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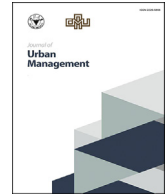
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Research Article

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ABSTRACT

Government interventions to limit the spread of the COVID-19 disease have decreased mobility, which, in turn, impacts aggregate economic activity. Understanding mobility during the COVID-19 pandemic may serve as a proxy for understanding its economic impact. This study aims to examine the relationship between pre-existing socioeconomic factors and the economic impact of COVID-19 using aggregate mobility data, particularly from emerging economies with a dominance of informal workers within economic activities. This study will utilize the public mobility dataset to provide an exploratory picture of the socioeconomic and policy determinants of mobility during the pandemic, focusing on Indonesia. The exploratory analytical findings indicate that the impact of COVID-19 on the economy, as indicated by mobility data, is highly correlated with various prior socioeconomic determinants. Moreover, more prosperous and urbanized areas have a larger formal sector, employ more people in manufacturing and/or tourism, possess a more educated labor force, and are more digitally connected; they tend to experience more significant decreases in mobility. The study has provided lessons to developing countries with a vast informal sector size and the gap in access to digital technology to design a more effective, timely, and well-targeted policy response in dealing with the COVID-19 pandemic.

1. Introduction

The COVID-19 pandemic has severely disrupted the global economy, with long-lasting repercussions on global development. Massive declines in mobility largely cause these disruptions because of government interventions to limit the spread of the disease, as well as voluntary actions by individuals to reduce the risk of contracting the virus. This decline in mobility, in turn, has an impact on aggregate economic activity. Firms, particularly those in contact-intensive sectors, have no choice but to reduce their production level amid various mobility restrictions. Additionally, firms are faced with a decrease in demand, as households increase precautionary savings and change their consumption patterns. This negative supply shock in most contact-intensive sectors may ultimately trigger changes in aggregate demand that are larger than the shock (Guerrieri, Lorenzoni, Straub, & Werning, 2020). The nature of this crisis as being mobility-induced implies that understanding mobility during the pandemic, as well as its determinants, may serve as a proxy to

^H Non-pharmaceutical interventions (NPIs); Indonesian National Socioeconomic Survey (SUSENAS); work from home (WFH); Pembatasan Sosial Berskala Besar (PSBB); Penerapan Pembatasan Kegiatan Masyarakat (PPKM); World Tourism Organization (UNWTO); older adults (OA); ordinary least squares (OLS) method.

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understand its economic impact as a whole. In this study, we focus on Indonesia, an emerging country with the fourth largest population in the world. Understanding mobility and its determinants in Indonesia is a valuable contribution to the literature, as prior studies have mostly focused on advanced economies, which have very distinct characteristics from emerging and developing countries. Furthermore, to the best of our knowledge, this is the first study to explore the correlation between mobility and its determinants in Indonesia.

Changes in mobility are associated with three key aspects: socioeconomic, policy, and technological. In the first aspect, prior socioeconomic characteristics have an impact on mobility. For example, populations residing in densely urbanized cities may have to (and can) reduce their mobility significantly more than populations residing in sparsely populated rural areas. Furthermore, prior studies have indicated that mobility during the pandemic is correlated with various socioeconomic factors such as wealth (Fraiberger et al., 2020), inequality, income (Bonaccorsi et al., 2020; Wright, Sonin, Driscoll, & Wilson, 2020; Khoirunurrofik, Abdurrachman, & Putri, 2022), age, and gender (Caselli, Grigoli, Sandri, & Spilimbergo, 2021) as proxied by various economic indicators, suggesting that socioeconomic variables significantly impact mobility and, ultimately, the economic impact of COVID-19. In addition to socioeconomic determinants, mobility is affected by government policies. In the face of rising cases and deaths, governments worldwide have turned to non-pharmaceutical interventions (NPIs) such as stay-at-home orders and lockdowns to contain the spread of the virus. Evidence suggests that these interventions decrease the number of infections and redistribute cases over time (Bento & Teixeira, 2020; Davies et al., 2020; Ferguson et al., 2020; Peak et al., 2020), reducing the risk that local healthcare systems are overwhelmed by surges in demand for health services (Keeling & Rohani, 2011). However, evidence of the effectiveness of such NPIs seems to be mixed in developing countries in comparison to similar NPIs in developed countries because of inadequate enforcement capacity and rule compliance (Barnett-Howell, Watson, & Mobarak, 2021; Yeyati & Sartorio, 2020). This may also be the case in Indonesia, where the government has introduced interventions aimed at reducing the spread of COVID-19 such as travel bans, “social distancing,” “stay at home” orders, business closures, and working-hours restrictions, which have all been implemented over the past few months. However, the majority of Indonesians work in the informal sector, which tends to be low-paying, and cannot work from home. Ultimately, this may incentivize NPIs’ non-compliance, undermining their effectiveness. The third key determinant affecting mobility is technology. In a world where access to digital services and information is becoming more widespread, it is likely that people’s preferences with regards to mobility will also be affected. Information-sharing devices and applications are democratizing mobility-related information. In the context of COVID-19, information can promote a higher awareness of benefits and costs associated with specific modal choices, depending on individual attitudes (Vecchio & Tricarico, 2019).

Understanding the correlation between these determinants and mobility requires the availability of population mobility data, which may be challenging to obtain through conventional sources of data (e.g., statistical surveys). Alternatively, researchers may rely on novel sources of real-time data from the private sector. One such data source is publicly available aggregate mobility data released by companies such as Google, Apple, and Facebook. These companies have released publicly available GPS-tracked aggregate mobility data, which indicates the aggregated change in mobility of users that accessed their services. This aggregate mobility data has proven to be useful as a crude proxy of economic activity in the absence of more detailed private-sector economic data (Ilin et al., 2020). Various studies have used this data in the literature to measure the impact of NPIs (Caselli et al., 2021, p. 2020), a proxy for consumption during the pandemic (Campos-Vazquez & Esquivel, 2021), and the monthly industrial production growth rate (Sampi & Jooste, 2020).

The use of unconventional sources of real-time data is becoming more common in the literature. In addition to mobility data, researchers have used real-time and disaggregated data related to economic activities such as household consumption from private-sector providers (Andersen, Hansen, Johannesen, & Sheridan, 2020; Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020; Carvalho et al., 2020; Chetty, Friedman, Hendren, Stepner, & The Opportunity Insights Team, 2020; Sheridan, Andersen, Hansen, & Johannesen, 2020; Watanabe & Otori, 2020). In particular, Chetty, Friedman, Hendren, and Stepner (2020), real-time tracking of business revenues, household spending, and employment growth using private-sector data, indicating the potential of these forms of data in providing researchers and policymakers with timely, disaggregated data, and policy-relevant information.

