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How Do Sectoral Employment Structures Affect Mobility during the COVID-19 Pandemic? [§]

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Abstract: *As people's mobility determines the spread of COVID-19 virus, this paper scrutinises factors that drive their mobility responses during the pandemic. Utilising Google mobility data, labour force statistics and daily COVID-19 data, this study finds that mobility changes are induced by various heterogeneous behavioural responses across provinces in Indonesia. Variations in the pre-pandemic labour structure, people's perception of health risks and local policy settings define the mobility changes. In addition, behavioural responses are larger in the early pandemic phase, indicating the importance of arrangements to manage the situation in the early period.*

Keywords: COVID-19, Google mobility, employment structure

JEL Classification: R23; I19; 033

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1. Introduction

Since the coronavirus disease (COVID-19) outbreak started, social distancing, travel bans, lockdown, quarantines, and other limits on people's movement have been some of the main tools to stop the spread of the virus. These policies were popularised using the slogan *flattening the curve*, with varying degrees of success. These control measures have been successful in mitigating the spread of COVID-19 in China (Kreamer et al., 2020); however, many other countries have failed to employ them as the virus has exponentially infected their populations. As those interventions can have major economic impacts, many governments made trade-offs between health and economic concerns. Moreover, aside from social distancing interventions, people also maintain judgmental views on health risks and economic decisions. Therefore, it is reasonable to expect that underlying economic characteristics may also influence the effectiveness of such policies. This study scrutinises the economic aspects that could affect people's mobility. We utilise variations in the employment structure and policy settings in different regions in Indonesia.

Despite knowing its lifesaving benefits, many people do not adhere to social distancing policies. While some people may voluntarily choose to stay at home, some only do so because it is required by law, and some even resist the policy altogether. Various studies have analysed the effectiveness of government interventions to restrict people's mobility, with Askitas et al. (2020) finding that not all types work, with results differing in various countries. Similarly, a multi-country study by Maloney and Taskin (2020) found that restriction policies might have different effects depending on the implementation strategy, and showed that people in less-developed countries do not abide by restriction policies as much as people in more developed countries. They also emphasised the significance of voluntary individual responses to COVID-19 in reducing people's mobility. People weigh the potential benefit of avoiding the risks of infection against the ever-increasing cost of not leaving their home. These decisions may be influenced by the perception of the current situation in their local areas, such as perceived risks from knowing the number of new cases or the total cases in their region.

In aggregate, the level of social distancing adherence can be observed by the changes in people's local mobility after policies were implemented. Within a country, mobility changes vary by area, with some areas seeing a rapid decline prior to any lockdown measure, and other areas barely seeing any changes weeks after the pandemic started. Several possible reasons behind these variations include cultural and political differences, the varying level of enforcement or socioeconomic reasons. Frey et al. (2020) found that political and cultural aspects define the effectiveness of policies reducing people's movements. Painter and Qiu (2020) suggested that political beliefs explain US citizen behaviour in following the government's order to stay at home. Durante et al. (2020) found that social capital (civic value and culture) explains the compliance of social distancing policies in Italy. Socioeconomic factors also explain the variations in mobility responses. Bargain and Aminjonov (2020) explained that the poverty rate influences the decision to reduce activities and to stay at home. Income distributions also play a role, in which regions that have higher inequality experience larger mobility contractions (Bonaccorsi et al., 2020). Moreover, variability in structures of the labour market and demographic factors determine the spatial variations in human mobility patterns in response to the social distancing policies (Gauvin et al., 2020). Different types of jobs and the feasibility of working remotely also affect local mobility changes (Caselli et al., 2020). The spatial concentration of industries also explains the local responses in Italy (Ascani et al., 2020). This study contributes to the discussion by focusing on economic reasons; more specifically, at how the sectoral composition of employment within a province affects the changes in people's mobility in Indonesia.

One of the most important aspects of social distancing is the work from home (WFH) arrangements. However, WFH cannot be uniformly implemented. Some sectors and professions, particularly in services, require employees to be in a specific location or in proximity to customers. Complicating the situation is the extent of the informal economy in developing countries. Without any formal work arrangements, WFH is an unaffordable luxury for some workers. This means the economically vulnerable are at an even greater risk than the rest of the workforce of contracting the virus.

The structure of an economy, and the resulting sectoral composition of jobs, are collectively determined by factors in place long before the pandemic started. This economic precondition can influence how people respond to the pandemic and thus its severity and recovery. For example, if a local economy is dominated by tourism, most workers may not be able to work from home. Moreover, the local government may be reluctant to enforce social distancing because it can have severe economic impacts. Even without these rules, the severe economic impacts of the pandemic on tourism may leave many unemployed. In this regard, Indonesia provides a case study, with a wide variety of regions with different sectoral composition and local government responses. Regions vary by level of economic development, with some regions dominated by the tertiary sectors and others by the primary or secondary sectors. These variations allow us to study how each of these factors affects people's mobility during a pandemic. Of particular interest for policymakers is how different local government responses may affect people's mobility.

This study tests how sectoral employment structure and the number of published daily new cases of COVID-19 have impacted people's mobility. We argue that a sector's employment composition, along with the perceived risk of the pandemic, has a significant role in influencing people's decision to change their mobility level. We also test the effects on mobility of social distancing policies implemented over a given period to check the effectiveness of partial lockdowns. Additionally, we also investigate how time affects mobility to gauge the limit of people's willingness to stay at home. We argue that, over time, people's responses to COVID-19 have changed. In doing so, we utilise various time controls that may influence the trend of mobility.[1]

We utilise province-level Google mobility data that are updated daily. The composition of sectoral employment per province is derived from the National Labor Force Statistics of Indonesia (SAKERNAS) as per August 2019. We use the published daily data on provincial COVID-19 cases and apply a 1-day lag on the

[1] We include time trend, time trend squared and dummies for weekend and public holidays as well as festive days. We also control for variations in months and days using month fixed effects and day of the week fixed effects. Furthermore, we also interact the time trend with island dummies to capture different characteristics of each region.

number of cases to reflect people's perceptions of regional risks. We collect information on the implementation of regional containment polices. Additionally, we include the Oxford Stringency Index as a control (Hale et al., 2020).

We find that mobility changes are induced by various heterogenous behavioural responses across provinces. First, the pre-pandemic local structure of labour, as well as people's perspectives on the health crisis, together explain the pattern of mobility changes. Regions with larger percentages of primary sector workers did not have significant changes in workplace mobility in the early pandemic (first 120 days); in the later period (days 121 to 220), mobility declined. We argue that this was due to the increase in COVID-19 cases in those regions. Interestingly, regions with higher shares of people working in the secondary sector did not respond to COVID-19 cases during the observed periods. Meanwhile, provinces with a higher proportion of workers in tertiary sectors immediately responded to the pandemic by reducing their activities. However, the responses mostly occured in the early months. After several months of COVID-19, the mobility level did not change as the number of cases increased.

