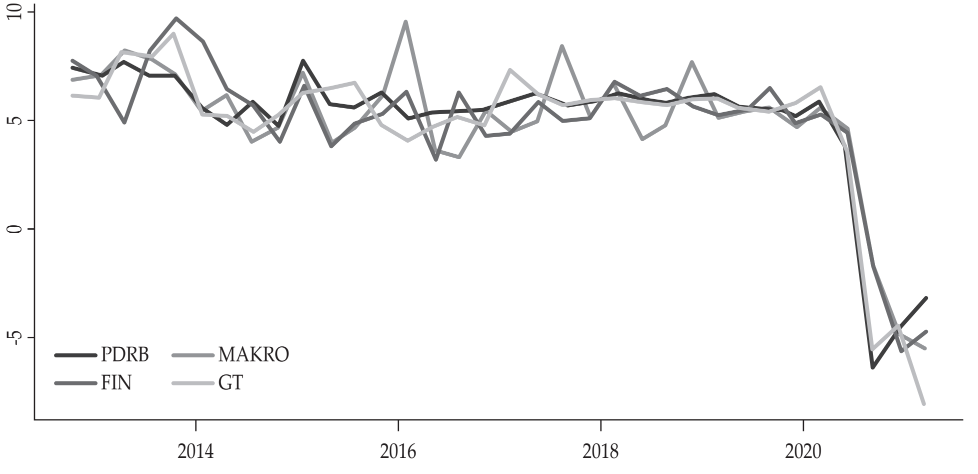
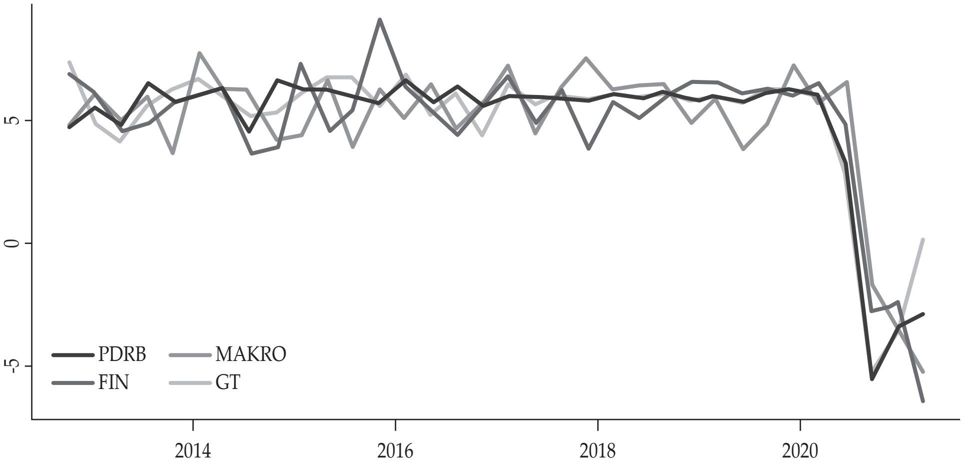