In this study, we attempt to utilize a public mobility dataset to provide an exploratory picture of the socioeconomic and policy determinants of mobility during the pandemic focusing on Indonesia. Our contribution to the literature is twofold. First, we contribute to the literature on the correlation between pre-existing socioeconomic factors and the economic impact of the COVID-19 pandemic, indicated through mobility specifically in Indonesia. This is significantly relevant, as the population in emerging and developing countries is likely to suffer more economic damage because of the pandemic. NPIs are also likely to cause more economic damage due to the vast size of the informal sector and the gap in access to digital technology. Unlike the population in developed countries, a substantially lower proportion of jobs can be performed from home (Alfaro, Chari, Greenland, & Schott, 2020). This is also worsened by weak social programs and the absence of unemployment benefits necessary to cushion households from the economic shock caused by the pandemic. Nevertheless, that is not to say that the population in developed countries was not affected. For example, in the Euro Area, people working in contact-intensive retail sectors, tourism, and small manufacturing are likely to also suffer from the impact of the pandemic (OECD, 2020). Fortunately, greater access to new forms of digital services such as electronic sales, geo-localization, and customer-adapted collection and delivery services can somewhat mitigate this effect for the population in developed countries (Tricarico & De Vidovich, 2021). Workers in developed countries may instead shift to these new types of jobs as a result. Second, this study contributes to the emerging literature on economic impact assessments of COVID-19 using aggregate mobility data. We use publicly available data from movement range maps under the Facebook Data for Good Initiative and the March 2019 Indonesian National Socioeconomic Survey (SUSENAS) to analyze the socioeconomic and policy determinants of mobility during the pandemic. Details regarding the data are contained in the Appendix.

The remainder of this paper proceeds as follows. In Section 2, we review the existing literature. Thus, we discuss our data and empirical strategy in Section 3 and conduct an exploratory analysis regarding the socioeconomic and policy determinants of mobility in Section 4. In the final section, we present the conclusions of this study.

2. Literature review

To have a better and quicker response to crises, we utilize newly available private-sector data, which has provided researchers with opportunities to estimate the impact of the pandemic in real-time. In the past, researchers had to rely on data from surveys and statistics published by public authorities to accurately estimate the impact of an exogenous crisis on the economy. Although they are complete and extensive, these surveys and statistics are of very low frequency (in the case of national accounts, every three months), with long time lags between data collection and data publication (Chetty et al., 2020).

The increasing adoption of digital technology in various economic transactions currently allows researchers and policymakers to track changes in various economic indicators in real-time. This is especially crucial as researchers and policymakers require fast and timely information for policy responses during the pandemic. Thus far, Chetty et al. (2020) is the most extensive research that uses these new real-time private-sector data. They obtain private-sector data on various economic indicators such as job openings, household spending, small business revenues, and employment in real-time down to the ZIP-code level. Their findings indicate that employment recovery for low-income earners is significantly slower than that for high-income earners (i.e., a K-shaped recovery). Their study also demonstrated that stimulus payments were effective in increasing household spending, particularly among the poor.

Other studies also utilize similar forms of private-sector data to assess changes in economic activity. Andersen et al. (2020) identify that aggregate spending in Denmark decreased by 27% seven weeks following the shutdown of the Danish economy due to the pandemic. Similar findings were also echoed by Baker et al. (2020), who identified that individuals initially increased their total spending by 40% in the early weeks of the pandemic, before decreasing their spending by 25–30% as the virus continued to spread. Similarly, using high-frequency transaction data from a large bank, Carvalho et al. (2020) determine sustained expenditure reductions among individuals immediately after the national lockdown. Unfortunately, such fine-tuned studies are only possible in developed countries with high financial and digital inclusion degrees.

In the previous literature, the role of employees in various business sectors on mobility improvements in these areas was also discussed. A study by Gauvin et al. (2020) in Europe indicates that the economic forces of a working-force local system with various phases and their associated policy of mitigation affecting separate categories of workforce primarily describe mobility distinction. Relatively smaller mobility reductions characterized areas with a relatively large labor force in the agricultural sector during the lockdown and the second wave of COVID-19. They argue that this is possible because the entire agricultural sector remains active to ensure food provision, even during the tightest lockdown periods. Furthermore, in provinces where more workers were working in the industry, mobility declined more before and after the lockdown, as more workers were not paid their salary. It also declined more in the face of relatively high unemployment, reflecting an added burden of constraints in low-employment areas. The proportion of workers in the service sector did not justify many improvements in mobility until lockdowns; however, reopening became a significant factor because they were linked in a constructive way to decrease mobility. One potential reason is that many people who work in facilities either work remotely or are unable to work. This can be verified by a study by Bonacini, Gallo, and Scicchitano (2021), which indicated that financial, information, and communications insurance; professional services; business services, and public administration are distinguished by a relatively large proportion of workers with a high level of work from home (WFH).

Previous literature has studied the socioeconomic determinants of mobility during the pandemic using aggregate mobility data. Using smartphone-location data from Indonesia, Colombia, and Mexico, Fraiberger et al. (2020) identify that mobility reductions for those in the top decile of wealth are twice as much as those in the bottom decile of wealth. Wright et al. (2020) also identified that residents in low-income areas in the United States complied less with social distancing measures compared to high-income areas. They also determine that stimulus transfers significantly improved social distancing. Similarly, Bennett (2021) identified that lockdowns effectively reduced the number of new cases in high-income areas, while null effects were identified in low-income areas. Dueñas, Campi, and Olmos (2020, p. 11850) study of mobility and socioeconomic characteristics in Bogota, Colombia identifies that mobility flows were higher in areas with good socioeconomic conditions before COVID-19. After COVID-19, mobility flows in areas with relatively bad socioeconomic conditions appear to decline less than those with good socioeconomic conditions. Bonaccorsi et al. (2020) analyzed mobility using Facebook mobility data in Italy and identified that mobility contraction due to lockdown is stronger in municipalities with relatively high inequality and low income per capita. Caselli et al. (2021, p. 2020) studied the heterogeneity in mobility reduction according to age and gender using smartphone mobility indicators in Italy, Portugal, and Spain. They identify that lockdowns have a stronger impact on women and younger cohorts. The literature on socioeconomic determinants of mobility during the pandemic indicates that areas with bad socioeconomic conditions tend to experience relatively lower mobility reductions because of lower compliance with mobility restrictions and higher costs of voluntary social distancing.

