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Tracking the Ups and Downs in Indonesia's Economic Activity During COVID-19 Using Mobility Index: Evidence from Provinces in Java and Bali

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Abstract: *A timely and reliable prediction of economic activities is crucial in policymaking, especially in the current COVID-19 pandemic situation, which requires real-time decisions. However, making frequent predictions is challenging due to the substantial delays in releasing aggregate economic data. This study aims to nowcast Indonesia's economic activities during the COVID-19 pandemic using the novel high-frequency Facebook Mobility Index as a predictor. Employing mixed-frequency, mixed-data sampling, and benchmark least-squares models, we expanded the mobility index and used it to track the growth dynamics of the gross regional domestic product of provinces in Java and Bali and performed a bottom-up approach to estimate the aggregated economic growth of the provinces altogether. Our results suggested that the daily Facebook Mobility Index was a considerably reliable predictor for projecting economic activities on time. All models almost consistently produced reliable directional predictions. Notably, we found the mixed data sampling-autoregressive model to be slightly superior to the other models in terms of overall precision and directional predictive accuracy across observations.*

Keywords: COVID-19, nowcasting, GDP, mobility, Mixed-frequency

JEL Classification: C20, C53, R11

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1. Introduction

Like governments in other parts of the world, the Indonesian government has been struggling to contain the impacts of the COVID-19 pandemic. On the one hand, the government needs to curb the spread of coronavirus infections by implementing either a full lockdown or restriction on social activities, such as large-scale social restrictions (*Pembatasan Sosial Berskala Besar*, or PSBB). On the other hand, it needs to maintain livelihoods and stimulate economic recovery by relaxing lockdowns or PSBB. To satisfy these conflicting goals, the Indonesian government needs to make real-time decisions promptly. If it keeps lockdowns or PSBB for too long, businesses will experience greater losses and workers will be left idle or unemployed for a longer time. Similarly, hasty economic reopening will result in the re-emergence of coronavirus infections and force the government to again implement lockdowns or PSBB, which would hurt the economy further.

Nonetheless, making real-time decisions is challenging due to substantial delays in releasing aggregate economic data, such as on gross domestic product (GDP) or the balance of payments (BOP). For instance, Statistics Indonesia (Badan Pusat Statistik, or BPS) releases the latest GDP data around one-and-a-half months after the reference quarter. Bank Indonesia also takes a similar amount of time to update the newest BOP figures. When aggregate economic data are unavailable, the government relies on disaggregated economic and financial data combined with a fair amount of expert judgment.

This study aims to fill this gap by providing nowcasting of Indonesia's GDP during the pandemic. The application of nowcasting in Indonesia has only been done recently and is still limited. For instance, Kurniawan (2014) was one of the earliest studies to assess the performance of dynamic factor model (DFM) and mixed-data sampling (MIDAS) regressions in nowcasting quarterly GDP. Luciani et al. (2015) used Indonesia's GDP growth data and the DFM model to highlight the challenges of nowcasting macroeconomic datasets from emerging markets.

Building upon Kurniawan's (2014) work, Tarsidin, Idham, and Rakhman (2018) attempted to develop a nowcasting model for quarterly household consumption and investment using the DFM model. Unlike other studies, Utari and Ilma (2018) only used MIDAS regression to nowcast Indonesia's quarterly GDP with the agricultural product's monthly export value.

Generally, on the one hand, macroeconomists and professional forecasters use the DFM model to build a complete nowcasting model by incorporating various high-frequency economic datasets issued monthly, weekly, or daily. On the other hand, MIDAS regression is used because of its simplicity. Unlike the DFM model developed as a system of equations, the MIDAS regression model uses a reduced form such that it is more parsimonious.

For instance, Foroni, Marcellino, and Stevanovic (2020) use MIDAS and unrestricted MIDAS (UMIDAS) regression models to improve forecasting accuracy during the pandemic. Their new forecasting results suggest that pandemic-driven economic crises in the United States and Group of Seven countries will last longer than initially predicted.

Sampi and Jooste (2020) also use the MIDAS regression model to improve forecasting accuracy. Nevertheless, their approach is different. Rather than using the MIDAS regression model to fine-tune forecast accuracy, they propose a novel dataset previously unobservable, the Google Mobility Index. After backcasting the index with daily pollution and temperature data, they make nowcasting estimates of the industrial production growth rates in selected economies in Latin America and the Caribbean.

This study will use the MIDAS regression model to nowcast the Indonesian economy, taking advantage of the recently available mobility index from Facebook, similar to Sampi and Jooste (2020). It is different in the way that the nowcasting is conducted at the regional level. Ideally, the availability of the Facebook Mobility Index at the municipal-level in Indonesia (i.e. *kabupaten* and *kota*) allows the prediction to be conducted at the district level, given data availability. The predictions can then be aggregated at the national or sub-national level to serve as 'bottom-up' predictions.

However, for this study's purpose, we limit our scope of work to conducting nowcasting for Java and Bali's provincial economies due to the limited availability of recent data at the municipal level. The provinces in Java and Bali are also amongst the top contributors to the Indonesian economy, making up more than 61% in 2019. This study is expected to provide better information for policy and decision-making, especially during a crisis, using novel datasets enabled by advancements in information technology.

2. Literature Review

2.1. Mobility and the economy during the COVID-19 pandemic

Human mobility is a potent indicator for measuring economic activities, as has been suggested by an array of empirical studies. For instance, Dong et al. (2017) found a strong positive relationship between various mobility records and economic indicators, such as local commercial revenues and sales, using geo-positioning data. Years later, Li et al. (2020) found that traffic flows explained disparities in economic activities amongst Chinese provinces. They also confirmed a strong link between spatial interactions and regional economic and development indicators like GDP. Lastly, Putra and Arini (2020) found a consistent, significantly positive association between satellite-sourced night-time light data and the Google Mobility Index, and regional GDP across Indonesian provinces.

Human mobility also has a strong relationship with interaction and socio-economic development. Pappalardo et al. (2016) observed a positive bidirectional relationship between mobility and socio-economic indicators in French municipalities using mobile phone data. They found that regions with more diverse mobility tend to be more developed. Consequently, more developed municipalities are those with highly varying mobility patterns.

On the downside, human mobility also helps spread contagious diseases like COVID-19. In line with that, human mobility has been confirmed in various studies to speed up COVID-19 transmission significantly. Oztig and Askin (2020) observed a positive relationship between a country's air passenger traffic and the number of COVID-19 patients in 144 countries. They also found that Schengen countries – which are more densely populated and have more elderly populations – tend to have more COVID-19 cases than other countries.

Shao, Xie, and Zhu (2021) found that human mobility was positively related with the COVID-19 transmission rate in 47 countries during the observed period from 22 February to 22 June 2020. A more granular study by Badr et al. (2020) confirmed that in 25 United States (US) counties with the highest number of cases in April 2020, mobility patterns were significantly related to COVID-19 case growth rates.

In the hope of curbing COVID-19 transmissions, numerous national governments began enacting social mobility measures. Some of them applied a very restrictive, complete lockdown policy. Others, like Indonesia, imposed only partial, more lenient mobility restrictions. Mobility restrictions, whilst necessary in some cases, have been confirmed costly for economies.

There is a long list of studies examining the negative impact of mobility restrictions on economic activities. Amongst them is Bonaccorsi et al. (2020), who found that mobility restrictions disproportionately slowed down economic activities in the Italian municipalities with lower fiscal capacity and higher income inequality. Next, Prawoto et al. (2020) observed a contraction in socio-economic activities in Indonesia following the first round of the COVID-19 outbreak in March 2020. Limited mobility also disrupted labour market outcomes. Gupta et al. (2020) found that social distancing policies heavily caused the declining employment rates in the US.

On a broader scope, Ozili and Arun (2020) reported that the lockdown duration and international travel restrictions affected economic activities in Japan, the United Kingdom, the US, and South Africa. Sectorally, the enacted lockdown policies worldwide were found to have halted economic activity, and more severely so for the transport, trade and manufacturing, and services sectors (Song and Zhou, 2020).

2.2. Mobility and weather indicators

For this study's purpose, we need to conduct backcasting for the mobility index to lengthen the forecasting period. Several indicators can be used for the backcasting, particularly weather indicators and air quality. Both indicators served as proxies to predict mobility and were used by Sampi and Jooste (2020). Daily temperature and air pollution, as measured by fine particulate matter (PM 2.5), were expected to partly explain the mobility index's dynamics as it is commonly believed that weather significantly affects people's preferences for going out. This has been supported by a spate of previous studies, such as Shao, Xie, and Zhu (2021), Böcker, Dijst, and Faber (2016), and Liu, Susilo, and Karlströmet (2014). Besides, people tend to engage in outdoor activities on warm days with comfortable (not too cold, not too hot) weather (Cools et al., 2010).