Figure 4.
MIDAS Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

E. Central Java



F. East Java

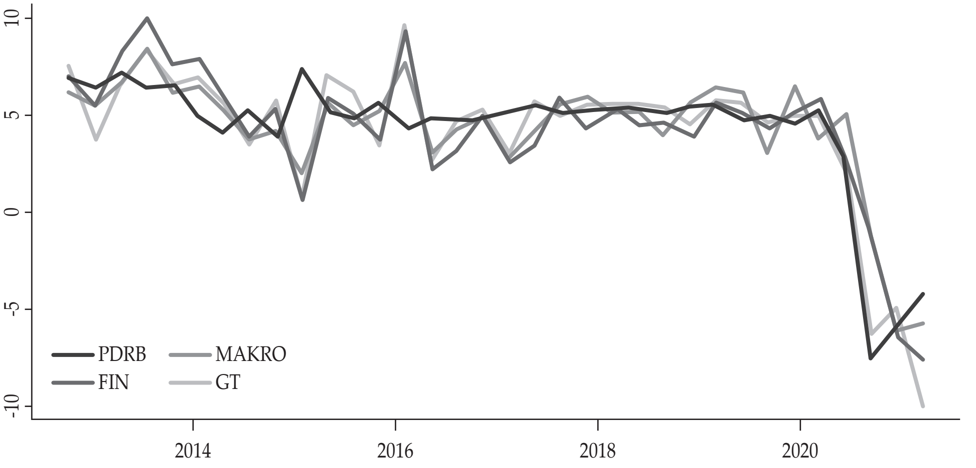
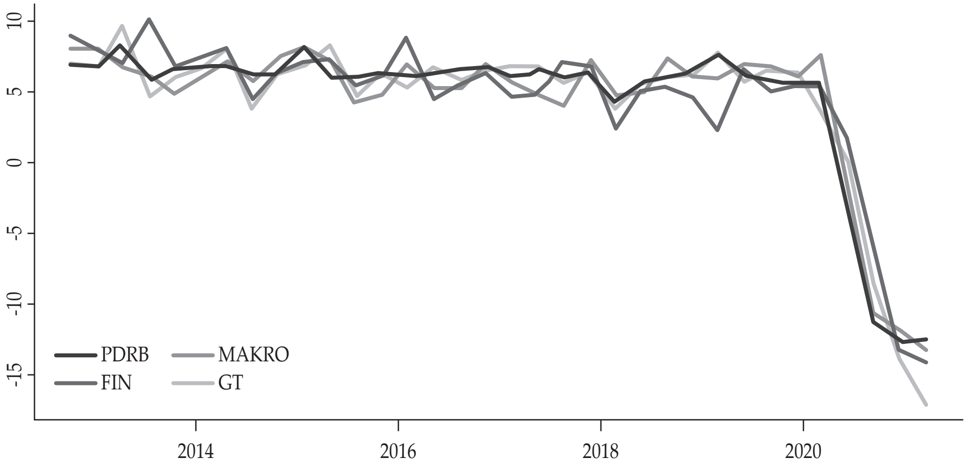


Figure 4.
MIDAS Nowcasting Results in 7 Provinces-by Sets of Variables (Continued)

G. Bali



In general, the nowcasting results in Figure 5 show that the MIDAS model accurately captures the fall in economic activity that happened in those six provinces during the COVID-19 pandemic. Except in West Sumatra, almost all models with macroeconomic variables reports negative magnitudes in the second quarter of 2020. Only the Riau Islands can capture negative values with the financial variables during that period. Several regions, like West Sumatra and the Bangka Belitung Islands, witnessed an increase in nowcasting direction in the fourth quarter of 2020, while Jambi continued to fall.

Figure 5.
MIDAS Nowcasting Results in 6 Provinces-by Sets of Variables

This figure shows the year-on-year growth rate of GRDP (black line) compared to MIDAS nowcast using financial variables (blue line), and macroeconomic variables (green line) in 6 Indonesian provinces.

A. West Sumatra

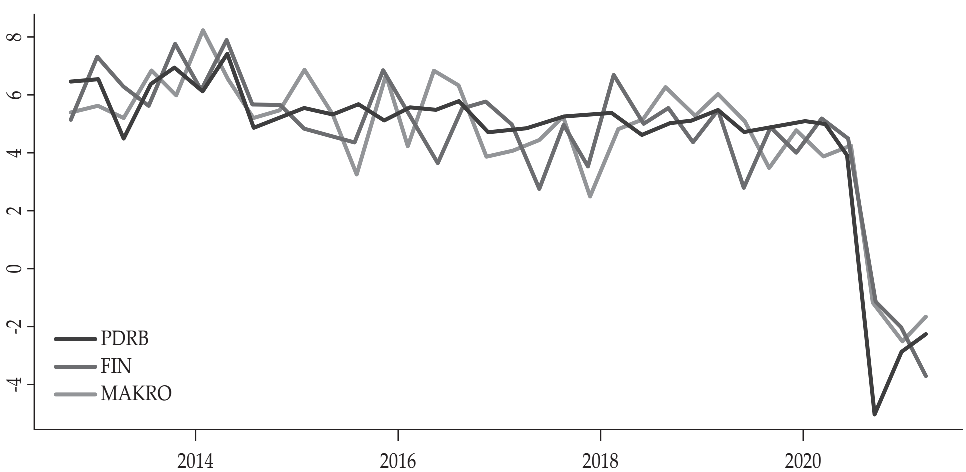
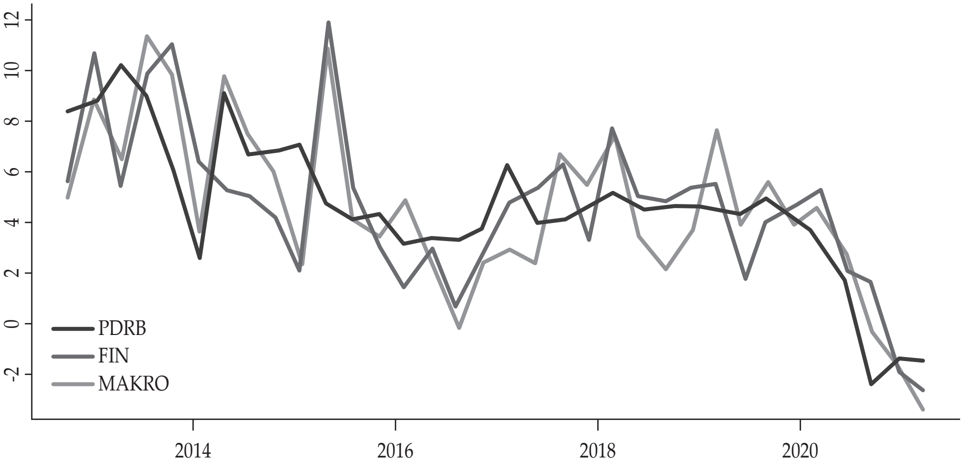