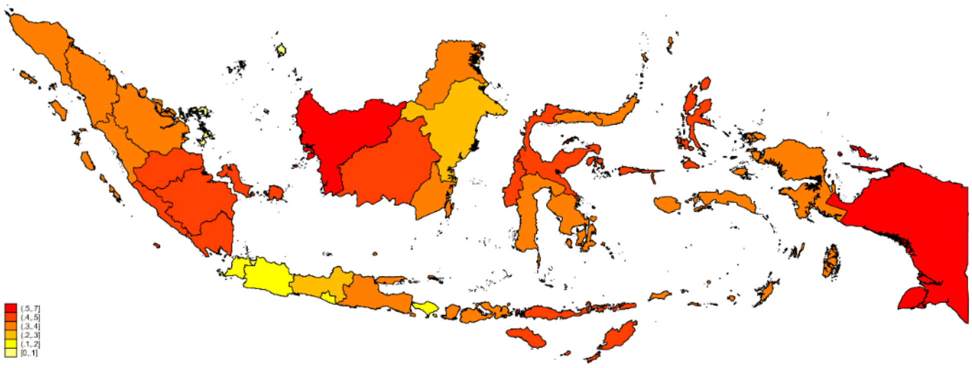
Second, this paper also finds that top-down nationwide intervention matters in reducing people's working mobility. Moreover, local social distancing policies are also effective at making people stay at home, but only in the early periods. Third, we find that people increase their activity at home and reduce their mobility in workplaces in the early months; however, the patterns are not linear. After several months, we find the opposite trend, where people tend to reduce their mobility in residential areas. This phenomenon shows that behavioural responses to a pandemic are larger in the early phase, indicating the importance of managing the situation in the early period. As time goes by, fatigue with both government- and self-initiated mobility restrictions can impact the number of COVID-19 infections.

2. Indonesian context

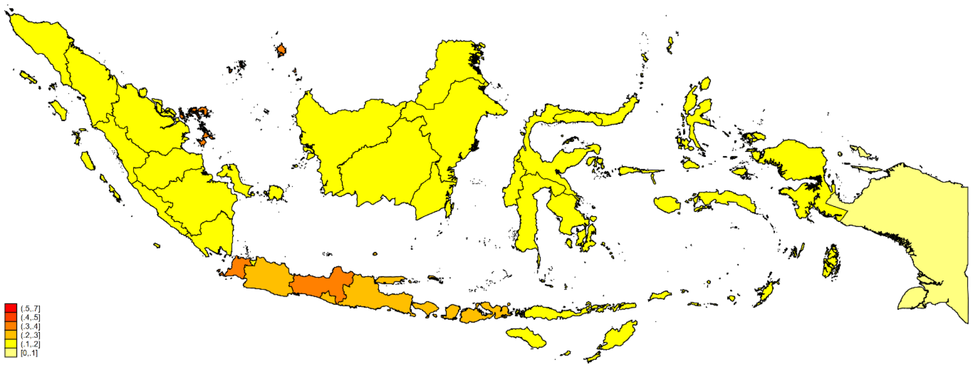
With more than 270 million people, Indonesia is the most populous country in Southeast Asia and also the fourth-most populous country in the world. Administratively, its thousands of islands are divided into 34 provinces. Each region has different characteristics, including economic structures. Many parts of Indonesia rely on resource-based sectors, such as agriculture, plantations, fisheries and mining. Due to infrastructure constraints in other regions, manufacturing is mostly located in Java, the most developed part of the country. Service sectors appear throughout the regions, but some high value-added services, such as information and communications technology, usually only thrive in the urban areas. Therefore, the composition of sectors and employment varies widely across provinces and districts (Figure 1a-c).

Figure 1. The Variations in Employment Sectors across Provinces

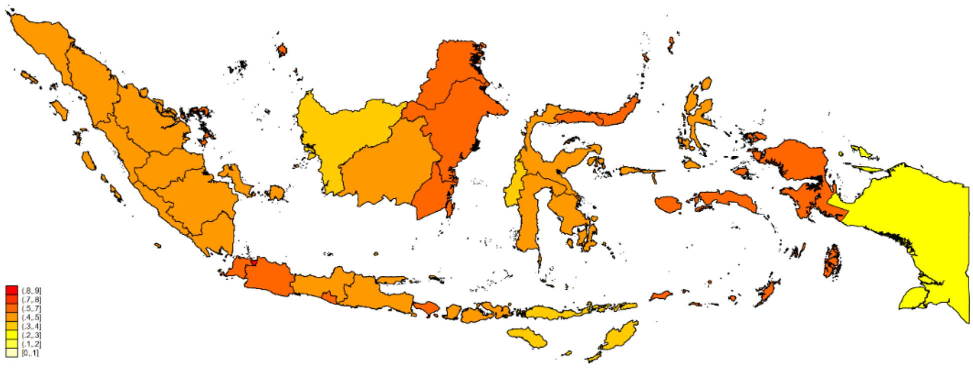
a. The proportion of primary sector employment in total employment (0–1)



b. The proportion of secondary sector employment in total employment (0–1)



c. The proportion of tertiary sector employment in total employment (0–1)