Air quality can also be an indicator that signifies the mobility rate. PM 2.5 is primarily used in many studies analysing the link between human mobility and overall air quality. It is known to be emitted by aeroplanes, diesel motor vehicles, and fossil-fuel power plants. Archer et al. (2020) and Zhu et al. (2020) found a significant positive association between PM 2.5 concentration and human mobility in the US and China. Thus, the greater the fuel combustion in a day, the higher the PM 2.5 concentration will be. Likewise, we expect higher mobility on days with higher PM 2.5, and vice versa.

In addition to average temperature and PM 2.5 information, we added rainfall intensity into the backcasting model as it could serve as a strong predictor of people's mobility in tropical countries like Indonesia. In general, people refrained from going out during rainy days. This is in line with findings in a study by Cools et al. (2010). Based on a survey of respondents in a Dutch-speaking area in Belgium, Flanders, the study confirmed that heavy rain caused people to limit their movements to closer destinations. Particularly in places with high precipitation rates and a long history of flooding, like numerous regions across Indonesia, heavy rains may prevent people from leaving their homes at all. Roughly, we may expect that mobility tends to decrease during sweltering days with highly polluted air and/or heavy rain. Conversely, it is natural to believe that mobility will surge on relatively cooler days with cleaner air without heavy rain.

2.3. Nowcasting method

According to Castle, Hendry, and Kitov (2013), there are five main nowcasting methods. First is the in-filling of missing disaggregates using an exponentially weighted moving average (EWMA) or autoregressive-integrated moving average (ARIMA) model. The United Kingdom's Office for National Statistics uses this method. Second is MIDAS regression introduced by Ghysels, Santa-Clara, and Valkanov (2004) to link low-frequency variables with high-frequency estimators. The third is the factor model, which has been divided into dynamic and static factor models. A variation of the factor model is factors with ragged edges, which handle missing observations at the end of the sample. Last is the bridge equations, which have better interpretability than the MIDAS and factor models.

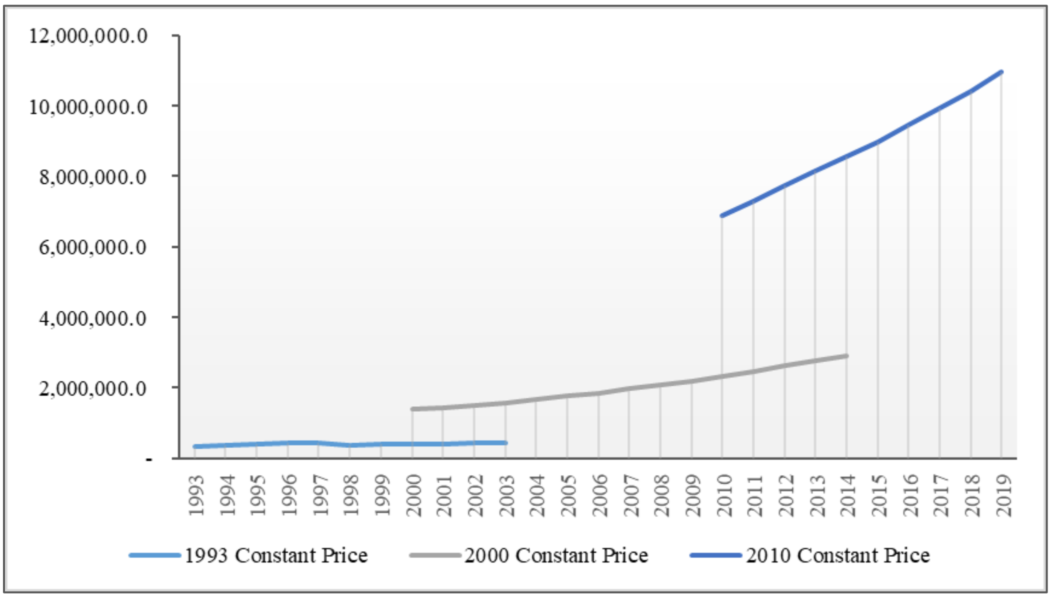
In the case of Indonesia, the application of nowcasting has only been done recently and is limited to four studies – Kurniawan (2014), Luciani et al. (2015), and Tarsidin, Idham, and Rakhman (2018), and Utari and Ilma (2018) – using DFM and MIDAS regression models. Except for Utari and Ilma (2018), these studies use the DFM model because they tried to develop an official nowcast model for their respective institutions, specifically Kurniawan (2014) and Tarsidin, Idham, and Rakhman (2018) for Bank Indonesia, the country's central bank, and Luciani et al. (2015) for the Asian Development Bank (see Doz, Giannone, and Reichlin [2011]).

The application of the DFM model is common amongst policymakers in the US central bank. For instance, the Federal Reserve Bank of Philadelphia uses the 'small data' DFM model developed by Aruoba, Diebold, and Scotti (2009). The Federal Reserve Bank of New York uses a 'big data' DFM model to produce early GDP growth estimates, which are updated as new data are released or data revisions are issued (see Bok et al. [2018]).

On the other hand, Luciani et al. (2015) highlighted a vital characteristic of Indonesia's GDP data. The slopes of Indonesia's real GDP change drastically whenever the country's statistical office, the BPS, makes a base year revision (see Figure 1). Although these changes reflect an improvement in the BPS's data collection methodology, this inconsistency will lead to an erroneous forecast model. Treatment is needed, and one possible remedy is backcasting the latest GDP dataset using quarter-on-quarter (QoQ) growth rates. However, this treatment requires seasonally adjusted QoQ growth rates, which the BPS does not have. As a solution for this issue, Luciani et al. (2015) propose using Indonesia's real GDP growth rates because the data fit each other with a small margin of error, despite the change in the base year (see Figure 2).

Figure 1: Indonesia's Real Gross Domestic Product at Various Base Years, 1993–2019

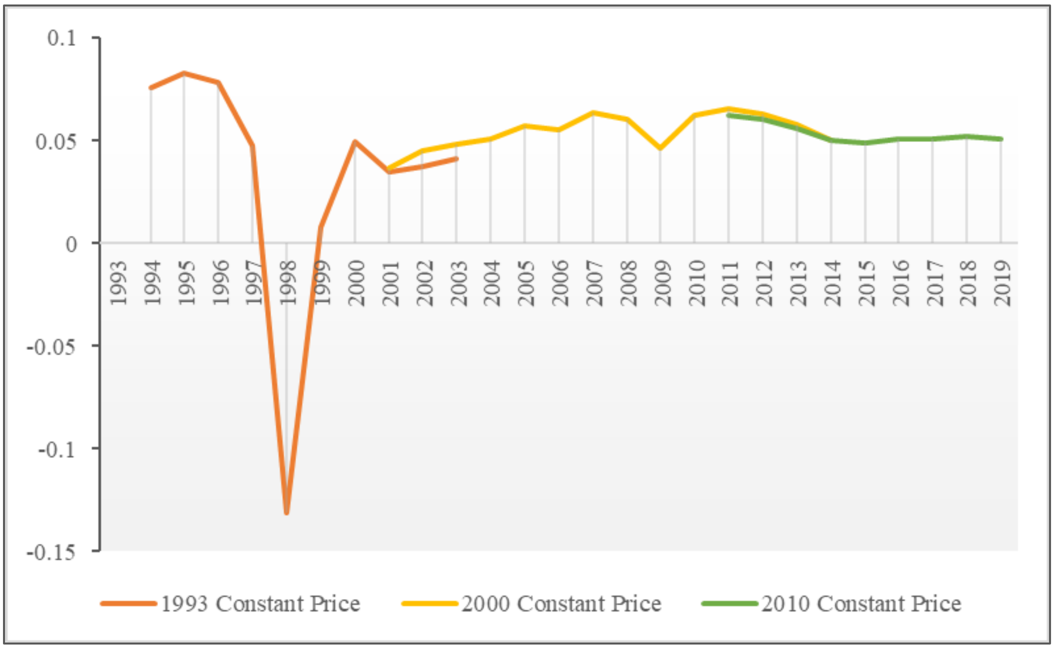
(Rp billion)



Source: Statistics Indonesia (BPS) and Bank Indonesia.