Figure 5.
MIDAS Nowcasting Results in 6 Provinces-by Sets of Variables (Continued)

B. Jambi



C. Riau Islands

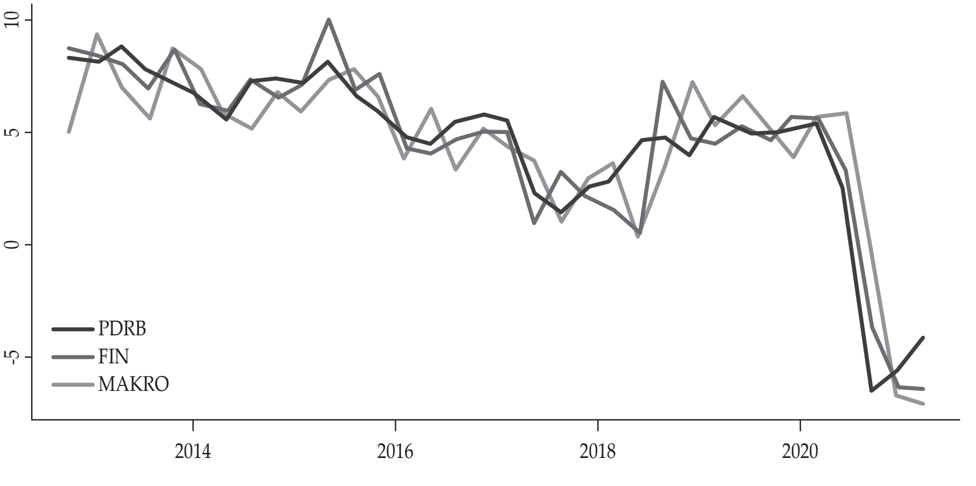
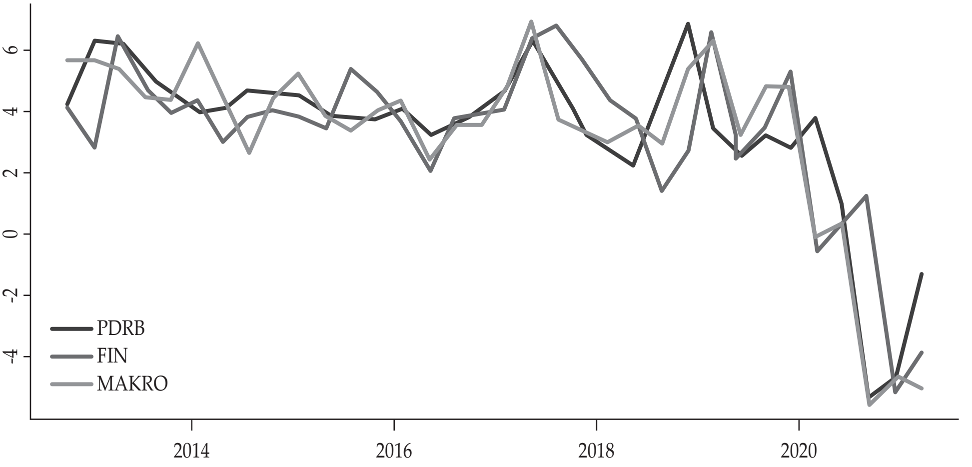