Past studies have also used aggregate mobility data to assess the impact of government restrictions on mobility limits. Using the Google aggregate mobility dataset, Mendolia, Stavrionova, and Yerokhin (2021) conclude that 14% of mobility reductions result from voluntary mobility restrictions, while the rest is because of government actions. Employing a generalized linear model using mobility data from Apple and Google, Snoeijer, Burger, Sun, Dobson, and Folarin (2020) identify that implementing lockdown measures and limiting public gatherings had the greatest effect on the rate of mobility change. Conversely, Chetty et al. (2020) identified that reopenings do not substantially increase mobility if COVID-19 cases are high as people voluntarily reduce their mobility to minimize the risk of contracting the disease. This is especially true for people in the relatively high-income bracket. Concerning this literature, studies differ in whether aggregate mobility declines are mostly caused by NPIs or by voluntary social distancing.

3. Materials and methods

We utilized the Facebook movement maps data to assess the level of and change in mobility in 480 Indonesian regencies

(Kabupaten) and cities from March 1, 2020, to January 18, 2021. The movement range maps data are obtained from the GPS location history of Facebook users who opted for location history functionality. These data were subsequently anonymized using differential privacy methods. Two movement variables were generated in the data. The primary variable used for mobility in this study is the change in the movement metric. The metric quantifies how much people move around by counting the number of level-16 Bing tiles (approximately 600 m × 600 m in the area at the equator) they are seen within a day (FB reference). The total number of tiles visited is subsequently divided by the total number of people in a region to create the average number of tiles visited for a region for any given day. This measure of mobility was subsequently compared with the values during the baseline period in the four weeks of February, from February 2 to February 29. The second variable is the Stay Put metric, which indicates the percentage of users who stay near or at home. This variable is calculated by measuring the percentage of users who are only observed in one single level-16 Bing tiles during a day.

For Indonesia, the level of data reaches the subnational level of the city and regency. Cities and regencies with fewer than 200 location-traceable users were excluded from the dataset. This guarantees that the aggregate mobility data for every regency and city in the database consist of at least 200 people. We opt to use aggregate mobility data from Facebook rather than from other sources, such as Google or Apple, because of several factors. First, aggregate mobility data from Facebook are available up to the city and regency level, which allows for higher sampling power and a more disaggregated analysis. This is in contrast to aggregate mobility data from other sources available only at the provincial level. Second, the definition of variables and the measurement process are clearly explained and described for the Facebook aggregate mobility data. This allows us to minimize the possibility of faulty and biased interpretations.

To determine the correlation between pre-pandemic socioeconomic indicators and reductions in aggregate mobility during the pandemic, we match the available public mobility data with regency and city-level data from the March 2019 SUSENAS. The survey is administered to approximately 1.3 million individuals in approximately 300,000 households across Indonesia and is representative up to the regency and city level. Thus, we conducted an exploratory analysis using simple regression techniques and scatterplot analysis to determine correlations between pre-pandemic socioeconomic indicators and changes in aggregate mobility. These indicators include indicators of urbanization, sectoral composition, income, poverty, and access to digital technology. We also conduct a regression analysis to determine the joint correlation and causation of these indicators on aggregate mobility. We performed three models using different methods and characteristics. Model 1 uses the ordinary least squares (OLS) method without any influence from the region. Model 2 uses the fixed-effect model by including the influence of seven islands in Indonesia compared to Sumatra Island. Finally, Model 3 uses a fixed-effect model but includes the influence of 34 provinces in Indonesia compared to Aceh Province. The three models are summarized as follows.

$$\begin{aligned}
 \text{Mobility}_{i,t} = & \alpha + \beta_1 \text{Formal}_{i,t} + \beta_2 \text{Education}_{i,t} + \beta_3 \text{Expenditure}_{i,t} + \beta_4 \text{Manufacture}_{i,t} + \beta_5 \text{Tourism}_{i,t} + \beta_6 \text{Agriculture}_{i,t} \\
 & + \beta_7 \text{Computer}_{i,t} + \beta_8 \text{Phone}_{i,t} + \beta_9 \text{Internet}_{i,t} + \beta_{10} \text{Urban}_{i,t} + \eta_i + u_{i,t}
 \end{aligned}$$

where ‘Formal’ is the proportion of workers in the formal sector, ‘Education’ is the proportion of high school graduates, ‘Expenditure’ is per capita expenditure at the household level on a logarithmic scale, ‘Manufacture’ is the proportion of workers in the manufacturing sector, ‘Tourism’ is the proportion of workers in the tourism sector, ‘Agriculture’ is the proportion of workers in the agricultural sector, ‘Computer’ is the proportion of households that have computers, ‘Phone’ is the proportion of households that own a phone, ‘Internet’ is the number of households using internet access, ‘Urban’ is a dummy variable where 1 implies that the district/city has a proportion of the population living in the urban area that is greater than 50%, and 0 is the opposite; and η_i is a fixed-effect control for the region (by island and province).

4. Results and discussions

We analyzed the relationships between the socioeconomic pre-pandemic and aggregate mobility shifts in a descriptive way. This includes urbanization metrics, demographic factors, sector diversity, and access to digital technologies. To determine the joint connection of these metrics with the overall mobility, we also performed regression analysis and the summary statistics of all factors.

4.1. Exploratory data on mobility

4.1.1. Mobility in general and urbanization metrics

We define three different periods of mobility reduction in line with changes in policy and public behavior (see Table 1 and Fig. 1).

Table 1
Summary Statistics of Change in Mobility (national population-weighted) Relative to February Baseline.

| | (1) | (2) | (3) |
|--------------------|-------------------------|------------------------------|-------------------------------|
| | March 1st – May 23rd | May 24th – September 13th | September 14th – January 18th |
| Mean | –21% | –9% | –9% |
| Standard Deviation | 0.124 | 0.054 | 0.030 |
| Minimum | –42% | –24% | –19% |
| Maximum | 3% | 1% | –1% |
| N | 84 | 113 | 127 |
| Total Observations | 324 | | |

The first period was from March 1 to May 23, 2020. March 1 marks the date when the first domestic COVID-19 case was confirmed. Voluntary mobility restrictions and policy interventions significantly decreased mobility. During this period, many cities and regencies in Indonesia saw substantial declines in mobility, as local governments imposed strict lockdowns through a program called the *Pembatasan Sosial Berskala Besar* (PSBB) or large-scale social restrictions. The aggregate mobility during this period was at its lowest, with the mean population-weighted mobility declining by 21% compared to the baseline in February 2020. May 23 marked the end of this period as Eid Fitr celebrations, Indonesia's most important public holiday, began. Shortly afterward, and intending to reinvigorate the economy, local governments across Indonesia began relaxing existing mobility restrictions and allowing the reopening of business establishments, mainly retail businesses.