Figure 2: Indonesia's Real Gross Domestic Product Growth Rate at Various Base Years, 1993–2019

(%)



Source: Statistics Indonesia (BPS) and Bank Indonesia.

Kurniawan (2014) also provides an important note. In his research, Kurniawan compares the performance of the DFM and MIDAS regression models. He finds no clear evidence that the former is superior compared to the latter. Reflecting on this finding, he suggests that a combination of individual DFM and MIDAS models might produce a more accurate result. Kurniawan's conclusion is in line with Bai, Ghysels, and Wright (2013). They showed that state-space models (DFM models) and MIDAS regressions give similar forecast results. Even though DFM models are more accurate in most cases, they are computationally more demanding than MIDAS regressions that utilise reduced-form or single equation.

Taking advantage of the MIDAS regression's simplicity, some researchers have turned to this model during the COVID-19 pandemic. Foroni, Marcellino, and Stevanovic (2020), for instance, use MIDAS and unrestricted MIDAS (UMIDAS) regression models to improve the accuracy of forecasting crises and recovery during the pandemic. Although this model is second-best compared to a nonlinear, time-varying model capable of capturing the current situation's specificities and previous crises, it requires less time and resources. Moreover, the lessons learned during the Great Recession of 2007–2009 can be employed as a pivot to correct forecast errors during the pandemic. The crises include similarity in terms of implied demand and supply shocks and unprecedented increases in uncertainty.

Sampi and Jooste (2020) also use a MIDAS regression to improve forecast accuracy during the pandemic. However, they take a different approach by introducing novel datasets that have only become available recently due to advancements in information technology, namely the Google Mobility Index. Because Google's dataset is only available from March 2020, they perform backcasting with daily pollution and temperature data until January 2019. Using the backcasted values, they conduct a nowcast for the industrial production growth rates of countries in Latin America and the Caribbean.

Sampi and Jooste's research is inspiring, but their method should be applied with caution to Indonesia's dataset. Luciani et al. (2015) found that Indonesia's GDP growth rate is weakly correlated with its year-on-year (YoY) industrial production growth rates at 0.35. In other words, a replication of Sampi and Jooste's research would not produce an optimal result to track the development of GDP in

Indonesia. Therefore, it is better to apply this novel dataset directly with GDP or its components, as done by Tarsidin, Idham, and Rakhman (2018).

3. Data and Methodology

3.1. Data

We consider using a novel real-time indicator, the Facebook Mobility Index, which the Centre for Strategics and International Studies (CSIS) has attempted to incorporate into their COVID-19 Dashboard. Since the Mobility Index is only available from 1 March, 2020, we need to expand it using several kinds of daily weather and climate data as well as air quality indicators. The complete list of series used in this study is presented in Table 1.

Table 1: Data Descriptions

Data	Source	Frequency	Observation
Gross regional domestic product of major provinces	Statistics Indonesia (BPS)	Quarterly	Q1 2019–Q4 2020
Facebook Mobility Index	Center for Strategic and International Studies COVID-19 Dashboard	Daily	1 March 2020–31 December 2020
Daily average temperature	Meteorology, Climatology, and Geophysical Agency (BMKG)	Daily	1 January 2019~~–8~~–31 December 2020
Daily particulate matter 2.5 mm (PM 2.5)	BMKG and IQAir	Daily	1 January 2019–31 December 2020
Daily rainfall rate (RR)	BMKG	Daily	1 January 2019–31 December 2020

Source: Compiled by authors.

3.1.1. Gross regional domestic product

This study employs the MIDAS model with an index of regional real GDP *(GDPI)* changes as the estimand. Transforming the raw, real GRDP into the GRDP index is expected to capture the economic dynamics better than the YoY GRDP growth. The index utilises Q4 2018 as the base period. Therefore, we equate real GRDP in Q4 2018 to 100 and make it the denominator to construct the index value as follows:

$$GDPI_t = \frac{GRDP_t}{GRDP_{2018}}$$

Then, we compute the index changes in each quarter 't', ($\Delta GDPI_t$), compared to Q4 2018 as follows:

$$\Delta GDPI_t = GDPI_t - GDPI_{2018}$$

Next, we feed it into the nowcasting model as the predicted indicator. Upon estimation, the forecasted index values are re-transformed to their original unit (Rp billion) and incorporated into the original series to compute YoY growth. Hence, the final nowcast result is presented and discussed in the form of YoY growth.

3.1.2. Facebook Mobility Index

The index is constructed by the Center for Strategic and International Studies (CSIS) using information available in the Facebook Movement Range data. The novel dataset has been made publicly accessible by Facebook to help experts and researchers examining how populations respond to social mobility restrictions (Facebook, 2021).

Two metrics in the data sets – change in movement and stay put—were employed to construct the mobility index. The index is formulated as follows:

$$Index = (1 - a) \times b$$

Let a stand for the percentage of the population that stays at home during the whole day compared to the baseline. Let b be the movement intensity of people (Facebook users) in contrast to the baseline period. The baseline period was set to February, as social activity limitation began to occur in Indonesia in early March 2020 before being formally enacted by the government in April 2020.

We chose the Facebook Movement Range over the Google Mobility Index and Apple Mobility Index due to several reasons. First, it is updated daily, making the data more up-to-date and more potent for real-time analysis. Also, the information is considered more granular, such that it gives room for a district-level analysis in the near future.

3.1.3. Weather and climate indicators

Due to the limited availability of Facebook Movement Range data, we utilise a set of weather and climate indicators to expand the mobility index backwards. It consists of the daily average temperature, PM 2.5, and the daily rainfall intensity (rainfall rate).

The average daily temperature and rainfall intensity series were retrieved from the online data platform of the Meteorology, Climatology, and Geophysical Agency (BMKG). Data on daily aerial particle concentration (PM 2.5) was obtained from IQAir. It indicates aerial particle concentration sized smaller than 2.5 mm, generally associated with fossil-fuel combustion by vehicles and electrical power plants. All series were recorded by multiple weather stations within each province. They were then aggregated into provincial-level information.

3.2. Methodology

The MIDAS regression model was first introduced by Ghysels, Santa-Clara, and Valkanov (2004) as a reduced-form regression technique to process time-series datasets at different frequencies. For instance, it can be utilised for regressing annual GDP data with monthly industrial production growth or higher frequency data like daily freight movement. As a reduced form regression, the MIDAS regression can be written as:

$$Y_t = \beta_0 + \beta_1\left(b(0;\theta)X_{t-0/m}^{(m)} + b(1;\theta)X_{t-1/m}^{(m)} + \cdots\right) + \varepsilon_t^{(m)} \qquad (1)$$

$$Y_t = \beta_0 + \beta_1 B\left(L^{1/m};\theta\right)X_t^{(m)} + \varepsilon_t^{(m)} \qquad (2)$$

where $L^{1/m}$ is the lag operator of the high-frequency independent variable X_t, with m representing the high-frequency data points included in one low-frequency data point. For example, when one aims to forecast a quarterly variable using a monthly predictor, then m takes the value 3. Lastly, $B\left(L^{1/m}\right) = \Sigma_{j=0}^{j^{max}} b(j)L^{j/m}$ is a polynomial of length j^{max} – could be finite or infinite – in the lag operator, and

Y_t is a low-frequency dependent variable.

According to Ghysels, Sinko, and Valkanov (2007), the MIDAS regression can be extended into a multivariate model

$$Y_{t+1} = B_0 + \sum_{i=1}^{K} \sum_{j=1}^{L} B_{ij}\left(L^{1/m_i}\right) X_t^{(m_i)} + \varepsilon_{t+1} \quad (3)$$

where Y, ε, and X are n-dimensional vector processes, B_0 are n-dimensional vectors, and B_{ij} are $n \times n$ matrices of polynomials. Clements and Galvão (2009) discussed the implementation of multivariate MIDAS (M-MIDAS). Using 10 real-time leading indicators, they concluded that M-MIDAS regression triumphs over the single indicator MIDAS.

3.3. Specification strategy

This study employs two bi-variate models, namely the Almon polynomial distributed lag (Almon PDL) MIDAS – known simply as 'MIDAS' – and the least-squares (LS) model. The MIDAS model and the LS model take both the unlagged form and the lagged form with autoregressive (AR) terms of GRDP index changes ($\Delta GDPI_{t-1}$). Therefore, throughout the analysis, we consistently deliver results corresponding to four specifications; MIDAS, MIDAS-AR, LS, and LS-AR.