Figure 5.
MIDAS Nowcasting Results in 6 Provinces-by Sets of Variables (Continued)

D. Bangka Belitung Islands



E. West Kalimantan

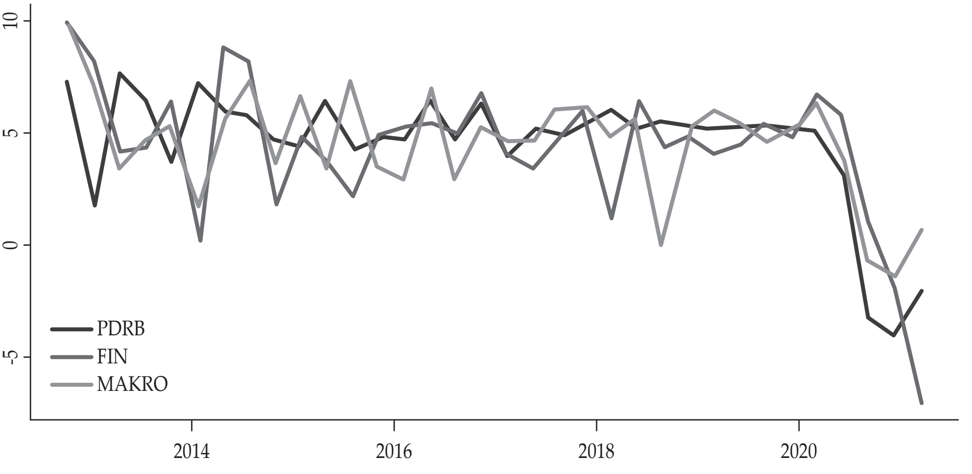
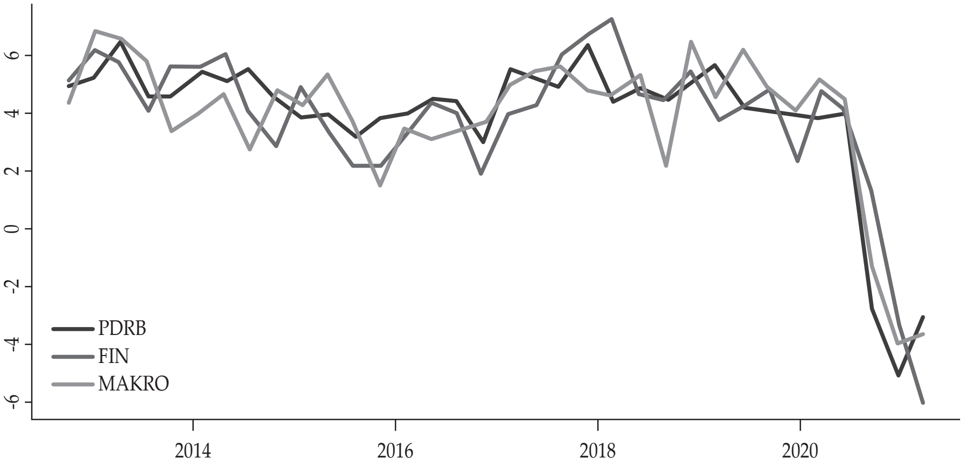


Figure 5.
MIDAS Nowcasting Results in 6 Provinces-by Sets of Variables (Continued)

F. South Kalimantan



Based on the comparison results between data ranges, the nowcasting before the COVID-19 pandemic provides better results (see Table 7). This indicates that the MIDAS model works better by removing the period of economic shock, except for the Google Trend variables in East Java. The results in East Java shows that the use of the Google Trend variables in the period that includes COVID-19 pandemic also significantly outperformed the other set of variables.

According to the result of nowcasting using the MIDAS method for two data ranges, the forecast with the Google Trend variables produced the smallest RMSE compared to financial and macroeconomic variables. Since this model can include information from all the months contributed to the current quarter, the availability of Google Trend variables in real-time is an additional advantage. Meanwhile, financial and macroeconomic variables only include information from the first month of the current quarter and its lags.

Table 7.
MIDAS RMSE of Nowcasting Using Financial, Macro, and Google Trends Sets of Variables-by Methodologies and Provinces

This table reports the accuracy measurement of the MIDAS model using Root Mean Squared Error (RMSE). FIN is not divided into nine variables as in Table 1 due to the number of variables in parsimony MIDAS model. FIN is divided into three variables of private deposit, loans, and credit to micro, small, and medium enteprise by aggregating the nine variables.