From May 24 until the end of August, mobility started increasing and almost returned to normal levels in August. The average mobility decline during this period was only 9%. However, the increasing number of cases and deaths eventually led to the reimposition of lockdowns and an increase in voluntary social distancing. Jakarta and the province of Banten reimposed the PSBB on September 14 and mobility dropped to a relatively low level, especially in Java. Interestingly, although Jakarta and Banten were the only two regions that reimposed PSBB, mobility indicated a decline in other provinces as well, suggesting a spillover effect from the reimposition of NPIs. We define September 14 as the beginning of the 3rd period, and mobility was recovered again in November. However, in mid-January, mobility began to decline sharply as the preceding holiday period led to an increase in the number of new cases, deaths, and hospitalizations. In response, the government imposed an NPI policy called the *Penerapan Pembatasan Kegiatan Masyarakat* (PPKM) from January 11, 2021. This policy is applied to the entirety of Java and Bali; however, it is far less stringent than past PSBB regimes. As of January 18, the policy is ongoing.

We also determined variations in aggregate mobility in different islands of Indonesia (Table 2). In the 1st period (March 1-May 23), the decline in mobility was drastic in all regions of Indonesia. However, the region of Java stands out as being the worst affected by mobility decline. During this period, mobility decreased by 21.7%, on average, and 7.4% more than a similar observed decline in the region of Maluku and Papua. In the 2nd period, the recovery in mobility and mobility across all regions was largely synchronized and least divergent. However, in the 3rd period, mobility across regions became increasingly divergent, as evidenced by the value standard deviation to daily mean between regions, which decreased in the 2nd period, and increased in the 3rd period. While Maluku and Papua's aggregate mobility largely returned to normal (mean 1.4%, above February 2020 levels), Java's aggregate mobility worsened compared to the 2nd period. This is because of the stronger restrictions imposed in Java and the relatively large number of cases. This indicates that regions outside Java are recovering significantly faster than Java (mobility proxies for various economic activities). These evidences are depicted in Fig. 2 and the findings are rather intriguing when looking at the map of mobility dispersion by district/city in Indonesia.

Like Table 2, mobility declined dramatically during the first period in all areas of Indonesia. The map clearly illustrates that the regions of Kalimantan and Sulawesi have had the most significant decline in mobility, as practically all locations are covered in red color. During the second phase, the rebound in mobility across all areas was substantially coordinated and least divergent. Nonetheless, movement among areas grew increasingly varied in the third period. While Sumatra, Sulawesi, and Papua have the highest aggregate mobility recovery, the territories of Java and Kalimantan have deteriorated during the second phase. This aligns with previous table findings, demonstrating that mobility outside of Java recovers faster than mobility inside Java.

We also identified differences in aggregate mobility when comparing urban and rural areas. We define urban areas as areas where more than 50% of the population lives in an urbanized area, as defined by the household answer in the SUSENAS. We define rural areas as the opposite, where more than 50% of the population lives in a non-urbanized area. This suggests that urban areas are comparatively affected by COVID-19 and subsequent recessions than rural areas (see Fig. 3). It may be due to the lower population density of rural areas and the concentration of jobs in agriculture, which are not as susceptible to COVID-19 spread compared to manufacturing and services jobs. These results are consistent with Bonaccorsi et al. (2020), who analyzed Facebook mobility data in Italy. The findings suggest that the impact of lockdowns is more substantial in municipalities with relatively high fiscal capacity. Furthermore, they determine evidence of a segregation effect since mobility contraction is more increased in cities where inequality is more elevated and in those with lower per capita incomes.

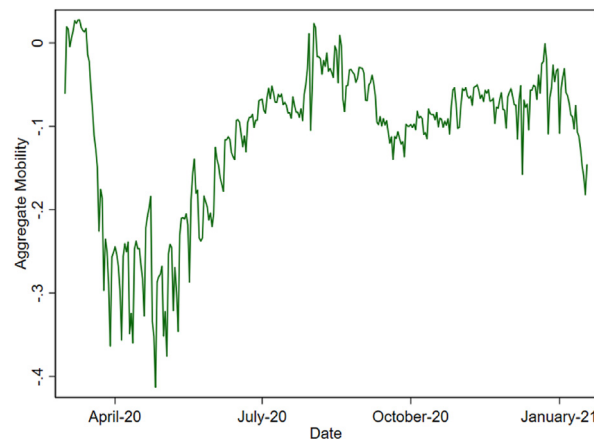


Fig. 1. National mobility.

Table 2Summary statistics of change in mobility by geographic characteristics (*population-weighted*) relative to February baseline.

| Period | (1) | | | (2) | | | (3) | | |
|--|----------------------|--------|-------|---------------------------|--------|-------|-------------------------------|--------|-------|
| | March 1st – May 23rd | | | May 24th – September 13th | | | September 14th – January 18th | | |
| | N | Mean | STDEV | N | Mean | STDEV | N | Mean | STDEV |
| Java | 84 | -21.7% | 0.133 | 113 | -10.7% | 0.059 | 127 | -11.6% | 0.021 |
| Sumatera | 84 | -17.2% | 0.104 | 113 | -6.4% | 0.040 | 127 | -5.7% | 0.032 |
| Kalimantan | 84 | -17.3% | 0.105 | 113 | -8.5% | 0.042 | 127 | -6.2% | 0.023 |
| Bali & Nusa Tenggara | 84 | -18.9% | 0.104 | 113 | -7.9% | 0.060 | 127 | -6.1% | 0.019 |
| Sulawesi | 84 | -19.5% | 0.119 | 113 | -7.3% | 0.061 | 127 | -2.4% | 0.020 |
| Maluku & Papua | 84 | -14.3% | 0.079 | 113 | -8.2% | 0.055 | 127 | 1.4% | 0.028 |
| Std. Dev to Daily Mean between Regions | 504 | 3.16% | | 678 | 2.18% | | 762 | 4.51% | |
| Urban | 84 | -23.0% | 0.133 | 113 | -12.5% | 0.053 | 127 | -12.7% | 0.022 |
| Rural | 84 | -16.8% | 0.109 | 113 | -5.6% | 0.053 | 127 | -4.6% | 0.021 |

4.1.2. Mobility and demographics

The following analysis is based on city and regency-level aggregate indicators. We also analyzed the correlation between mobility and labor indicators (Fig. 4). Our analysis indicates that cities and regencies with higher percentages of formal jobs experienced larger mobility declines than those with lower percentages of formal jobs. A 10% increase in formal jobs is associated with a 3.1% decline in aggregate mobility. We posit that this is because of the nature of informal jobs that are usually performed outdoors and cannot be performed from home. Furthermore, those in informal jobs could be less capable of staying at home, as their income is comparatively lower than those in formal jobs. This result is consistent with another study in Columbia, which identified that informal workers were more mobilized than formal workers since the lockdown was implemented (Dueñas et al., 2020, p. 11850) and in Indonesia (Khoirunurrofik, Abdurrachman, & Putri, 2022).