Our objective is to nowcast a lower-frequency variable, changes in the GRDP index, *Y*, in Q4 2020. In doing so, this study utilises the pseudo-out-of-sample approach, meaning that we treat Q4 2020 as a pseudo-out-of-sample observation. This means all models are estimated using data from Q1 2019 to Q3 2020 as part of training samples to predict the YoY GRDP growth value in Q4 2020. This routine is useful to examine how our models would perform in real-world practice (Armesto, Engemann, and Owyang, 2010). To be precise, the method mimics the actual scenario when the estimands' actual values are available to forecasters only up to time *t* and the predictors' values are available up to *t+1* to estimate the estimands' values at time *t+1*.

First, let us define the MIDAS model as:

$$Y_t = \beta_0 + \sum_{i=0}^{k-1} X_{t-i}^{(d)} \left(\sum_{j=0}^{p} \tau^j \theta_j \right) + \varepsilon_t^{(d)} \quad (4)$$

In equation (4), τ is the lag of the high-frequency variable. The coefficients for each high-frequency lag up to *k,* are governed by p, the dimensional lag polynomial with parameters θ. In our case, p took the value of 3 to maintain comparability with other MIDAS-based studies. The *d* term stands for the high-frequency observation number within each low-frequency period. Since we employ predictors with a daily frequency to predict quarterly variables, *d* would be between 90 and 93, representing the number of days in 1 quarter.

The AR model has been a benchmark specification for forecasting GDP. Also, explicitly incorporating the lagged value of the dependent variable has been proven to significantly improve prediction power and avoid severe bias, especially in a relatively short observation span (see Wilkins [2017]). Therefore, we aim to extend the MIDAS model by incorporating the AR term into equation (4).

Hence, if equation (4) is augmented with an autoregressive term of Y_t, we get the following MIDAS-AR specification:

$$Y_t = \beta_0 + \lambda Y_{t-1} + \sum_{i=0}^{k-1} X_{t-i}^{(d)} \left(\sum_{j=0}^{p} \tau^j \theta_j \right) \left(1 - \lambda \sum_{j=0}^{p} \tau^j \right) + \varepsilon_t^{(d)} \qquad (5)$$

Where λ is the autoregressive correlation coefficient explaining the relationship between GRDP index changes at time *t* and its past values. The predictor X_t is lagged up to a particular value of *i.* The models' lag length is automatically chosen based on the Akaike information criterion and the Schwartz information criterion.

Our third model is the LS, which is written as follows:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \qquad (6)$$

Similarly, we augment equation (6) with an autoregressive term of Y_t. Throughout the rest of our study, we coin it the 'LS-AR' specification, as formulated in equation (7):

$$Y_t = \beta_0 + aY_{t-1} + \beta_1 X_t + \varepsilon_t \qquad (7)$$

Unlike MIDAS models that weigh each lagged value X_t differently, the LS models only use a simple aggregation approach relying on the average value of X_t. LS models automatically average the mobility index's daily values for the particular quarter (q). Because of this limitation, the LS model might generate a less accurate result but is still useful for comparison. Hence, this study employs the LS and LS-AR specifications as the baseline for comparing the results against the MIDAS and MIDAS-AR models.

3.4. Nowcast approximation

Using the models shown in equations (4)–(7), we present the nowcast approximations for each specification. Amongst others, the forecast (nowcast) approximation has been extensively discussed by Timmermann (2006) and Kim and Swanson (2014). According to Andreou, Ghysels, and Kourtellos (2013), using the approximate combination of multiple models could improve the nowcast accuracy. It also provides an opportunity to address inherent instability within the models, mainly caused by structural breaks, as in the case of the COVID-19 pandemic.

The method used for making an approximate combination is the 'forecast averaging' procedure. Instead of assigning equal weights in averaging the nowcast result, we use the mean squared-error (MSE) combination method as suggested by Stock and Watson (2004). The averaging process can be written as:

$$\omega^{h}_{\{i,t\}} = \frac{\left(\lambda^{-1}_{i,t}\right)^{k}}{\sum_{\{j=1\}}^{n}\left(\lambda^{-1}_{j,t}\right)^{k}} \tag{8}$$

$$\text{For } \lambda_{i,t} = \sum_{\tau=T_0}^{t-h} \sigma^{t-h-\tau} \left(Y^{Q,h}_{\tau+h} - \hat{Y}^{Q,h}_{i,\tau+h}\right)^{2} = \text{MSE}$$

The weights, $\omega^{h}_{\{i,t\}}$, automatically penalise nowcast values with lower accuracies. Simply put, the MSE-combination method improves the overall nowcast performance by giving more weight to predicted values with better accuracies at any point in time (t).

3.5. Expanding the Mobility Index

The CSIS's Facebook Mobility Index suffers from an availability issue, as it is only available from 1 March 2020. Consequently, the data need to be backcasted to meet the minimum observation requirement for performing the nowcasting procedure. In doing so, we utilised daily average temperature data and daily PM 2.5 data for backcasting the provinces' mobility index. The backcasting was done back to 1 January 2019.

Our backcasting procedure follows Sampi and Jooste (2020). The general formula used to backcast the data is as follows:

$$f_{\{j-1\}} = \frac{f_j}{1 + \sum_{i=1}^{N} \rho_i \times p_i} \tag{9}$$

The formula employs a dynamic backcasting method, as every single back-casted value was attained based on information available in the subsequent period. In equation (9), *f* stands for the backcasted series, the mobility index. The term p_i is proxy 'i', normalised and employed to expand the mobility index, whilst ρ_i is the correlation coefficient between proxy *i* and the mobility index. Unlike for Sampi and Jooste (2020), the number of proxies used to expand the mobility index backwards, *N,* takes the value of 3. *N=3* corresponds to three climate and weather indicators we utilised to approximate the mobility index for earlier than 1 March 2020.

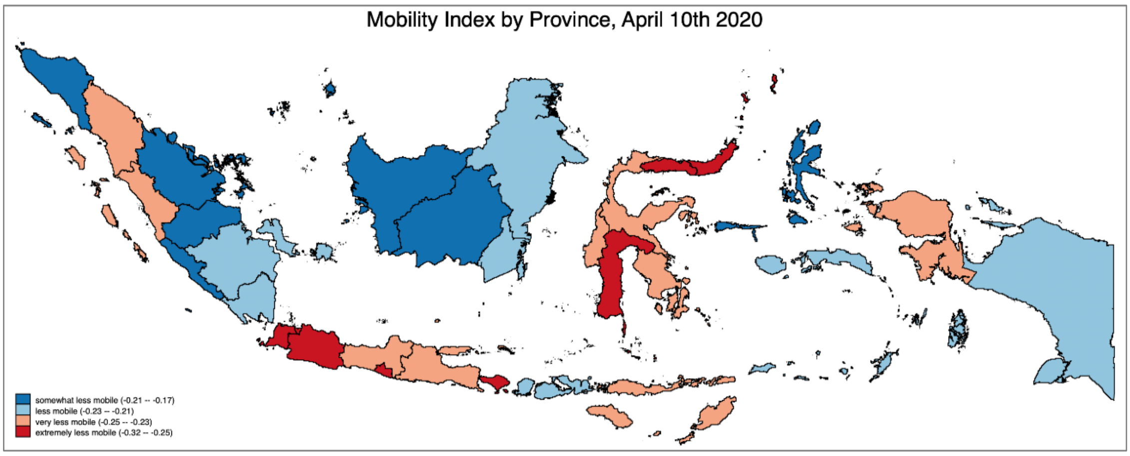
It is important to note that the resulting expanded mobility index cannot perfectly reflect the real dynamics in mobility as it uses predicted values. An ideal way would be to use the mobility index's actual values. That way, the nowcast accuracies would likely improve. However, since the data are only available from 1 March 2020, backcasting the mobility index is a feasible option to proceed with.

3.6. Scope

The main features of the COVID-19 pandemic are its uneven spatial diffusion and geographical impacts. In Indonesia, the first COVID-19 case was first detected in Greater Jakarta in March, resulting in the first implementation of large-scale social restrictions (PSBB) in the capital city on 10 April. Then, East Java followed on 28 April and West Java on 6 May. Outside Java, the first PSBB was implemented in Makassar, the capital city of South Sulawesi, and Banjarmasin, the capital city of South Kalimantan, on 24 April.

Since COVID-19 allows for human-to-human transmission, the COVID-19 pandemic hit densely populated places more severely. In Indonesia, the pandemic struck Indonesia's central economic and population nodes much earlier. Consequently, during the first round of the large-scale social restriction (PSBB), mobility dropped more dramatically in provinces with higher population density and contributions to the national economy, as depicted in Figure 3.