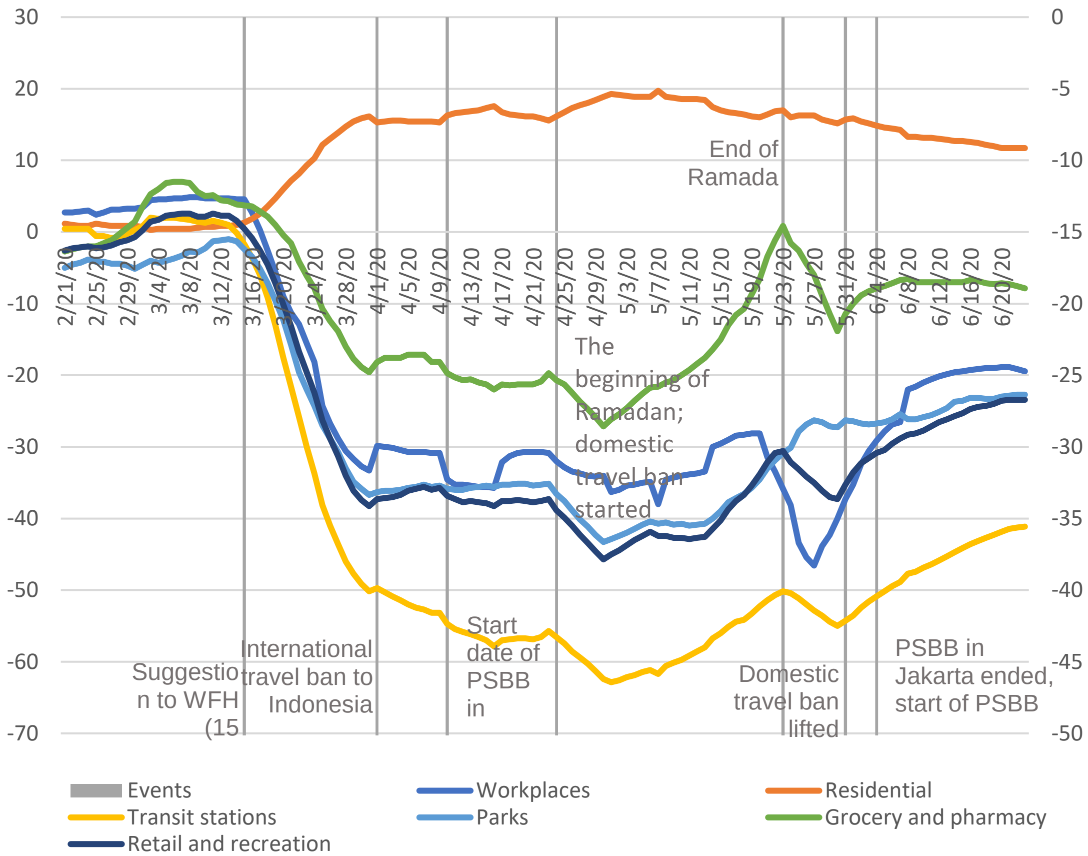


Source: SAKERNAS, August 2019.

Like many other countries, the pandemic has hit Indonesia severely. By 7 January 2021, the total number of confirmed COVID-19 cases reached nearly 1.13 million, with around 12,000 new ones each day. The pandemic has massively disrupted the social and economic situation in most regions. After the first few cases were found in Indonesia in early March 2020, the government applied several gradual measures throughout the country that significantly affected people's mobility. Starting March 15, the president announced a nationwide recommendation to do WFH if possible and let local governments (provinces and districts) decide whether lockdown was necessary. Meanwhile, schools in some regions also started to close after mid-March, even though the nationwide 'study from home' measure only started on April 24. In early April, some provinces implemented large-scale social restrictions (*Pembatasan Sosial Berskala Besar* [PSBB]) after approval from the central government, but some regions' applications for PSBB were rejected.

Until 30 September, out of the 34 provinces, only Jakarta, West Sumatra, Gorontalo and West Java implemented provincewide PSBB, while several other regions implemented it at the city or district level. Air and train travel were also restricted in April. Although the government campaigned to limit the traditional 'Mudik' travels early in Ramadan, much of the travel policy was already relaxed one month later, at the end of Ramadan. Correspondingly, many local restriction policies were also relaxed in early June as the social and economic impacts of restrictions started to mount. Since then, most of the more recent restriction policies implemented have not affected people’s mobility as much as those in March, despite the exponential increase in COVID-19 cases in Indonesia, which still have not reached their peak. Figure 2 shows mobility changes in the early period of the pandemic.

Figure 2. Changes in Mobility (7 Days Moving Average) and Notable Events



PSBB = Pembatasan Sosial Berskala Besar, WFH = work from home.
Source: Google Mobility Index and various sources.

The effectiveness of social distancing depends on the condition of each region. While it can be applied in some jobs, WFH is impossible to implement in many others, such as in various manufacturing industries. Additionally, Indonesia has a high share of informality in its economy. In 2016, about 30% of total employment was informal (Dong and Manning, 2017), where WFH was not a viable option. Furthermore, Indonesia’s social safety net, while vastly improved over the past decade (Burke and Siyaranamual, 2019), has not reached a level where it can guarantee sufficient livelihood for unemployed people during a prolonged, deliberate economic shutdown. Therefore, the level of social distancing, as well as the motivation to voluntarily stay at home, might be lower for people with lower socioeconomic status. Appendix 1 shows provincial maps of the changes in workplace mobility during the first 210 days of our observation. These changes correspond to the effectiveness of social distancing and WFH.

3. Concepts and data

To test the impact of sectoral employment structure on mobility, we use several databases: the Google mobility index, province-level employment data from SAKERNAS from Statistics Indonesia (BPS), the numbers of daily cases of COVID-19, and local PSBB policy schedules that we gathered from various government websites and news sources, as well as national public holidays.

3.1. Mobility

It is important to note that the definition of *mobility* in this database is closer to that of *daily activities*. Therefore, the measurement is highly short-term (daily), and should not be confused with the changing of domiciles or occupations within one's lifetime. We decided to retain the term mobility, in line with the database, for simplicity. Google tracks human mobility consistently across 131 countries, and data at the subnational level are available for a subset of countries, including Indonesia.

The human mobility data aggregate anonymised sets from users' mobile device location history. These reports record changes in the number of visits or length of stay at various locations compared to a baseline value for that day of the week. The baseline day is the median value from the 5-week period from 3 January to 6 February 2020. Google collects the data from mobile phone users that give access to their location. The data are aggregated within an area; hence, Google does not report individual user location data, but it reports an index of aggregated mobility at the country or sub-national level.

Google does not provide any detail about the number or distribution of tracked mobile phone users in each area. Since the characteristics, accuracy and categorised places for the data collection vary across regions, comparing mobility changes between regions can be problematic. To address this problem, we will focus on within-province variations across time. This will be discussed in our methodology section.

The mobility data are divided into six location categories: workplaces; public transport; grocery and pharmacy; retail and recreation; parks (public gardens, dog parks, beaches, etc.); and residential areas. While these categories are intuitive, Google's inclusion criteria are idiosyncratic. For example, pharmacies are categorised in the same group as groceries, because a trip to a pharmacy is generally necessary, while museums and galleries are categorised as a park, whereas open fields in rural areas are not. Although we cannot verify the consistency and accuracy of Google's classification method, we argue that the dataset is the most viable way to measure daily activity changes.

We are particularly interested in mobility in workplaces and residential areas. Increased mobility in residential areas is different from other locations because it can be interpreted as a decrease in overall mobility, i.e. people choosing to stay at home. We interpret a decrease in mobility at workplaces as the intensity with which people have switched to WFH, stopped working or lost their usual job. Google's Mobility Index allows scrutinising people's pandemic behaviour based on their jobs. Comparing workplace and residential area mobility might suggest that workers in some sectors could apply WFH, but others cannot.