The correlation between mobility and the proportion of high school graduates is similar to that between mobility and per capita expenditure. If the proportion of high school graduates in the area increases by 10%, the level of mobility will decrease by 2.5%. Meanwhile, for every 10% increase in per capita spending, mobility decreases by 0.98%. This is quite natural because those who graduate from high school have a relatively high level of spending, resulting in individuals isolating themselves more easily and working by moving to remote jobs than low-income people with low skills. These results are consistent with those of Dueñas et al. (2020, p. 11850), who indicated that since the lockdown was implemented in Bogotá, Colombia, residents with bad socioeconomic conditions have indicated a lower decline in mobility flows and the opposite for relatively good socioeconomic conditions. During the partial lockdown, the gap between reduced mobility flows for relatively low and high socioeconomic strata increases, indicating that residents with higher socio-economic conditions can maintain lower mobility for longer periods.

We also analyze the relationship between several economic sectors and mobility (see Fig. 5). Our first results in this section indicate a positive association between the number of workers in the manufacturing sector and aggregate mobility, with the result that each 10% increase in the proportion of workers in the manufacturing sector correlated with a 2.7% decrease in aggregate mobility. The percentage of labor in the tourism sector is also related to mobility. We define labor in the tourism sector as the percentage of the labor force that works in the transportation, dining, and accommodation sectors, according to the SUSENAS. Each 10% increase in the percentage of labor in the tourism sector is negatively related to a 6% decrease in aggregate mobility. This is quite natural considering travel restrictions and large-scale social restrictions that lead the tourism sector, which requires high mobility, to be one of the most impeded sectors. Consequently, regions that depend on the tourism sector experienced a decrease in mobility. Gössling, Scott, and Hall (2020) affirm that global tourism has declined significantly because of travel restrictions and lockdowns, which have caused the number of global flights to decline by more than half. The latest data from the World Tourism Organization (UNWTO) also states that international arrivals dropped by 74%, and destinations worldwide welcomed 1 billion fewer international arrivals in 2020 than in 2019.

The results further indicate a positive relationship between the percentage of labor in the agricultural sector and the level of mobility. A 10% increase in the workforce in the agricultural sector correlates with a 1.4% increase in aggregate mobility. This result is similar to that of Gauvin et al. (2020), with a sample from all regions in Europe. The results indicate that areas with a relatively large labor force in the agricultural sector were characterized by relatively small mobility reductions, both during the lockdown and in the second wave of COVID-19. They argue that this is possible because the entire agricultural sector remains active to ensure food provision, even during the tightest lockdown periods.

We also analyzed the correlation between mobility and various indicators of digital inclusion (see Fig. 6). Our analysis indicates that for every 10% increase in phone ownership in a city or regency, mobility decreases by 2.8%. For computer ownership, every 10% increase was associated with a mobility decrease of 2.7%. Similarly, for Internet use, every 10% increase is associated with a mobility decrease of 2.7%. We believe this is because increased access to digital technology encourages people to perform economic activities at home rather than outside, lowering the cost of complying with social distancing measures. Banskota, Healy, and Goldberg (2020) indirectly confirm this through their research, which summarizes 15 cell phone applications that can improve the quality of life of older adults (OA), especially during social distancing or self-quarantine. They indicated that cellular technology such as applications could help them stay connected with family remotely and maintain mobility, considering that OA are at a relatively high risk of contracting the virus.

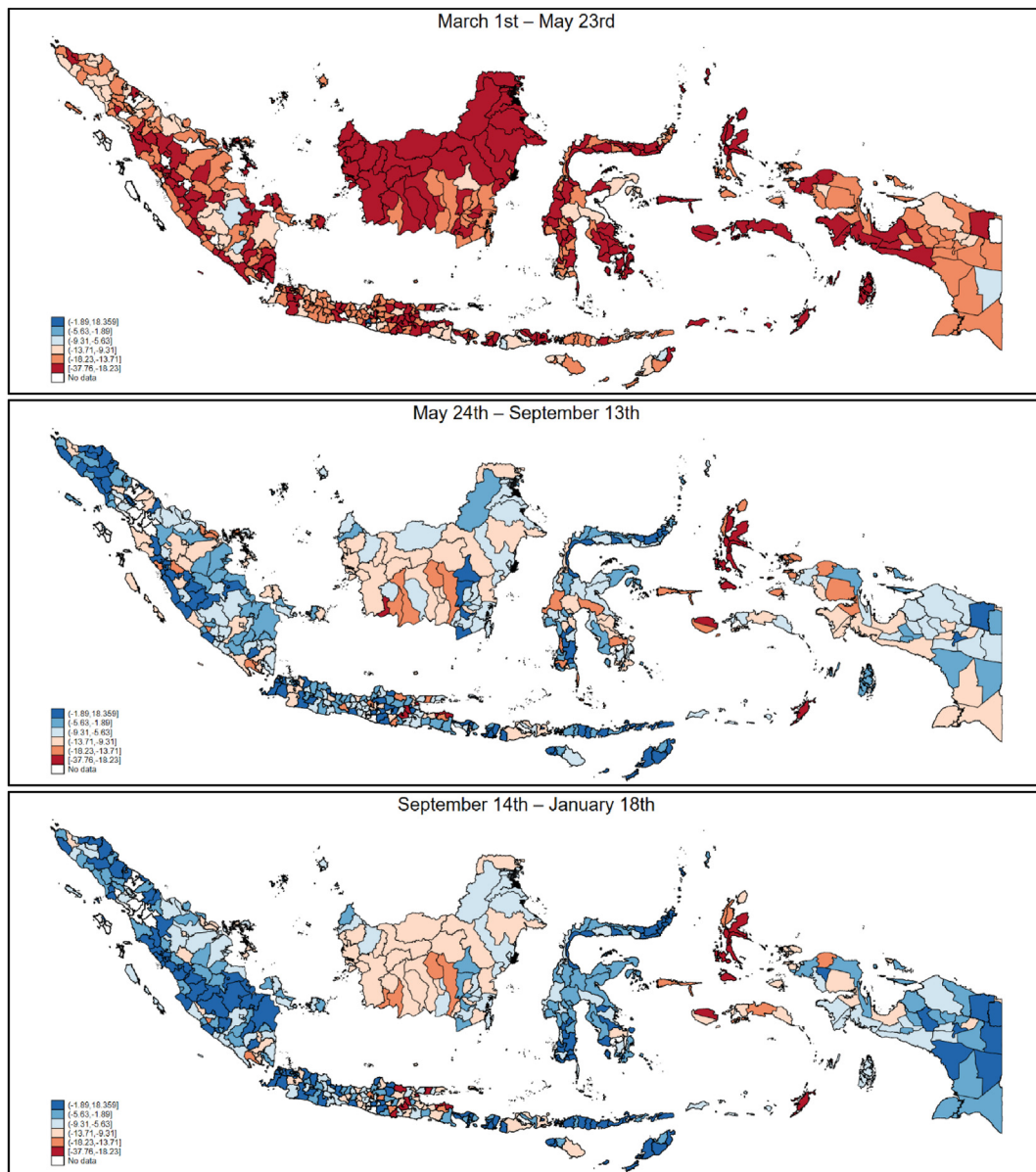


Fig. 2. Map of change in mobility across regions (*population-weighted*) relative to February baseline.