Figure 3: Mobility Index by Province, 10 April 2020



Source: Facebook Mobility Index, processed by CSIS.

The map in Figure 3 suggests that Bali and all provinces in Java responded more immediately than others, as marked by the red and orange shades. Also, mobility responses in Java provinces and Bali were more uniform than those in other regions. It is important to note that despite Sulawesi provinces also exhibiting immediate responses, their shares in Indonesia's economy are not as big as those in Java and Bali, making them less preferable for this study.

Considering this characteristic and the limited data availability, we focused our study on provincial-level analysis for the provinces in Java and Bali. This is preferable over a more aggregated, national-level analysis since the uneven spread of economic nodes across Indonesian regions could lead to biased estimation results. In addition, mobility restrictions' impacts on Java and Bali economies are likely associated with their population density. Six provinces in Java are amongst those with the highest population density in Indonesia, followed by Bali (Statistics Indonesia, 2020). Java and Bali's regions also make good approximations of the national economy since they constitute more than 61% of the economy. The region is also relatively homogenous in terms of the economic structure amongst the regencies and municipalities within the provinces, in which service and industrial activities dominate. This pattern ensures a more consistent relationship between the public's mobility and economic activities.

Whilst the Facebook Mobility Index is available at the district level, a provincial approximation is more feasible when compared to the time-consuming analysis at the municipal level. Some proxies and official statistics, such as GRDP, are either not published on time or unavailable for certain time lags at the municipal level. Since the Mobility Index is only available from 1 March 2020, backcasting the index at the municipal level would be very difficult.

Conversely, less-populated Indonesian regions with a lower intensity of services and industrial activities may have a weaker and less-robust relationship between the mobility index and economic productivity. In areas with lower purchasing power and less technologically savvy populations, the Facebook Mobility Index cannot serve as a reliable measure of movements or economic activity. This is due to the much fewer people whose mobilities or activity logs are recorded in the Facebook Movement Range Map.

4. Results and Discussion

4.1. Expanded mobility index

We begin our analysis by expanding the Facebook Mobility Index using the formula presented in equation (9). We use the daily average temperature, daily particle concentration in the air (PM 2.5), and daily rainfall intensity (rainfall rate) to expand the mobility index.

The resulting expanded mobility index is presented in Figure 4. The graph's shaded area marks the Facebook Mobility Index's backcasted values, whilst the remaining unshaded area marks the index's actual values. After the expansion, the Facebook Mobility index now contains more data points and a longer observation horizon sufficient to proceed with the nowcasting routine.

It is easy to see that before Indonesia's first COVID-19 outbreak in early March 2020, the average mobility had been much higher and much closer to zero – meaning that there was not much change in people's mobility compared to the baseline period of February 2020.

It is not until mid-March 2020 that we can spot a steep drop in the mobility index as the government started to recommend mobility reductions following the confirmation of the country's first COVID-19 case on 2 March that year. By the end of March 2020, we can observe a further fall, as the government began to formalise its mobility restriction policy – coined as large-scale social restrictions (PSBB) – through Government Regulation No.21/2020.

From March 2020 onwards, the mobility index was relatively lower compared to before. Nonetheless, we can still observe the dynamics of the mobility index after the PSBB was enacted. Approaching May–June 2020, mobility rose (although not as high as pre-March level) as the Eid Al-Fitr holiday season took place. After June 2020, there was a gradual increase in mobility as the government enacted a less restrictive version of the PSBB, coined as 'transitional PSBB', and implemented the 'New Normal' policy, which allowed workplaces to reopen and religious facilities to operate partially starting from 9 June 2020.

Figure 4: Expanded Mobility Index

Source: Authors' calculations (back-casted) and Facebook Mobility Index.

In mid-September, mobility fell again as the government implemented a stricter PSBB starting 14 September 2020. This version of the PSBB involved the full closure of almost all public spaces, including religious facilities and recreation places. Restaurants were only allowed to serve takeaways, whilst all social events and any crowds were prohibited. From mid-October onwards, a gradual increase in mobility occurred as the PSBB loosened, before spiking around the Christmas holiday.

4.2. Nowcast results

We backcasted the Facebook Mobility Index from 29 February 2020 backwards. Then, we splined it with the actual values from 1 March to 31 December 2020. This procedure produced the expanded Facebook Mobility Index, spanning 2 years from 1 January 2019 to 31 December 2020 – sufficiently long to predict GDP index changes 1 quarter ahead in Q4 2020.

Next, we nowcasted each province's GRDP index changes ($\Delta GDPI_{t-1}$) with its expanded mobility index as a single predictor using all models (LS, LS-AR, MIDAS, and MIDAS-AR). The predicted values of the GRDP index changes were then converted into GRDP YoY growth. We also conducted a bottom-up approach to predict an aggregated growth prediction for the provinces in Java and Bali. All outputs are provided in Table A2 along with the simple means, simple medians, and MSE-based combinations.

In both the index changes and YoY growth forms, it is noticeable that the models predicted the actual values within the in-sample observations from Q1 2019 to Q3 2020 more accurately. The predicted values in Q4 2020 seem to deviate much further from the actual ones.

As expected, our models tend to be more precise in projecting the estimand's actual values before the pandemic-induced crisis started in Q1 2020/Q2 2020. Likewise, the prediction errors tend to be higher, and the estimated values tend to be explosive during the crisis. This is partly because during either crises or recoveries, the estimated parameters' performance usually deteriorates due to anomalous economic relationships amongst the variables (Foroni, Marcellino, and Stevanovic, 2020). Aside from the narrow observation horizon, the half-backcasted mobility index fed into the nowcasting model might also cause this issue.

Interestingly, the four models produced reliable predictions on directions, and this is particularly true for the MIDAS and MIDAS-AR models as they were much less likely to incorrectly predict the precise directions compared to the LS and LS-AR models. The LS and LS-AR models sometimes even failed to produce the correct estimated direction for in-sample observations. In contrast, the MIDAS and

MIDAS-AR models almost always accurately predicted the estimand's direction, even for the out-of-sample observations (see Figure 5).

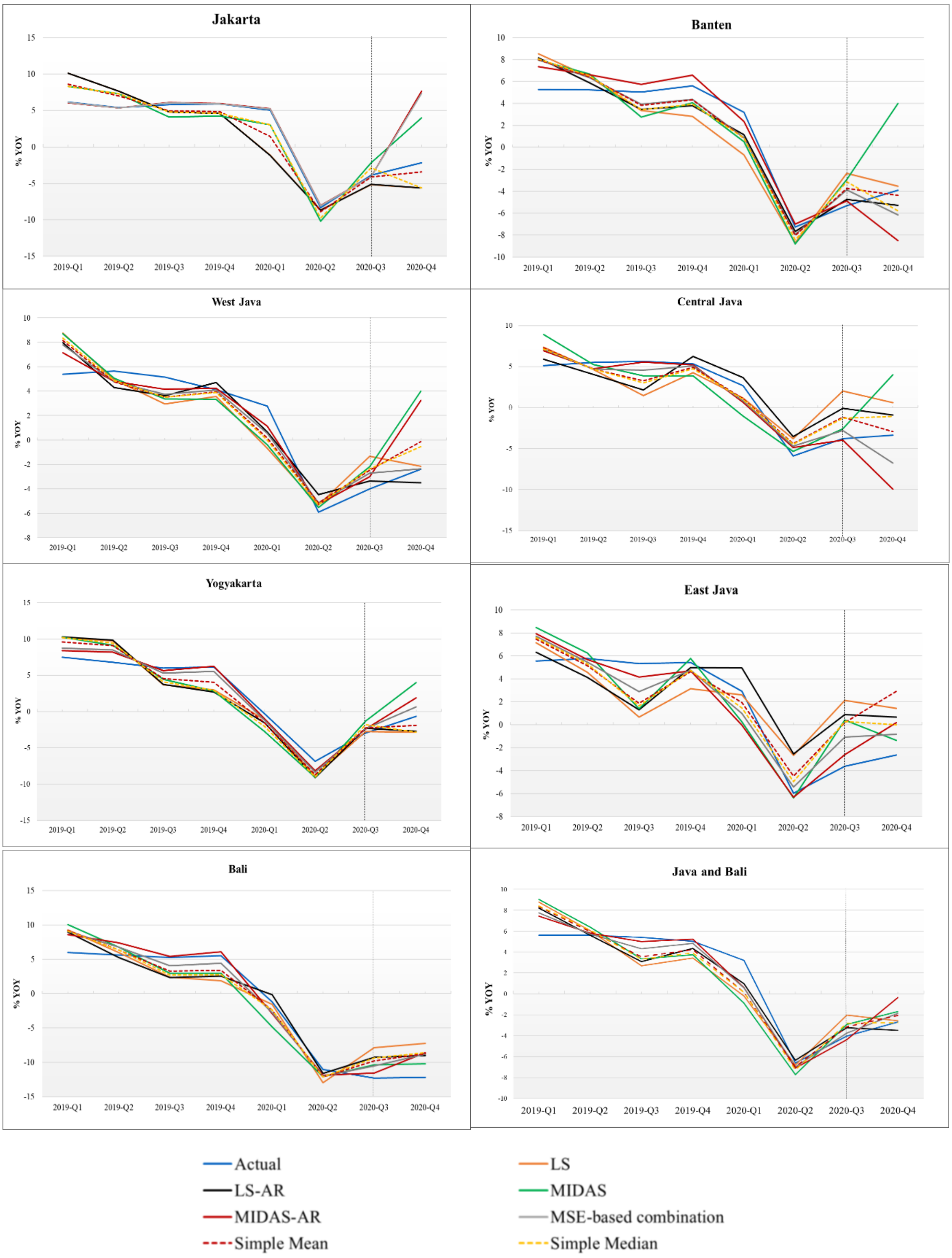
MIDAS and MIDAS-AR's downside probably lies in their tendencies to produce explosive predictions of the out-of-sample observations. The two models' projections were closer to the actual values for in-sample observations but produced much less-accurate projected values for out-sample observations due to their more flexible parameters (see Figure 5).