Province	*AR*(2)	MIDAS			Relative to *AR*(2)		
		FIN	MACRO	GT	FIN	MACRO	GT
				Panel A: 2019Q4			
SU	0.4545	0.1152	0.1872	0.0024	0.2534	0.4119	0.0054
RI	2.7956	6.6534	5.0195	1.3032	2.3800	1.7955	0.4662
LA	1.2916	1.4660	0.9418	0.3810	1.1350	0.7292	0.2949
JT	1.2577	0.8151	0.5906	0.4045	0.6481	0.4696	0.3216
BT	1.4237	1.2523	0.9694	0.5371	0.8796	0.6809	0.3773

Table 7.
MIDAS RMSE of Nowcasting Using Financial, Macro, and Google Trends Sets of Variables-by Methodologies and Provinces (Continued)

Province	*AR*(2)	MIDAS			Relative to *AR*(2)		
		FIN	MACRO	GT	FIN	MACRO	GT
BA	1.3052	1.3881	0.8532	0.1086	1.0635	0.6537	0.0832
JI	0.5317	0.1908	0.2490	1.6820	0.3588	0.4683	3.1634
SB	1.0741	0.5397	0.6595		0.5025	0.6140	
JA	2.6125	6.1407	4.1465		2.3505	1.5872	
BB	1.7924	2.4549	1.0979		1.3696	0.6125	
KR	1.0314	0.8766	1.3440		0.8499	1.3030	
KB	2.7152	5.2611	3.4639		1.9377	1.2757	
KS	1.2595	0.6759	1.0195		0.5366	0.8095	
Panel B: 2020Q4							
SU	1.26	1.2259	0.3187	0.0070	0.9730	0.2530	0.0056
RI	1.892	6.8862	4.8062	1.6820	2.4281	1.6946	0.5931
LA	2.836	1.9058	1.2122	0.9718	1.1116	0.7070	0.5668
JT	2.629	1.5882	2.0516	0.4159	0.7813	1.0092	0.2046
BT	1.715	2.5014	2.6631	0.7080	1.0882	1.1586	0.3080
BA	1.941	3.1114	1.1810	1.0907	1.3798	0.5237	0.4837
JI	2.352	1.8717	2.0334	0.0525	1.0938	1.1884	0.0307
SB	2.033	1.5054	1.5673		0.7956	0.8284	
JA	2.299	6.3408	4.7507		2.4120	1.8072	
BB	2.255	4.0595	1.5255		2.0919	0.7861	
KR	1.711	1.6655	4.1195		0.7081	1.7515	
KB	2.94	6.8001	5.5033		2.3127	1.8717	
KS	1.798	1.7151	1.4742		0.9540	0.8200	

F. Robustness Check

The robustness test is established by testing the residual of the models to confirm the model adequacy. Table 8 reports results of the ADF unit root test. Our results indicates that the residual of the fitted models is white noise. The *t*-test value is compared to Mackinnon's critical value and once the *t*-test value is less than the critical value, the test results are considered in the rejected region. The critical value of Mackinnon is -1,95 and according to the results, all the *t*-test values are less than the critical value. Therefore, the residuals of all the fitted DFMs are concluded to be statistically white noise.

Table 8.
DFM Robustness Check-ADF Test

This table reports the results of the ADF test of DFM's residuals with the null hypothesis of a unit root.

Province	2019Q4				2020Q4			
	FIN+MACRO		GT		FIN+MACRO		GT	
	t-Stat	*p*-value	*t*-Stat	*p*-value	*t*-Stat	*p*-value	*t*-Stat	*p*-value
SU	-7.6407	0.01	-6.1859	0.01	-5.4886	0.01	-6.2133	0.01
RI	-8.6342	0.01	-5.9486	0.01	-8.8206	0.01	-6.4598	0.01
LA	-6.1122	0.01	-6.2876	0.01	-5.9483	0.01	-6.0108	0.01
BT	-9.543	0.01	-7.1830	0.01	-7.8082	0.01	-5.4060	0.01
JT	-12.0953	0.01	-6.8009	0.01	-8.3887	0.01	-6.1365	0.01
JI	-7.7764	0.01	-6.8003	0.01	-6.0545	0.01	-6.6142	0.01
BA	-10.2676	0.01	-6.6241	0.01	-8.3873	0.01	-5.5662	0.01
SB	-9.8484	0.01			-8.909	0.01		
JA	-8.5525	0.01			-8.9187	0.01		
KR	-5.2809	0.01			-6.5007	0.01		
BB	-6.6305	0.01			-6.3656	0.01		
KB	-10.8239	0.01			-9.9954	0.01		
KS	-10.3879	0.01			-8.0919	0.01		

Table 9 reports results of an ADF unit root test for the residual obtained from MIDAS modelsOur results inicate that all the t-test values are less than the critical value. Therefore, the residuals of all the fitted MIDAS models are also statistically white noise.