4.2. Determinant factors of mobility

Although the previous findings are plausible and applicable to the literature, statistical relationships cannot be concluded as causation. Therefore, we must conduct a regression analysis to determine whether the statistical association of factors from previous findings has a causal relationship with aggregate mobility when combined into a single regression model. We summarize the data statistics for all the above variables, as presented in Table 3.

The total observations of 154,737 households indicate that the national average aggregate mobility reduced by approximately 9% from March 1, 2020, to January 18, 2021. Subsequently, the average proportion of formal sector workers to the total workforce was 29.1%. In other words, there is a sizeable gap between formal and informal sector workers in Indonesia. The proportion of the population with high school graduates dominates among different levels of education, which is approximately 26.5% of the total population over 15 years of age. Before being converted to logarithmic form, the average per capita expenditure at the household level was approximately IDR 1 million. Regarding business fields per sector, the average workforce in the agricultural sector continues to dominate the labor sector, accounting for 37.2% of the total workforce. Meanwhile, the average workforce in the manufacturing and tourism sectors was 8.85% and 9.53%, respectively. Concerning digital inclusion, the percentage of households that own a phone

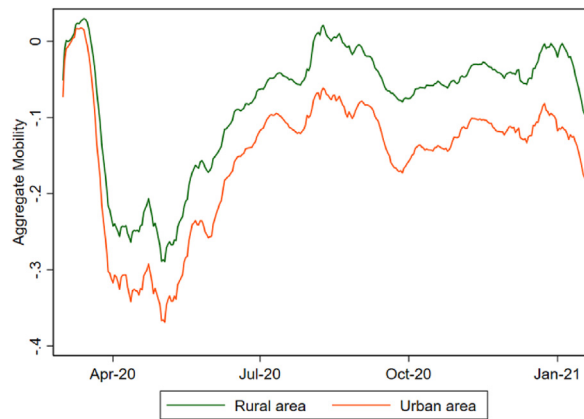
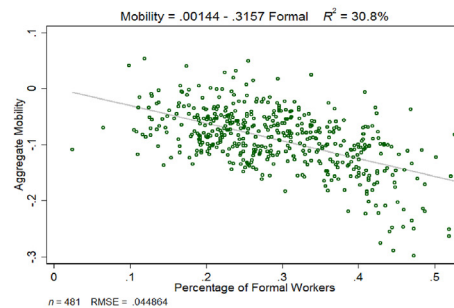
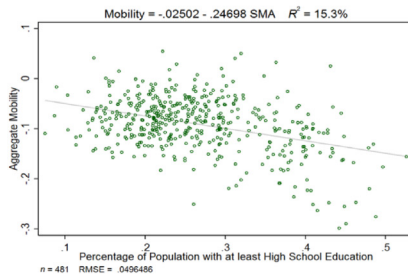


Fig. 3. Mobility in urban and rural areas.

A. Mobility and Size of Formal Sector



B. Mobility vs Proportion of High School Graduates



C. Mobility and Expenditure per Capita

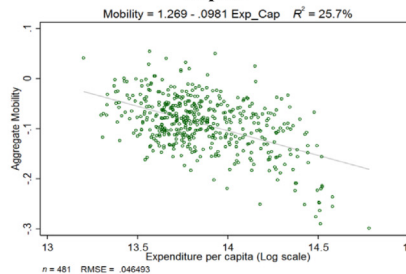


Fig. 4. Association between mobility and socioeconomic factors.

(55.5%) is significantly higher than that of households that own a computer (19.6%). Regarding Internet usage, the average number of households in a district/city that has used the Internet is approximately 241,000 residents, or approximately 38% of households in the area. Finally, the population in the urban area variable is a dummy variable, where 1 indicates that the district/city has a proportion of the population living in the urban area that is greater than 50%, and 0 indicates the opposite. In other words, districts/cities classified as urban areas accounted for 43.7% of the total area.

Subsequently, we performed a regression analysis, as presented in Table 4. Model 1 uses the OLS method without any influence from the region. Model 2 uses the fixed-effect model by including the influence of seven islands in Indonesia compared to Sumatra Island. Finally, Model 3 uses a fixed-effect model but includes the influence of 34 provinces in Indonesia compared to Aceh Province.

Although the formal sector worker results in Model 3 indicate a positive correlation, Models 1 and 2 indicate the same negative correlation and significant impact on aggregate mobility, as in the previous section. In Model 2, this implies that a 1% increase in the proportion of formal sector employees significantly reduces aggregate mobility by 3.54%. We believe this is because of the nature of informal employment, which is typically performed outside and cannot be performed from home. Furthermore, since their compensation is lower than that of those working in formal employment, those working in informal employment may be less able to stay at home.

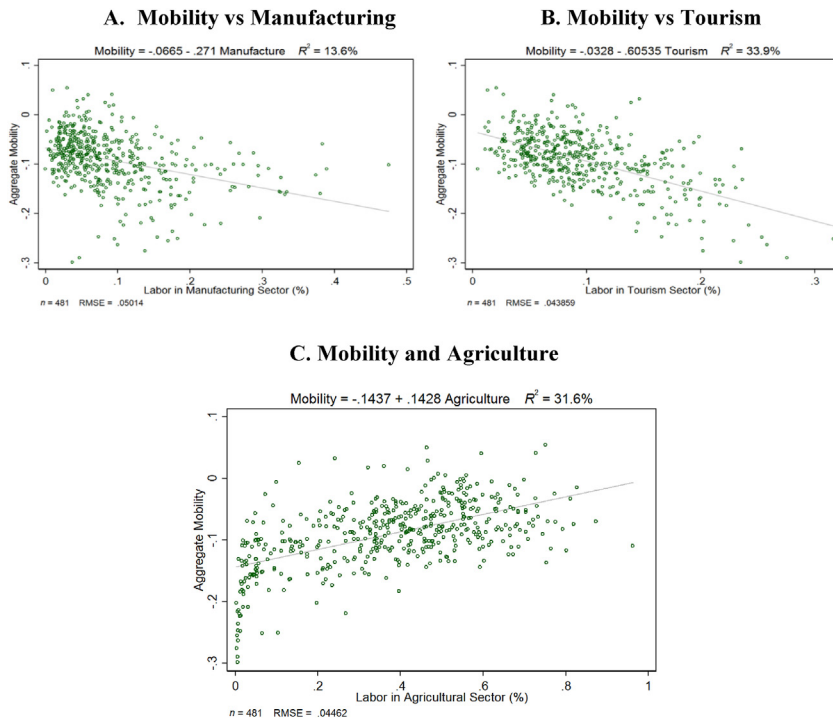


Fig. 5. Association between mobility and job sectors.