One can alleviate such shortcomings by computing nowcast combinations. By combining the nowcasted values of different models, overestimation and underestimation can be reduced. We found that MSE-based, simple mean, and simple median combinations pulled the predictions closer to their actual values in each province.

In terms of the overall accuracies, the MIDAS-AR model consistently showed significantly lower errors than the other models, as depicted by its MSEs. Broadly, we also observed lower MSEs for MIDAS models than their LS counterparts, which suggests that incorporating the estimand's autoregressive term is generally useful in improving nowcast precision. This pattern is consistent with previous studies' findings and holds for every province and aggregated analysis of Java and Bali.

The results from each province's predictions in Java and Bali can be aggregated to see the region's economic level and growth. The aggregated results for Java and Bali seem to be more accurate than those for the analysis of the individual provinces, as depicted in the last panel of Figure 5. This applies to the out-of-sample projection as well. Although some of the models remained explosive, the nowcast combination effectively brought about estimates quite close to the actual values. This gives some basis for this 'bottom-up' approach for future work on predictions of the Indonesian economy using the mobility index at the municipal or provincial levels.

Figure 5: Real Gross Regional Domestic Product Year-on-Year Growth



Source: Authors' calculations.

5. Conclusion

This study attempts to construct a model for nowcasting Indonesia's economic activities during the COVID-19 pandemic using the novel high-frequency Facebook Mobility Index as a predictor. Employing mixed frequency MIDAS and the benchmark LS model, we expanded the mobility index until Q1 2019 and used it to track the dynamics of real GRDP growth in Indonesian provinces in Java and Bali. We also explored options for the models with the estimand's AR term and combined nowcasts across specifications to check the effective methods for correcting nowcast errors.

Our results suggested that the daily Facebook Mobility Index was a considerably reliable predictor for projecting economic activities on time, considering data availability. In each province, all models almost consistently produced accurate predictions of the directions. Notably, we found the MIDAS-AR to be slightly superior to the other models in terms of overall precision and directional predictive accuracy across observations.

We also noted significant errors and explosive estimates, especially for the out-of-sample observation, Q4 2020. These could originate from the analyses' inevitable limitations, namely the narrow observation window and sparse data availability. In the meantime, we resorted to several nowcast combinations to alleviate the nowcast errors and pull the estimates closer to the actual values.

This study also presented a bottom-up approach for forecasting economic activities with a greater observation scope by delivering accumulative GRDP growth nowcasts of Bali and Java provinces altogether. The nowcast output appeared to be reliable despite the given constraints, especially after performing nowcast combinations.

Finally, our study delivers insightful exercises for predicting economic activities using non-traditional, recently available mobility data. With the existing publication lags of traditional macroeconomic indicators, the high-frequency Facebook Mobility Index can be an alternative predictor for nowcast economic activities – as measured by GDP – in a timelier manner.

Another valuable point of this study is the nowcast result for Java and Bali's accumulated GRDP growth. It sheds light on a bottom-up approach for predicting

GRDP growth with a more aggregated scope. The approach is rarely used to the best of our knowledge, especially in analysing the Indonesian economy.

Timely and frequent economic activities are utterly crucial in policymaking, especially in today's pandemic situation as, more often than not, efforts to curb the spread of contagious diseases like COVID-19 can cost the economy. Hence, a reliable and timely prediction of policies' economic impacts may allow policymakers to carefully plan mitigation attempts to minimise adverse outcomes that otherwise may be severe if left unanticipated.

6. Discussion for Future Work

Our study can be extended in several ways. In the future, once the data length is sufficient, one might want to use the full version of the mobility index without backcasted values. This way, the actual mobility dynamics can be captured. Using the full-length actual mobility index is expected to increase the nowcasting models' explanatory power and improve overall nowcast accuracy.

In the context of COVID-19 containment, it is essential to note that mobility dynamics may differ from one area to another. Also, the impacts of mobility restrictions on people's mobility may vary across regions. Each city and municipality may react differently to the government's mobility restriction policy due to varying economic and demographical structures. Whenever possible, more disaggregated analyses at the city or municipality levels are strongly encouraged to produce highly relevant policymaking insights that can be specifically tailored to each region's circumstances.

It is also possible to improvise on the specification strategy. First, if backcasting the mobility index is inevitable, one could experiment on other proxies to expand the mobility index. Potential proxies include high-frequency proxies like night-time light, ship arrival, plane arrival, and traffic congestion data. Second, one can use multivariate MIDAS (M-MIDAS) once a high-frequency economic indicator becomes available for the sub-national level in the future.

Lastly, the bottom-up nowcast approach can be extended in various ways. Future applications could take the form of nowcasting national economic activities using provincial data or even city and municipality data, estimating provincial economies using city-level or district-level data, or even estimating national economies with a granular prediction at district-level economies.

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Appendix

Table A1: Correlations between the Mobility Index and Weather Indicators

		Jakarta		
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	-0.237	1		
PM 2.5	0.445	0.052	1	
Rainfall Rate	-0.320	-0.295	-0.429	1
		Banten		
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	0.166	1		
PM 2.5	0.276	0.212	1	
Rainfall Rate	-0.159	-0.438	-0.373	1
		West Java		
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	0.154	1		
PM 2.5	0.199	0.010	1	
Rainfall Rate	-0.206	-0.295	-0.209	1
		Central Java		
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	0.054	1		
PM 2.5	0.357	0.010	1	
Rainfall Rate	-0.147	-0.178	-0.465	1

Yogyakarta				
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	-0.088	1		
PM 2.5	-0.087	0.030	1	
Rainfall Rate	-0.413	-0.016	-0.037	1
East Java				
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	-0.229	1		
PM 2.5	-0.167	0.290	1	
Rainfall Rate	-0.446	0.285	-0.115	1
Bali				
	Mobility Index	**Avg. Temperature**	**PM 2.5**	**Rainfall Rate**
Mobility Index	1			
Avg. Temperature	-0.179	1		
PM 2.5	-0.268	0.055	1	
Rainfall Rate	-0.310	0.091	-0.084	1

Source: Authors' calculations.