3.2. Employment data

We combine mobility data with employment composition data at the provincial level. Specifically, we look at the proportion of labor working in each sector within a province using August 2019 SAKERNAS report to capture the pre-pandemic employment composition. As robustness checks, we also check the February 2020 SAKERNAS report.[2] The observation in the individual level is

[2] The results are presented in Table A.1-3 in the appendix. We do not use the most recent employment survey in August 2020 to ensure the exogeneity of the variable. As COVID-19 has slowed economic activity, the structural composition of labour has been changed. Many companies reduced the number of their workers, especially in urban areas. As a result, many people went back to their hometown, migrated to rural areas or moved to agricultural sectors or informal sectors (BPS, 2020; World Bank Survey on Business, 2020).

aggregated to the provincial level by sectoral proportion. Table 1 shows the sectoral employment composition in Indonesia, divided into 17 sectors.

Table 1. Sectoral Employment Composition in Indonesia's 34 Provinces

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Agriculture, livestock, forestry, and fishery	34	31.61%	0.144	0.00%	67.76%
Mining	34	2.16%	0.027	0.34%	14.14%
Manufacturing industry	34	10.59%	0.055	2.02%	24.09%
Water, sewage and waste management	34	0.32%	0.002	0.07%	0.76%
Electricity and gas	34	0.34%	0.001	0.15%	0.69%
Construction	34	6.16%	0.01	2.70%	10.15%
Wholesale and retail trade	34	17.40%	0.03	7.68%	24.78%
Transport and storage	34	4.62%	0.02	2.24%	11.55%
Accommodation and food services	34	5.62%	0.03	1.10%	13.12%
Information and communication	34	0.62%	0.00	0.15%	2.42%
Finance and insurance activities	34	1.25%	0.01	0.43%	3.65%
Real estate	34	0.22%	0.00	0.00%	2.18%
Business activities	34	1.32%	0.01	0.40%	4.71%
Public administration and defence	34	6.13%	0.03	2.30%	13.45%
Education	34	5.70%	0.01	2.80%	11.97%
Human health and social work	34	1.82%	0.01	1.06%	4.67%
Other services activities	34	4.12%	0.02	1.14%	11.07%

Source: SAKERNAS BPS August 2019, derived from CEIC database (https://www.ceicdata.com/en).

3.3. Large-scale social restrictions (PSBB) and nationwide stringency index

PSBB varies between regions because only a limited number of provinces implemented it and not all applications were approved by the Ministry of Health. Each PSBB started at different dates, usually a few days after the Ministry of Health approved the proposal.

Although some PSBBs were implemented provincewide and others only at the district or city level, we decided to treat the district-level PSBB the same way as province-level PSBB. This is because our observation is at the province level and

PSBBs are generally implemented in population centers. However, we also test for different levels by distinguishing between provincewide and localised PSBB.[3]

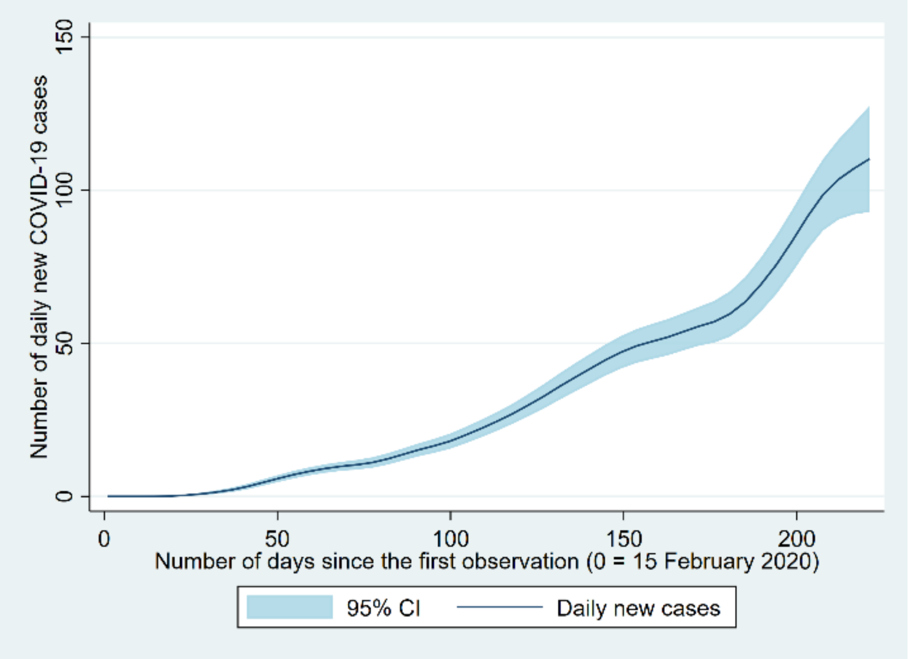
To our knowledge, there is no centralised source for information about the approval and implementation of PSBB. As such, we gathered information from various sources, including reputable news sources and government websites. Using this information, we constructed a dataset of PSBB implementation, which includes the first and last date of the implementation, the level of implementation (district or province), and whether the PSBB is extended to a later date. As a complement to PSBB data, we also include the government response stringency index, constructed by the Oxford COVID-19 Government Response Tracker (Hale et al. 2020) to measure the time-variant nationwide measures.

3.4. COVID-19 Cases

We compiled data on the number of daily COVID-19 cases from CEIC Global Database and verified their consistency with official data from the government's website and the independent (non-government) 'Kawal Covid' database, which consistently reports data and information about COVID-19 in Indonesia.[4] The daily number of cases are available at the national and provincial level. Figure 2 shows the descriptive statistics of the number of new cases in Indonesia's 34 provinces, revealing high variations amongst provinces. While the average number of cases may seem low, the number of cases in some provinces are very high and are still growing at the time of writing.

[3] This is specifically the case when we use Google Mobility Index and utilize across-province variation.
[4] https://kawalcovid19.id/

Figure 3. Average Number of New Cases in 34 Provinces



CI = confidence interval.
Source: CEIC Database (https://www.ceicdata.com/en).