Table 9.
MIDAS Robustness Check-ADF Test

This table reports the results of the ADF test of MIDAS' residuals with the null hypothesis of a unit root.

Province	FIN		MACRO		GT	
	t-Stat	*p*-value	*t*-Stat	*p*-value	*t*-Stat	*p*-value
			Panel A: 2019Q4			
SU	-5.03	0.01	-6.0839	0.01	-4.9854	0.01
RI	-6.0553	0.01	-6.3129	0.01	-5.2437	0.01
LA	-6.3996	0.01	-6.7547	0.01	-5.2949	0.01
BT	-4.212	0.015	-4.5101	0.01	-7.0843	0.01
JT	-6.1316	0.01	-5.4985	0.01	-4.6146	0.01
JI	-5.2226	0.01	-4.5264	0.01	-5.5617	0.01
BA	-5.971	0.01	-5.274	0.01	-4.6859	0.01
SB	-5.8778	0.01	-5.0079	0.01	-5.8962	0.01
JA	-5.5877	0.01	-5.8066	0.01	-6.0575	0.01
KR	-5.0118	0.01	-6.0602	0.01	-4.631	0.01
BB	-4.6231	0.01	-5.9785	0.01	-4.9594	0.01
KB	-5.6407	0.01	-6.176	0.01	-6.9523	0.01
KS	-5.6889	0.01	-4.6871	0.01	-5.7938	0.01

Table 9.
MIDAS Robustness Check-ADF Test (Continued)

Province	FIN		MACRO		GT	
	t-Stat	*p*-value	*t*-Stat	*p*-value	*t*-Stat	*p*-value
Panel B: 2020Q4						
SU	-4.6183	0.01	-10.0129	0.01	-5.9585	0.01
RI	-4.926	0.01	-5.6935	0.01	-6.3188	0.01
LA	-4.8337	0.01	-5.8354	0.01	-5.4395	0.01
BT	-6.4209	0.01	-4.5637	0.01	-5.6331	0.01
JT	-5.32	0.01	-9.2904	0.01	-8.7746	0.01
JI	-5.001	0.01	-4.7999	0.01	-8.0197	0.01
BA	-5.9125	0.01	-5.434	0.01	-8.2113	0.01
SB	-5.3242	0.01				
JA	-6.3516	0.01				
KR	-5.7286	0.01				
BB	-5.5299	0.01				
KB	-5.8105	0.01				
KS	-5.5471	0.01				

IV. CONCLUDING REMARKS

The urge to learn about the current economic conditions based on data is strong; however, it is limited due to substantial delays in the release of GRDP growth data. Based on the nowcasting results using a selected set of variables, this study concludes that nowcasting quarterly GRDP growth can be achieved at the provincial level in Indonesia using macroeconomics, financial, and Google Trends data. As the COVID-19 pandemic began in the first quarter of 2020, the DFM and MIDAS models are able to capture the reduction in economic activity. Apart from the pandemic, the two models accurately reflect several economic expansions and contractions that occurred in several provinces. The results of nowcasting using the DFM method were adapted to economic growth in the fourth quarter of 2020. Except for the macroeconomic variables in the Jambi and Bangka Belitung Islands, the MIDAS model also produces negative magnitudes.

The DFM and MIDAS model performance shows better accuracy in a data range that does not include periods of economic shocks. Model accuracy across the same set of variables and provinces is slightly reduced once the pandemic period is included. Furthermore, the use of Google Trends variable produces the best accuracy when compared to other categories of variable using the MIDAS model, both before and after the COVID-19 pandemic. Using the DFM model, the use of Google Trends variables also produces the best accuracy, but only in the period leading up to the pandemic.

The nowcasting procedure can be adopted by researchers and policy makers, including the central bank and local government. Every time new monthly data is provided, the nowcasting model can be updated. Therefore, the local government can adapt the Federal Reserve Bank of New York’s method, which publishes the most recent nowcasting results on their official website. This can be useful for provincial development plans, as well as information for policy makers.

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