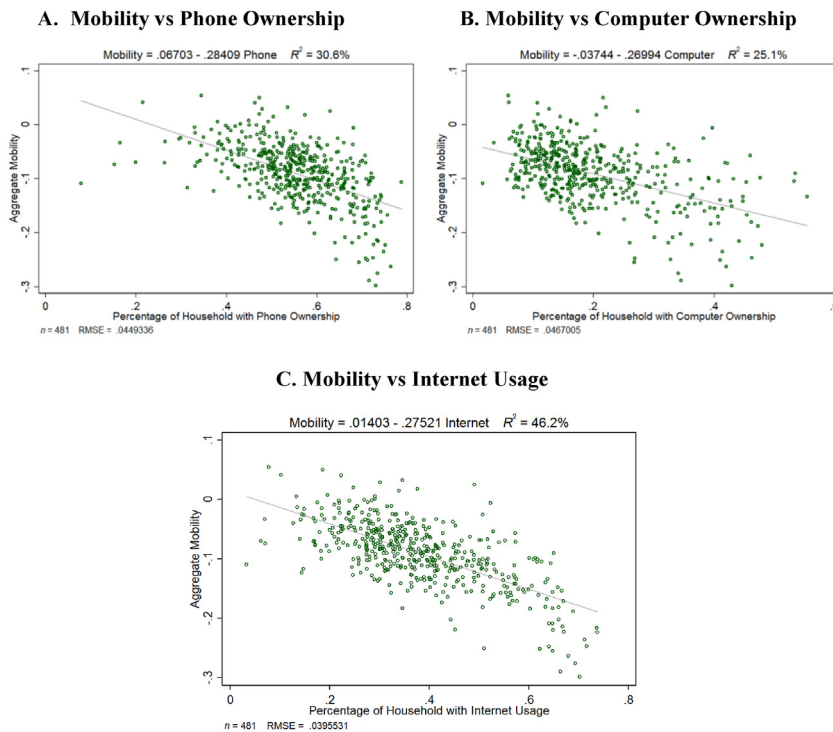


Fig. 6. Association between mobility and digital inclusion.

In Model 1, the percentage of high school graduates and per capita spending in Models 2 and 3 have a negative correlation, consistent with the statistical relationship in previous findings. A 1% increase in the proportion of high school graduates decreases aggregate mobility by 9.5–9.8%. Additionally, an increase in per capita expenditure considerably decreases aggregate mobility. The two variables

Table 3
Summary statistics.

| Variables | Mean | Stdev | Min | Max |
|------------------------------------|---------|---------|---------|-----------|
| Aggregate Mobility | −0.0906 | 0.115 | −0.800 | 1.288 |
| Size of Formal Sector (%) | 0.291 | 0.0937 | 0 | 0.526 |
| High School Education (%) | 0.265 | 0.0848 | 0.0350 | 0.527 |
| Expenditure per Capita (Log Scale) | 13.86 | 0.278 | 12.96 | 14.78 |
| Labor in Manufacturing Sector (%) | 0.0885 | 0.0733 | 0 | 0.475 |
| Labor in Tourism Sector (%) | 0.0953 | 0.0515 | 0 | 0.317 |
| Labor in Agricultural Sector (%) | 0.372 | 0.210 | 0.00298 | 1 |
| Computer Ownership (%) | 0.196 | 0.0992 | 0 | 0.555 |
| Phone Ownership (%) | 0.555 | 0.102 | 0.0716 | 0.787 |
| Internet Using | 241,173 | 361,181 | 0 | 3.013e+06 |
| Population in Urban Area | 0.437 | 0.307 | 0 | 1 |

Note: Observation = 154,737.

have the same correlation because those who graduate from high school have a relatively high level of spending, allowing them to isolate themselves and work remotely more readily than those with low incomes.

Furthermore, the regression results for the business sectors indicated varied results. According to all models, a 1% increase in jobs in the tourism industry decreases aggregate mobility by 2–5%. The results that are consistent with the statistical relationship in the previous findings are quite reasonable because Indonesia implements a strict travel restriction, resulting in a substantial decrease in aggregate mobility in regions with a relatively high concentration of tourism-sector workers. Conversely, the manufacturing sector reveals a positive correlation, which contradicts previous findings. This is because the manufacturing sector is still running and is not adversely affected by the existence of social restriction policies, resulting in greater mobility in regions with a higher concentration of manufacturing workers. The agricultural sector results also demonstrate contradictions with previous findings. Apart from indicating negative and significant results in Models 1 and 2, the results in Model 3 do not indicate any significance. We suspect that this negative outcome is because of disruptions in food distribution in Indonesia and the government's rice import policy. This makes it difficult for areas with a relatively high percentage of agricultural workers performing their jobs, resulting in reduced mobility in these regions.

Regarding the three digital inclusion variables, almost all models indicate consistent results with the explanatory analysis in the previous section, except for the phone-ownership variable in Model 3. This significant and negative correlation indicates that access to digital technology has an impact on aggregate mobility. Another study indirectly confirms this result, stating that technology such as apps would help OA stay connected with their families remotely, causing them to stay at home (Banskota et al., 2020).

Another intriguing finding was the variation in the correlation between the islands. Only the Java-Bali, Kalimantan, and Sulawesi islands indicate a significant and negative correlation with aggregate mobility, with a base value on Sumatra Island. The island of Java-Bali has the highest coefficient, with a 4.4% decrease in aggregate mobility compared to Sumatra Island. The islands of Nusa Tenggara and Maluku, conversely, indicate a positive correlation. All the regression results are in line with the findings in Table 2 of the explanatory analysis section. The insignificant results from the island of Papua are presented in Table 4 since the islands of Papua and Sumatra have a similar level of mobility. These findings suggest that the social restriction policy, particularly for the PPKM, which is primarily enforced in the Java-Bali region, has a substantial impact on the decrease in mobility in that region compared to other regions.