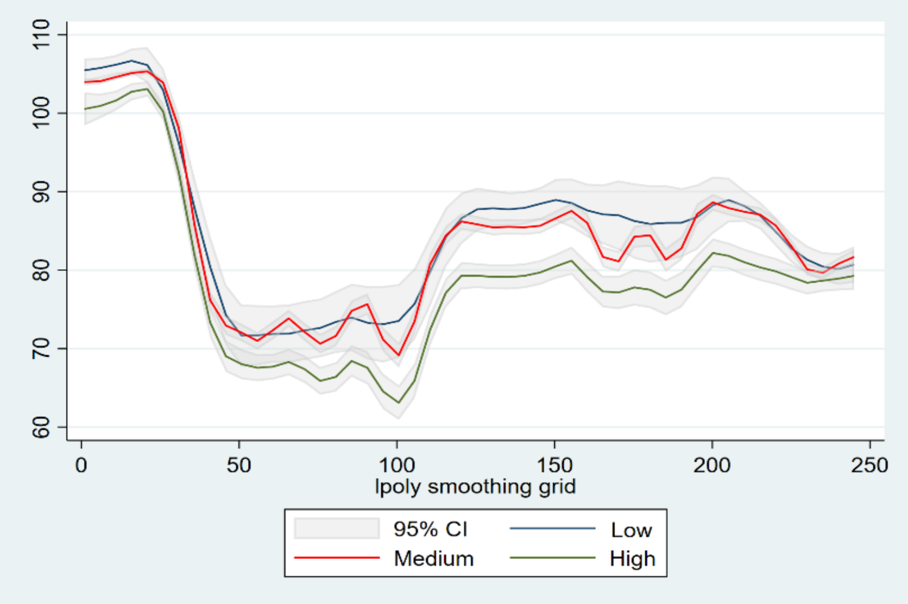
4. Empirical Approaches

Mobility in workplaces in most regions in Indonesia fell after the WFH recommendation and the implementation of other restriction policies from the central government. However, there have been cross-region variations in mobility. In this paper, we hypothesise that, other than due to the stringency differences between regions, the variation is also due to other local factors. We argue that local employment compositions also explain cross-regional variations. Figures 4a-c illustrate our initial conjecture and provide a visual examination of regional mobility patterns over the employment composition when sectors are simply classified into three aggregate groups (primary, secondary and tertiary). These figures show that there are cross-province variations in mobility, in which provinces that have a low share of employment in the primary sector (2a), a high share of employment in the secondary sector (2b), or a high share of employment in the tertiary sector (2c) tend to have a deeper reduction in people's mobility at workplaces compared to the median provinces.

Figures 4a-c also show that there have been massive mobility changes during the observed period. The first was in the early phase when the government started to impose social distancing measures in mid-March 2020. Such policies significantly reduced workplace mobility in all provinces in Indonesia. The second was when the government started to relax the intervention in early June 2020. This increased workplace mobility, although not back to the pre-pandemic level. To capture these conditions in our analysis, we divided the observed periods into three phases: period I from day 1 to day 120;[5] period II from day 121 to 220; and the total period from day 1 to 220. We argue that spatial and sectoral responses to mobility vary across these periods.

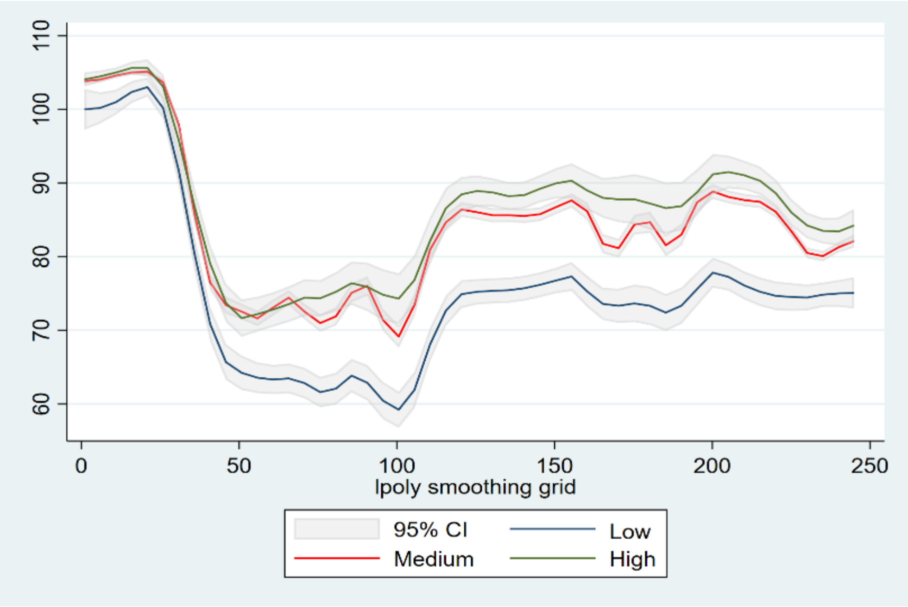
Figure 4. Mobility in Workplaces by Regional Employment Composition

a. Primary Sector

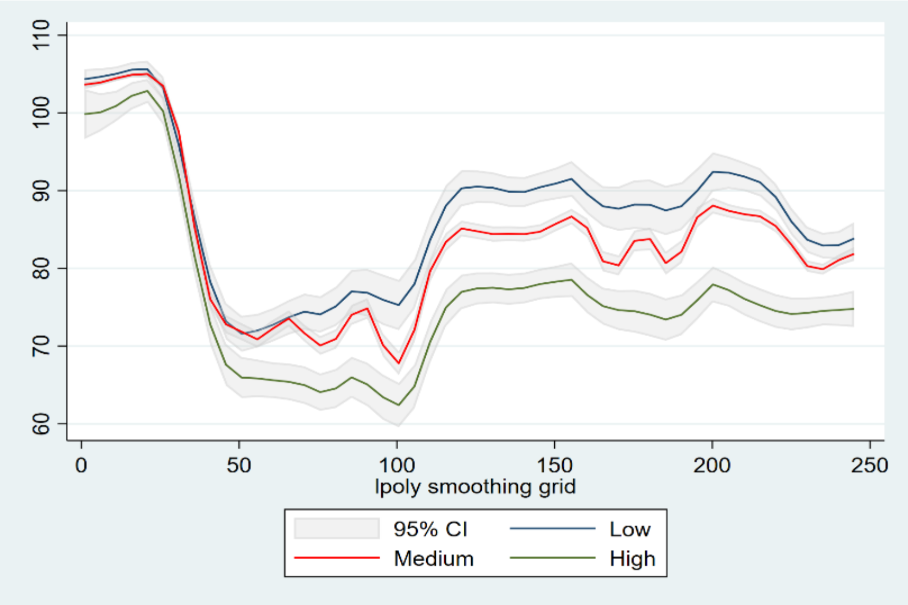


[5] It started from 15 February 2020.

b. Secondary sector



c. Tertiary sector



CI = confidence interval.
Notes: 100 = baseline day mobility level. The primary sectors include agriculture, fisheries, forestry and mining; the secondary sectors include manufacturing, and utilities; the tertiary sectors include education, healthcare, services and government services. Local polynomial fit with 95% CI of daily mobility across provinces. Share is defined as low if the share of employment in the primary sectors is less than 1 standard deviation (sd) from the median. Share is defined as medium if the share of employment is between 1 sd below the median to 1 sd above the median. Share is defined as high is the share of employment is more than 1 sd higher than the median.
Source: Authors' calculation based on Google Mobility data (in workplaces) and employment composition data from SAKERNAS.