Table A2: Nowcast Results (Real GRDP Year-on-Year Growth)

Jakarta								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	6.15	10.11	10.12	8.30	6.04	6.10	8.64	8.30
2019-Q2	5.40	7.66	7.67	7.32	5.34	5.38	7.00	7.32
2019-Q3	5.82	4.79	4.79	4.09	6.11	6.08	4.94	4.79
2019-Q4	5.91	4.60	4.59	4.24	5.97	5.94	4.85	4.60
2020-Q1	5.04	-1.13	-1.15	3.04	5.27	5.19	1.47	3.04
2020-Q2	-8.33	-8.63	-8.66	-10.19	-8.05	-8.07	-8.88	-9.74
2020-Q3	-3.89	-5.17	-5.13	-2.17	-4.06	-4.05	-4.14	-2.87
2020-Q4	-2.14	-5.64	-5.62	4.00	7.69	7.39	-3.40	-5.64

Banten								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.27	8.53	8.15	7.95	7.36	8.00	8.00	8.05
2019-Q2	5.23	6.42	5.87	6.68	6.62	6.35	6.40	6.52
2019-Q3	5.05	3.36	3.48	2.76	5.75	3.95	3.84	3.42
2019-Q4	5.62	2.81	3.80	4.07	6.59	4.36	4.32	3.94
2020-Q1	3.18	-0.69	1.14	0.52	2.36	0.90	0.83	0.83
2020-Q2	-7.27	-8.70	-7.64	-8.81	-6.98	-7.92	-8.03	-8.44
2020-Q3	-5.32	-2.37	-4.75	-2.94	-4.87	-3.88	-3.74	-3.15
2020-Q4	-3.92	-3.55	-5.26	-7.71	-8.50	-6.14	-4.38	-5.77

West Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.39	8.76	7.97	8.69	7.13	7.77	8.14	8.33
2019-Q2	5.64	4.93	4.31	5.07	4.78	4.75	4.77	4.86
2019-Q3	5.14	2.93	3.62	3.36	4.14	3.75	3.51	3.49
2019-Q4	4.12	3.55	4.72	3.32	4.23	4.09	3.95	3.89
2020-Q1	2.77	-0.69	0.66	-0.39	1.14	0.54	0.17	-0.02
2020-Q2	-5.91	-5.33	-4.48	-5.53	-5.26	-5.16	-5.15	-5.29
2020-Q3	-4.01	-1.34	-3.35	-2.18	-3.01	-2.72	-2.47	-2.35
2020-Q4	-2.39	-2.15	-3.51	1.92	3.25	-2.36	-0.13	-0.55

Central Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.12	7.36	5.87	8.91	6.92	7.09	7.27	7.14
2019-Q2	5.52	4.65	4.05	5.27	4.71	4.70	4.67	4.68
2019-Q3	5.63	1.45	2.16	3.89	5.53	4.54	3.26	3.03
2019-Q4	5.33	4.27	6.26	3.86	5.21	5.08	4.90	4.74
2020-Q1	2.65	1.16	3.66	-1.04	0.64	0.83	1.09	0.98
2020-Q2	-5.91	-3.79	-3.54	-5.34	-4.87	-4.67	-4.39	-4.46
2020-Q3	-3.79	2.04	-0.07	-2.59	-3.97	-2.81	-1.18	-1.27
2020-Q4	-3.34	0.62	-0.90	-1.48	-9.94	-6.77	-2.93	-1.07

Yogyakarta								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	7.51	10.18	10.30	10.23	8.38	8.76	9.57	10.21
2019-Q2	6.77	9.76	9.85	9.16	8.21	8.48	9.09	9.46
2019-Q3	6.01	3.67	3.75	4.43	5.65	5.31	4.56	4.09
2019-Q4	6.15	3.00	2.71	2.84	6.22	5.54	4.06	2.92
2020-Q1	-0.31	-1.09	-1.58	-2.76	-1.03	-1.22	-1.54	-2.08
2020-Q2	-6.88	-8.91	-9.10	-9.06	-8.17	-8.35	-8.72	-9.00
2020-Q3	-2.98	-2.78	-2.33	-1.30	-2.42	-2.34	-2.23	-1.81
2020-Q4	-0.68	-2.87	-2.71	-6.67	1.91	0.65	-1.90	-2.85

East Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.56	7.13	6.32	8.47	7.94	7.73	7.47	7.60
2019-Q2	5.78	4.56	4.12	6.26	5.68	5.45	5.16	5.30
2019-Q3	5.33	0.66	1.30	1.41	4.16	2.88	1.88	1.64
2019-Q4	5.42	3.13	4.97	5.79	4.71	4.77	4.65	4.74
2020-Q1	2.92	2.60	4.95	0.25	-0.03	0.98	1.93	1.45
2020-Q2	-5.98	-2.66	-2.54	-6.39	-6.30	-5.41	-4.48	-4.95
2020-Q3	-3.61	2.14	0.91	0.41	-2.60	-1.07	0.19	0.30
2020-Q4	-2.64	1.42	0.67	-1.36	0.19	-0.82	2.91	0.01

Bali								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.98	9.31	8.95	10.08	8.63	9.07	9.24	9.13
2019-Q2	5.64	5.99	5.28	6.79	7.39	6.78	6.36	6.39
2019-Q3	5.28	2.39	2.37	2.99	5.40	4.08	3.29	2.69
2019-Q4	5.51	1.89	2.55	2.95	6.12	4.41	3.38	2.75
2020-Q1	-1.20	-1.58	-0.18	-4.84	-2.92	-2.76	-2.39	-2.39
2020-Q2	-11.06	-12.97	-11.64	-12.11	-11.87	-12.03	-12.15	-12.17
2020-Q3	-12.32	-7.85	-9.28	-10.40	-11.56	-10.53	-9.79	-9.39
2020-Q4	-12.21	-7.23	-9.04	-10.22	-8.59	-8.82	-8.77	-8.61

Java and Bali								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2019-Q1	5.61	8.79	8.20	9.05	7.45	7.75	8.34	8.42
2019-Q2	5.60	6.04	5.62	6.39	5.82	5.73	5.95	6.09
2019-Q3	5.42	2.68	3.08	3.36	5.01	4.33	3.56	3.31
2019-Q4	5.04	3.43	4.36	3.76	5.24	4.84	4.25	3.93
2020-Q1	3.20	-0.21	0.99	-0.88	0.60	0.58	0.13	0.14
2020-Q2	-6.61	-6.79	-6.34	-7.72	-7.10	-6.96	-6.98	-7.26
2020-Q3	-4.03	-2.03	-3.22	-2.90	-4.37	-3.74	-3.14	-2.80
2020-Q4	-2.69	-2.56	-3.50	-1.68	-0.33	-1.85	-2.04	-2.74

Source: Authors' calculations.

Table A3: Nowcast Results (Changes in GRDP Index, Q4 2018=0) and Nowcast Evaluation

Jakarta								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-5.52	-5.60	-5.60	-5.60	-5.60	-5.60	-5.60	-5.60
2018-Q2	-3.50	-3.51	-3.51	-3.51	-3.51	-3.51	-3.51	-3.51
2018-Q3	-0.61	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	0.28	3.95	3.96	2.24	0.11	0.16	2.56	3.09
2019-Q2	1.72	3.89	3.89	3.56	1.65	1.68	3.25	3.72
2019-Q3	5.17	4.19	4.19	3.49	5.51	5.47	4.34	4.19
2019-Q4	5.91	4.60	4.59	4.24	5.97	5.94	4.85	4.59
2020-Q1	5.34	2.78	2.76	5.34	5.39	5.37	4.07	4.06
2020-Q2	-6.76	-5.08	-5.10	-7.00	-6.53	-6.53	-5.93	-5.82
2020-Q3	1.09	-1.20	-1.16	1.25	1.22	1.20	0.03	0.03
2020-Q4	3.65	-1.30	-1.29	-6.38	14.11	13.77	1.29	-1.30
MSE	**-**	**0.000509**	**0.000509**	**0.000509**	**0.000187**	**0.000128**	**0.000232**	**0.000536**
MAE		**0.024564**	**0.024555**	**0.022103**	**0.01426**	**0.013401**	**0.014102**	**0.019247**
R-squared	**-**	**0.535**	**0.691**	**0.886**	**0.897**			
Adj. R-squared	**-**	**0.458**	**0.537**	**0.886**	**0.896**			

Banten								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-5.48	-5.48	-5.48	-5.48	-5.48	-5.48	-5.48	-5.48
2018-Q2	-3.60	-3.60	-3.60	-3.60	-3.60	-3.60	-3.60	-3.60
2018-Q3	-0.96	-0.96	-0.96	-0.96	-0.96	-0.96	-0.96	-0.96
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	-0.51	2.58	2.22	2.03	1.47	2.07	2.07	2.12
2019-Q2	1.44	2.59	2.06	2.83	2.77	2.52	2.56	2.68
2019-Q3	4.04	2.36	2.49	1.77	4.73	2.95	2.84	2.42
2019-Q4	5.62	2.81	3.80	4.07	6.59	4.36	4.32	3.94
2020-Q1	2.66	1.87	3.39	2.56	3.86	2.99	2.92	2.98
2020-Q2	-5.94	-6.33	-5.74	-6.23	-4.40	-5.61	-5.67	-5.98
2020-Q3	-1.49	-0.06	-2.38	-1.22	-0.37	-1.05	-1.01	-0.80
2020-Q4	1.47	-0.83	-1.67	-3.96	-2.47	-2.05	-0.25	-1.25
MSE	**-**	**0.000347**	**0.000212**	**0.000229**	**0.000174**	**0.000170**	**0.000180**	**0.000273**
MAE		**0.01704**	**0.014582**	**0.013595**	**0.015972**	**0.010995**	**0.011165**	**0.013675**
R-squared	**-**	**0.729638**	**0.835**	**0.821**	**0.832**			
Adj. R-squared	**-**	**0.676**	**0.752**	**0.821**	**0.818**			

West Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-4.74	-4.74	-4.74	-4.74	-4.74	-4.74	-4.74	-4.74
2018-Q2	-1.32	-1.32	-1.32	-1.32	-1.32	-1.32	-1.32	-1.32
2018-Q3	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	0.40	3.60	2.85	3.54	2.05	2.67	3.01	3.20
2019-Q2	4.25	3.55	2.93	3.68	3.40	3.37	3.39	3.47
2019-Q3	5.65	3.43	4.12	3.86	4.64	4.25	4.01	3.99
2019-Q4	4.12	3.55	4.72	3.32	4.23	4.09	3.95	3.89
2020-Q1	3.18	2.88	3.53	3.14	3.22	3.22	3.19	3.18
2020-Q2	-1.91	-1.97	-1.68	-2.06	-2.04	-1.96	-1.94	-2.00
2020-Q3	1.42	2.05	0.64	1.60	1.49	1.41	1.45	1.55
2020-Q4	1.64	1.32	1.04	5.31	7.62	1.64	3.82	3.32
MSE	**-**	**0.000236**	**0.000202**	**0.000161**	**0.000065**	**0.000245**	**0.000188**	**0.000176**
MAE		**0.009993**	**0.009818**	**0.012926**	**0.012316**	**0.010132**	**0.009423**	**0.00922**
R-squared	**-**	**0.598**	**0.726**	**0.656**	**0.837**			
Adj. R-squared	**-**	**0.518**	**0.590**	**0.656**	**0.805**			

Central Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-3.21	-3.21	-3.21	-3.21	-3.21	-3.21	-3.21	-3.21
2018-Q2	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25
2018-Q3	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	1.75	3.92	2.48	5.42	3.49	3.66	3.83	3.70
2019-Q2	5.25	4.39	3.79	5.01	4.45	4.44	4.41	4.42
2019-Q3	7.86	3.60	4.32	6.09	7.77	6.75	5.44	5.21
2019-Q4	5.33	4.27	6.26	3.86	5.21	5.08	4.90	4.74
2020-Q1	4.44	5.13	6.22	4.32	4.14	4.51	4.95	4.72
2020-Q2	-0.97	0.43	0.11	-0.60	-0.63	-0.44	-0.17	-0.24
2020-Q3	3.77	5.71	4.25	3.35	3.49	3.75	4.20	3.87
2020-Q4	1.81	4.91	5.30	2.32	-5.25	-2.03	1.82	3.62
MSE	**-**	**0.000442**	**0.000294**	**0.000274**	**0.000052**	**0.000259**	**0.000152**	**0.000198**
MAE		**0.019357**	**0.016851**	**0.014738**	**0.013419**	**0.010686**	**0.009397**	**0.011185**
R-squared	**-**	**0.358**	**0.573**	**0.602**	**0.847**			
Adj. R-squared	**-**	**0.230**	**0.359**	**0.602**	**0.816**			

Yogyakarta								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-6.51	-6.51	-6.51	-6.51	-6.51	-6.51	-6.51	-6.51
2018-Q2	-5.94	-5.94	-5.94	-5.94	-5.94	-5.94	-5.94	-5.94
2018-Q3	-0.66	-0.66	-0.66	-0.66	-0.66	-0.66	-0.66	-0.66
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	0.50	3.00	3.11	3.05	1.32	1.68	2.62	3.03
2019-Q2	0.43	3.24	3.32	2.67	1.78	2.03	2.75	2.96
2019-Q3	5.32	2.99	3.07	3.75	4.95	4.62	3.69	3.41
2019-Q4	6.15	3.00	2.71	2.84	6.22	5.54	3.69	2.92
2020-Q1	0.19	1.88	1.49	0.20	0.28	0.44	0.96	0.89
2020-Q2	-6.48	-5.96	-6.08	-6.63	-6.54	-6.49	-6.30	-6.31
2020-Q3	2.17	0.13	0.67	2.40	2.41	2.17	1.40	1.53
2020-Q4	5.43	0.05	-0.08	-4.02	8.25	6.22	19.62	-0.01
MSE	**-**	**0.000526**	**0.000517**	**0.000357**	**0.000039**	**0.000450**	**0.002765**	**0.000717**
MAE		**0.025526**	**0.024886**	**0.024378**	**0.100109**	**0.080349**	**0.030552**	**0.021422**
R-squared	**-**	**0.483**	**0.650**	**0.758**	**0.870**			
Adj. R-squared	**-**	**0.396**	**0.475**	**0.758**	**0.849**			

East Java								
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-5.00	-5.00	-5.00	-5.00	-5.00	-5.00	-5.00	-5.00
2018-Q2	-1.78	-1.78	-1.78	-1.78	-1.78	-1.78	-1.78	-1.78
2018-Q3	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	0.28	1.77	1.00	3.04	2.54	2.34	2.09	2.16
2019-Q2	3.90	2.70	2.27	4.37	3.80	3.58	3.29	3.25
2019-Q3	7.50	2.72	3.38	3.49	6.30	4.99	3.97	3.44
2019-Q4	5.42	3.13	4.97	5.79	4.71	4.77	4.65	4.84
2020-Q1	3.21	4.43	6.00	3.30	2.51	3.34	4.06	3.86
2020-Q2	-2.31	-0.03	-0.33	-2.29	-2.74	-2.03	-1.35	-1.31
2020-Q3	3.61	4.92	4.32	3.91	3.54	3.86	4.17	4.11
2020-Q4	2.64	4.60	5.68	4.34	4.91	3.91	7.70	5.14
MSE	**-**	**0.000573**	**0.000465**	**0.000345**	**0.000111**	**0.000160**	**0.000553**	**0.000358**
MAE		**0.020655**	**0.019294**	**0.036001**	**0.013784**	**0.009346**	**0.017689**	**0.014773**
R-squared	**-**	**0.303**	**0.377**	**0.616**	**0.786**			
Adj. R-squared	**-**	**0.187**	**0.127**	**0.616**	**0.743**			

					Bali			
Period	**Actual**	**LS**	**LS-AR**	**MIDAS**	**MIDAS-AR**	**MSE-based Combination**	**Simple Mean**	**Simple Median**
2018-Q1	-7.01	-7.01	-7.01	-7.01	-7.01	-7.01	-7.01	-7.01
2018-Q2	-3.91	-3.91	-3.91	-3.91	-3.91	-3.91	-3.91	-3.91
2018-Q3	-0.59	-0.59	-0.59	-0.59	-0.59	-0.59	-0.59	-0.59
2018-Q4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2019-Q1	-1.45	1.65	1.31	2.36	1.02	1.42	1.59	1.48
2019-Q2	1.51	1.85	1.17	2.62	3.19	2.61	2.21	2.23
2019-Q3	4.66	1.79	1.77	2.38	4.79	3.47	2.68	2.09
2019-Q4	5.51	1.89	2.55	2.95	6.12	4.41	3.38	2.75
2020-Q1	-2.63	0.04	1.13	-2.59	-1.93	-1.38	-0.84	-0.95
2020-Q2	-9.71	-11.36	-10.61	-9.81	-9.06	-9.73	-10.21	-10.21
2020-Q3	-8.23	-6.20	-7.67	-8.26	-7.33	-7.43	-7.37	-7.50
2020-Q4	-7.37	-5.48	-6.72	-7.57	-2.99	-4.80	-5.69	-6.10
MSE	**-**	**0.000644**	**0.000573**	**0.000393**	**0.000158**	**0.000261**	**0.000315**	**0.000357**
MAE		**0.022729**	**0.018528**	**0.01265**	**0.014404**	**0.013634**	**0.01585**	**0.016464**
R-squared	**-**	**0.786**	**0.809**	**0.869**	**0.948**			
Adj. R-squared	**-**	**0.743**	**0.714**	**0.869**	**0.938**			

Source: Authors' calculations.

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