Finally, when the findings are examined at the provincial level, they are highly coherent for all regions. When compared to Aceh Province, 27 provinces indicated a significant and negative correlation. The provinces of Bali, Jakarta, and Yogyakarta had the highest decreases in mobility, with scores of 13.8%, 11.2%, and 7.7%, respectively. Conversely, only Gorontalo and Maluku provinces had positive and significant results, while only four provinces, namely North Maluku, East Nusa Tenggara, Central Sulawesi, and Southeast Sulawesi, had insignificant results. This finding supports the results of the regression model by island, which indicates that provinces on Java-Bali Island have experienced the greatest decline compared to other areas.

Our findings indicate that there are significant heterogeneities in mobility that are directly correlated with various indicators such as urbanization, employment sectors, labor market indicators, level of education, and income (indicated through expenditure per capita). In general, wealthier and more urbanized areas have a relatively sizeable formal sector, employ more people in manufacturing and/or tourism, possess a more educated labor force, and are more digitally connected; they tend to experience relatively large declines in mobility. These correlations persist even when these determinants are jointly regressed. Furthermore, our analysis reveals that specific regions in Indonesia are significantly more affected than other regions. Mobility in denser areas in Java and Bali experienced a more significant decrease in mobility compared to other regions. Our exploratory analysis indicated that there are clear correlations between pre-pandemic socioeconomic determinants, policy factors, and changes in aggregate mobility.

5. Conclusion

The COVID-19 pandemic has created massive disruptions in the global economy. The impact on public health and economic and social insecurity has jeopardized people's long-term livelihoods and well-being. Millions could not go to work, leading to a remarkable drop in occupation and unprecedented job losses. Our exploratory analytical findings indicate that the impact of COVID-19 on the economy, as indicated by mobility data, is highly correlated with various prior socioeconomic determinants. In general, areas that are richer and more urbanized have a relatively large formal sector, employ more people in manufacturing and/or tourism, possess a more

Table 4
Regression results.

| Aggregate Mobility | Model 1 | Model 2 | Model 3 |
|------------------------------------|----------------------------|----------------------------|----------------------------|
| Size of Formal Sector | −0.0750*** (0.00635) | −0.0354*** (0.00686) | 0.0411*** (0.00758) |
| High School Education | 0.0174*** (0.00517) | −0.0980*** (0.00570) | −0.0954*** (0.00673) |
| Expenditure per Capita (Log Scale) | 0.00284 (0.00196) | −0.00621*** (0.00222) | −0.0119*** (0.00263) |
| Labor in Manufacturing Sector | −0.0575*** (0.00585) | 0.0384*** (0.00644) | 0.0365*** (0.00693) |
| Labor in Tourism Sector | −0.290*** (0.0114) | −0.206*** (0.0110) | −0.0504*** (0.0125) |
| Labor in Agricultural Sector | −0.0910*** (0.00424) | −0.0615*** (0.00447) | 0.000725 (0.00506) |
| Computer Ownership | −0.0805*** (0.00575) | −0.0838*** (0.00586) | −0.107*** (0.00712) |
| Phone Ownership | −0.121*** (0.00528) | −0.0419*** (0.00602) | 0.00273 (0.00709) |
| Internet Using | −5.15e-08*** (1.01e-09) | −3.58e-08*** (1.04e-09) | −3.82e-08*** (1.13e-09) |
| Urban Area | −0.0227*** (0.00237) | −0.0104*** (0.00236) | −0.00959*** (0.00265) |
| Constant | 0.0589** (0.0258) | 0.136*** (0.0291) | 0.153*** (0.0340) |
| Observations | 154,704 | 154,704 | 154,704 |
| Island fixed effect | No | Yes | No |
| Province fixed effect | No | No | Yes |
| R-squared | 0.114 | 0.128 | 0.152 |

Note: Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

educated labor force, and are more digitally connected; they tend to experience relatively large declines in mobility. We hope that this will expand the literature regarding the socioeconomic determinants of mobility during the pandemic, with a particular reference to the case of a developing country, Indonesia. We also hope that policymakers in Indonesia will derive lessons from this study that will allow a more effective, timely, and well-targeted policy response.

This study has some limitations. First, the data that we possess can only connect socioeconomic determinants with mobility data, rather than more fine-tuned data such as consumer spending or business revenue data. The data and the statistical analysis in this paper are also cross-sectional rather than panel nature, which may limit the conclusions taken from this research. Second, due to data availability issues, we can only relate this mobility data to pre-pandemic socioeconomic indicators rather than compare it with post-pandemic indicators. For future research, it is required to have up-to-date data on socioeconomic indicators during and after the pandemic to better understand the socioeconomic determinants of mobility. Notwithstanding, in line with the emerging literature on this subject, our study indicates the novelty of using real-time data sources from the private sector, which holds promise as a novel data source in the future.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Facebook mobility data

Facebook movement range maps data are obtained from the GPS spot history of Facebook users who use the location history functionality. These data are then anonymized by applying different confidentiality methods. The final information reports two-movement variables: the change in movement metric and the “stay put” metric. The former calculates how much people move by counting the number of level-16 Bing tiles (approximately 600 m × 600 m in the area at the equator) within a day (Herdağdelen et al., 2020).

The aggregate number of tiles visited is then divided by the total number of people in the area to generate the average number of tiles visited for an area in a given day. This number is then compared with a similar number during the baseline period (February 2, 2020–February 29, 2020), to create a normalized index of aggregate mobility change. Change in mobility is thus calculated in the following manner:

$$\text{Change in mobility} = \frac{\text{Average number of tiles visited in a given day}}{\text{Average number of tiles visited in a similar day of week in February 2020 (baseline)}} - 1$$

The “stay put” metric captures those who stay near or at home by quantifying the percentage of users who are only noticed in one single level-16 Bing tile in a day. In this paper, only the change in movement metric is utilized. The dataset can be accessed online through this link: <https://data.humdata.org/dataset/movement-range-maps?>

SUSENAS (national socioeconomic survey)

The National Socioeconomic Survey is a biannual national survey conducted by Statistics Indonesia, the Indonesian government statistics agency. Conducted every year in the month of March and September, the survey covers a nationally representative sample of around 300,000 households. The March survey is representative up until the provincial level, while the September survey is representative up until the city/regency level. This paper uses data from the September 2019 survey. The survey asks questions that are related to socioeconomic indicators relevant for development. These indicators include educational attainment, employment, household expenditure, asset ownership, nutritional fulfillment, and others.

The data is proprietary and can be purchased from Statistics Indonesia. Further information regarding the data can be accessed through this link: <https://sirusa.bps.go.id/sirusa/index.php/dasar/view?kd=1558&th=2019>.

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