Furthermore, we argue that the effects of employment composition on mobility are also influenced by how workers in each sector respond to COVID-19 shocks. Workers in sectors that naturally need high physical interaction may reduce their mobility more than workers in sectors that do not. To test our hypothesis, we use a panel of regions-days and apply the following model:

$$
\begin{aligned}
Mobility_{pt}^{j} = \beta_s\left(Share\ of\ Employment_{sp} \times PC_{p,t-1}\right) + \delta_1 TC_{p.t-1} \\
+ \delta_2 PSBB_{pt} + \delta_3 PSBB\_SQ_{\ pt} \\
+ \delta_4\ SI_t + Time\ Controls_t + \alpha_p + \varepsilon_{pt}
\end{aligned}
$$

where $Mobility_{pt}^{j}$ is the mobility level of province p in day t, expressed as an index as used in Bargain and Aminjonov (2020).[6] We use daily data on two locations j of workplaces and residential areas from Google Mobility.

The variable of interest in the study is the interaction term of $Share\ of\ Employment_{sp} \times PC_{p,t-1}$. $Share\ of\ Employment_{sp}$ is the share of employment of sector s in a region. The composition of sectoral employment per region is derived from SAKERNAS as per August 2019. The employment is classified into 17 sectors using the the International Standard Industrial Classification of All Economic Activities. The variable of $Share\ of\ Employment_{sp}$ is time-invariant. $PC_{p.t-1}$ is the lag number of new positive cases in the province each day from the published COVID-19 data. β_s are the coefficients for the interaction between the employment share and the new province cases, which measures how the proportion of the sector employment affects people's mobility given the number of new cases in the province. The number of new cases is uniform for all sectors in the province. We interact the regional labor proportion with the number of new cases because the response each sector has should also depend on the perceived severity of the pandemic in the region. Furthermore, the interaction gives time variability to the time-invariant sectoral employment proportion, which is necessary for panel regression.

[6] The original Google Mobility data are expressed as the deviation of mobility from baseline day. As in Bargain and Aminjonov (2020), we transform the percent changes into an index on a 0–100 scale, in which the reference mobility takes the value of 100.

We include various control variables. First, we include $TC_{p,t-1}$, a lag of the accumulated total number of positive cases in each province, including both active and non-active cases. We control for the accumulated cases to see the sensitivity of both new cases and total cases in people perception of the severity of COVID-19 that drive their mobility decision. This method is also applied in Maloney and Taskin (2020).

Second, we control for local and provincial restriction policies. $PSBB_{pt}$ is the number of implemented days of PSBB large-scale social restrictions.[7] The start and end dates of PSBB vary between provinces. $PSBB\_SQ_{\ pt}$ is the squared number of days of PSBB implementation. It is included to test whether the impact of PSBB on mobility diminishes across time. We expect the cost of mobility restriction, i.e. the burden of not being able to travel, to increase with each additional day of PSBB. This may affect the level of adherence and, consequently, people's mobility level. If this is the case, the general mobility level will decline sharply during the early days of PSBB implementation and will gradually increase with each additional day. Including the number of days and squared number of days of PSBB allows the model to test the possibility of this U-shaped mobility pattern.

As a comparison, we also define PSBB as a dummy variable in a separate model, where 1 means PSBB was officially implemented that day. Also, we include the SI_t, that we collected from the nationwide Oxford Stringency Index (Hale et al., 2020).

Third, since mobility changes and the number of cases have daily variation, many factors could affect the trend. To address this issue, we use various time controls to absorb as much as possible the factors that drive these daily variations. The $Time\ Controls_t$ includes: T_t, T_SQ_t, $(T_t \times Island_p)$, Day_t, $Holiday_t$, Eid_t and $Month_t$. T_t is the time trend variable in days since the first observation (15 February), and T_SQ_t is the time trend squared. We include the squared form of the time trend because data show that mobility changes tend to have a U or an inverted-U shape. By doing so, we can estimate the peak and trough of the mobility changes

[7] In the main model using Google Mobility, we combine the provincewide PSBB and district level PSBB into one variable. However, when we use Facebook Mobility Data, we use the variation of PSBB in district level.

during the observation period. The $island_p$ variable, which is interacted with the time trend control for differences between the five largest islands (Sumatra, Java and Bali, Kalimantan, Sulawesi, and Papua) and one archipelago (Maluku and Nusa Tenggara) in Indonesia.

We include Day_t fixed effects to control for the day of the week since mobility might vary across days. $Holiday_t$ is a dummy variable that controls for public holidays and weekends. Although the mobility variable compares the level with a baseline of the same day, we argue it is still necessary to control for weekends and various public holidays. The Ied_t variable controls for the week before and after the Eid-al Fitr holiday, during which millions of people usually travel to their hometown. Lastly, $Month_t$ is the month fixed effects, which control for the different calendar months.

Google does not recommend comparing changes across locations since the characteristics, accuracy and the categorised places of the data collection vary. To address this problem, we use the province fixed effects to rely on within-province variations across time and to absorb the differences between provinces. Therefore, we include α_p as province fixed effects.

In our model, we include various variables to control for unobservable bias. However, there could be other unobservable factors, especially if we have a longer daily time frame. Therefore, in the study, we investigate two different time frames. First, we focus on a shorter time frame: 60 days after the first official announcement of restriction by the government (15 March). This is because we want to observe spontaneous responses to the pandemic in each region. We expect that the regional labor compositions have higher contributions in defining mobility patterns in this time frame compared to the longer one. Second, we also examine the pattern in a longer time frame, until 30 September.

5. Results

Table 2-4 shows the main results of how the interaction of sectoral employment structures and the number of new cases affect mobility in workplaces and residential areas. We divide the employment into three sectors: primary, secondary and tertiary sectors. Later (Table 5), we also discuss the mobility effects using a more detailed 17-sector classification of employment across provinces.[8]

Generally, the signs of effects on mobility in workplaces are the opposite of those on residential areas. This is intuitive, considering higher mobility in residential areas means people spend less time outside their home, including at work. The interactions between new daily cases and employment shares indicate how variations in the proportion of workers in each sector across provinces affect the average mobility. The results show that the shares of primary sector employment that are interacted with daily new cases do not significantly change mobility in the first period of observations, both in residential areas and in workplaces.

Even though the primary sector absorbs the largest number of labor forces in most provinces, the jobs mostly occur in open space areas and do not demand a high degree of direct human interactions. Therefore, the primary sector, especially agriculture, has been resilient to the pandemic.[9] The increasing number of new daily cases at the province level does not necessarily affect how people in the primary sector do their activities. This could be one of the explanations of the insignificant result. Compared to the situation before the pandemic, the activity, as well as the mobility, of workers in the sector together do not change significantly during the first period of the observation. However, in the second period of the observation, situations had changed, as shown by the increased mobility in residential areas. One explanation might be due to the crowding into agriculture after many other sectors had been hit by the pandemic. Meanwhile, the mobility level in workplaces has also slightly been decreased during the second period of observations. This might be due to the seasonal agriculture activities in which the harvest time for paddy fields was

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[8] We also use the composition of labour from SAKERNAS February 2020 as robustness checks. The results are in the appendix.
[9] See https://www.thejakartapost.com/news/2020/08/08/agriculture-resilient-to-pandemics-impact.html.

usually in March–April. Therefore, during Period II, the intensities of farmer activities reduced.

Interestingly, the coefficient of the secondary sector on workplace mobility is not significant, suggesting there are no significant differences in workers' activities in the sector during the pandemic (see Table 3). Workers in the sector do not respond to the increase of daily new cases in deciding whether they are going to workplaces or staying at home. One possible explanation is government regulations that still allow manufacturing firms to operate with strict health protocols during PSBB.[10] While most manufacturing activities cannot be conducted from home, most companies asked their employees to come to the factories.[11]

[10] The Ministry of Industry of Indonesia has allowed manufacturing firms to operate with licences. Companies need to apply for the licences and implement the operational and mobility protocols (Surat Izin Operasional dan Mobilitas Kegiatan Industri [IOMKI]) to make sure the health and safety standards are applied during the business activities.

[11] The number of workers in each firm might be reduced due to the physical distancing protocols. However, in this study, we only can show the provincial variation, not the firm variation.

Table 2. Main Results: The Impact of Share of Primary Sector Employment to Mobility

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Simplified Mobility in Residentials			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Primary Sectors x Lagged Daily New COVID Cases	3.19e-05	0.0156***	0.0184***	0.0116	–0.0208**	–0.00340
	(0.0113)	(0.00466)	(0.00508)	(0.0269)	(0.00858)	(0.0111)
Lagged Total Accumulated Cases	0.000286*	2.10e-05	–2.60e-07	–0.00101*	–5.43e-05	–5.36e-05
	(0.000147)	(1.55e-05)	(1.98e-05)	(0.000585)	(4.54e-05)	(7.84e-05)
PSBB (days)	0.0818***	0.000689	0.0162	–0.116	0.0148	–0.0562*
	(0.0297)	(0.0109)	(0.0131)	(0.0773)	(0.0177)	(0.0300)
PSBB (days squared)	–0.00137***	7.53e-05	–0.000119	0.00149	–9.27e-05	0.000404*
	(0.000405)	(6.39e-05)	(9.63e-05)	(0.00126)	(0.000120)	(0.000207)
Stringency Index	0.0828***	0.0649***	0.155***	–0.0425**	–0.0557***	–0.174***
	(0.00847)	(0.00870)	(0.00835)	(0.0192)	(0.0180)	(0.0118)
Time (days)	0.614***	–0.202***	0.226***	–1.562***	0.00396	–0.677***
	(0.0254)	(0.0282)	(0.00969)	(0.0589)	(0.0497)	(0.0267)
Time (days squared)	–0.00392***	0.000560***	–0.000776***	0.0101***	0.000272	0.00234***
	(0.000151)	(8.08e-05)	(3.30e-05)	(0.000335)	(0.000166)	(7.17e-05)
Weekend and Holiday	3.943***	4.265***	4.595***	–21.18***	–34.02***	–25.70***
	(0.138)	(0.276)	(0.161)	(0.338)	(0.692)	(0.399)
Eid Week	0.00862		–2.481***	–6.800***		0.294
	(0.182)		(0.242)	(0.296)		(0.325)
Time x Sumatera	–0.0433***	0.0124*	–0.0102***	0.0316	–0.0121	0.0116
	(0.0102)	(0.00634)	(0.00321)	(0.0330)	(0.0193)	(0.0131)

Time x Kalimantan	–0.0389***	–0.00129	–0.00587	0.0654**	–0.0280	0.0105
	(0.00841)	(0.00840)	(0.00364)	(0.0321)	(0.0200)	(0.0126)
Time x Sulawesi	–0.0258**	–0.00523	–0.00895**	0.0663*	–0.000868	0.0295*
	(0.0125)	(0.00697)	(0.00361)	(0.0388)	(0.0207)	(0.0152)
Time x Maluku	–0.0304***	–0.0151	–0.00901	0.0784**	0.00541	0.0294
	(0.00840)	(0.0112)	(0.00554)	(0.0385)	(0.0246)	(0.0190)
Time x Papua	–0.0132	–0.0182***	–0.0140***	0.0313	–0.0208	0.0162
	(0.00902)	(0.00530)	(0.00476)	(0.0329)	(0.0192)	(0.0135)
Constant	89.17***	116.5***	88.63***	148.1***	134.4***	152.7***
	(0.524)	(2.209)	(0.698)	(0.946)	(4.701)	(1.082)
Province fixed effects	yes	yes	yes	yes	yes	Yes
Monthly fixed effects	yes	yes	yes	yes	yes	Yes
Daily dummy	yes	yes	yes	yes	yes	Yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.839	0.584	0.765	0.799	0.849	0.770
Number of id_region	34	34	34	34	34	34

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

Table 3. Main Results: The Impact of Share of Secondary Sector Employments to People Mobility

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Simplified Mobility in Residentials			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Secondary Sectors x Lagged Daily New COVID Cases	0.0192	0.00776	0.0180***	–0.0297	–0.0117	1.11e-05
	(0.0239)	(0.00464)	(0.00533)	(0.0459)	(0.00805)	(0.0149)
Lagged Total Accumulated Cases	0.000186	1.17e-05	–9.89e-06	-0.000783	–3.92e-05	–6.01e-05
	(0.000114)	(1.65e-05)	(2.06e-05)	(0.000507)	(4.75e-05)	(8.50e-05)
PSBB (days)	0.0755***	0.00897	0.0237	–0.102	0.00330	–0.0569*
	(0.0259)	(0.0144)	(0.0147)	(0.0668)	(0.0224)	(0.0295)
PSBB (days squared)	–0.00121***	1.49e-05	–0.000209*	0.00113	–7.99e-06	0.000415**
	(0.000369)	(8.43e-05)	(0.000116)	(0.00104)	(0.000139)	(0.000198)
Stringency Index	0.0829***	0.0654***	0.155***	–0.0428**	–0.0564***	–0.173***
	(0.00847)	(0.00851)	(0.00830)	(0.0191)	(0.0180)	(0.0119)
Time (days)	0.613***	–0.206***	0.225***	–1.562***	0.00879	–0.677***
	(0.0253)	(0.0303)	(0.00990)	(0.0589)	(0.0516)	(0.0264)
Time (days squared)	–0.00392***	0.000581***	–0.000768***	0.0101***	0.000246	0.00234***
	(0.000151)	(8.82e-05)	(3.37e-05)	(0.000339)	(0.000170)	(7.25e-05)
Weekend and Holiday	3.943***	4.260***	4.593***	–21.18***	–34.02***	–25.70***
	(0.138)	(0.276)	(0.163)	(0.338)	(0.692)	(0.400)
Eid Week	0.00426		–2.487***	–6.789***		0.293
	(0.181)		(0.245)	(0.292)		(0.325)
Time x Sumatera	–0.0428***	0.0121*	–0.00968***	0.0311	–0.0117	0.0117

	(0.0102)	(0.00697)	(0.00351)	(0.0331)	(0.0195)	(0.0128)
Time x Kalimantan	–0.0384***	–0.00156	–0.00474	0.0651*	–0.0278	0.0106
	(0.00833)	(0.00901)	(0.00445)	(0.0320)	(0.0204)	(0.0123)
Time x Sulawesi	–0.0253**	–0.00811	–0.00851**	0.0660*	0.00286	0.0298*
	(0.0124)	(0.00705)	(0.00373)	(0.0387)	(0.0203)	(0.0148)
Time x Maluku	–0.0301***	–0.0182	–0.00908	0.0784**	0.00947	0.0297
	(0.00841)	(0.0110)	(0.00578)	(0.0385)	(0.0241)	(0.0187)
Time x Papua	–0.0125	–0.0190***	–0.0125***	0.0315	–0.0198	0.0163
	(0.00893)	(0.00523)	(0.00409)	(0.0327)	(0.0193)	(0.0132)
Constant	89.17***	116.9***	88.64***	148.1***	133.9***	152.7***
	(0.528)	(2.374)	(0.692)	(0.946)	(4.865)	(1.086)
Province fixed effects	yes	yes	yes	yes	yes	yes
Monthly fixed effects	yes	yes	yes	yes	yes	yes
Daily dummy	yes	yes	yes	yes	yes	yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.839	0.578	0.764	0.799	0.848	0.770
Number of id_region	34	34	34	34	34	34

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

Table 4. Main Results: The Impact of Share of Tertiary Sector Employments to People Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Simplified Mobility in Residentials**			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Tertiary Sectors x Lagged Daily New COVID Cases	0.0289**	0.00145	0.00283	–0.0570**	–0.00313	–0.00906**
	(0.0121)	(0.00206)	(0.00174)	(0.0223)	(0.00349)	(0.00377)
Lagged Total Accumulated Cases	–0.000148	1.16e-05	6.99e-06	–8.03e-05	–2.82e-05	2.86e-05
	(0.000104)	(2.45e-05)	(2.55e-05)	(0.000457)	(6.59e-05)	(7.33e-05)
PSBB (days)	0.0592**	0.00866	0.0225	–0.0669	0.00236	–0.0649**
	(0.0222)	(0.0154)	(0.0154)	(0.0542)	(0.0234)	(0.0311)
PSBB (days squared)	–0.000840**	1.95e-05	–0.000206	0.000327	–1.44e-06	0.000516**
	(0.000413)	(9.34e-05)	(0.000125)	(0.000891)	(0.000150)	(0.000225)
Stringency Index	0.0830***	0.0650***	0.155***	–0.0429**	–0.0559***	–0.173***
	(0.00852)	(0.00846)	(0.00840)	(0.0191)	(0.0181)	(0.0119)
Time (days)	0.613***	–0.207***	0.227***	–1.561***	0.00960	–0.677***
	(0.0247)	(0.0312)	(0.00972)	(0.0577)	(0.0521)	(0.0260)
Time (days squared)	–0.00391***	0.000589***	–0.000767***	0.0101***	0.000234	0.00233***
	(0.000144)	(8.84e-05)	(3.49e-05)	(0.000327)	(0.000167)	(7.02e-05)
Weekend and Holiday	3.936***	4.256***	4.590***	–21.16***	–34.02***	–25.71***
	(0.136)	(0.275)	(0.162)	(0.341)	(0.691)	(0.399)
Eid Week	0.0111		–2.480***	–6.801***		0.314
	(0.182)		(0.246)	(0.290)		(0.323)
Time x Sumatera	–0.0435***	0.0110	–0.0116***	0.0323	–0.00905	0.0134
	(0.00993)	(0.00753)	(0.00397)	(0.0328)	(0.0206)	(0.0130)
Time x Kalimantan	–0.0394***	–0.00306	–0.00668	0.0668**	–0.0252	0.0112

	(0.00771)	(0.00918)	(0.00479)	(0.0315)	(0.0207)	(0.0128)
Time x Sulawesi	–0.0261**	–0.00961	–0.0106**	0.0675*	0.00561	0.0307*
	(0.0120)	(0.00743)	(0.00399)	(0.0382)	(0.0206)	(0.0152)
Time x Maluku	–0.0313***	–0.0197*	–0.0111*	0.0806**	0.0124	0.0309
	(0.00800)	(0.0113)	(0.00600)	(0.0381)	(0.0249)	(0.0188)
Time x Papua	–0.0134	–0.0204***	–0.0148***	0.0330	–0.0169	0.0174
	(0.00872)	(0.00598)	(0.00450)	(0.0323)	(0.0203)	(0.0131)
Constant	89.17***	117.1***	88.65***	148.1***	133.7***	152.7***
	(0.514)	(2.403)	(0.687)	(0.939)	(4.821)	(1.074)
Province fixed effects	yes	yes	yes	yes	yes	yes
Monthly fixed effects	yes	yes	yes	yes	yes	yes
Daily dummy	yes	yes	yes	yes	yes	yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.840	0.577	0.764	0.800	0.848	0.770
Number of id_region	34	34	34	34	34	34

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

Meanwhile, the results in Table 4 suggest that workers in the tertiary sector respond to the number of daily new cases, especially during the early phase of the pandemic. They tend to reduce their activities as the number of new cases increases by deciding to stay at home instead of going to work. Since most subsectors in tertiary sector demand higher intensity of direct human interactions, this result is expected. Workers in the sector may want to have less contact with others by reducing their activities in workplaces and by WFH. As a result, provinces with a higher proportion of workers in the tertiary sector have lower mobility in workplaces as the number of new cases increases. However, after several months, workers in tertiary sectors do not respond to COVID-19 cases as much as in the early period. Later, we elaborate on each subsector to see which ones drive the results on the tertiary sector.

The effects of other variables are also interesting. The coefficients of total accumulated cases are not significant in most specifications. One possible explanation is people do not perceive the total accumulated cases as sensitively as the number of new cases since the later might show the severity of the current condition. Another explanation is the time variables have absorbed the effects of the total cases.

The variable of days of PSBB is significant for mobility in residential areas but is not significant for mobility in workplaces. This suggests that there is a significant increase in activities in residential areas due to people staying at home as directed by the government. The government forced all students from primary level to university level to study from home. In contrast, the government only campaigns for WFH for working people as a suggestion. People are allowed to work in their working places as long as they follow stricter health protocols. Some companies make WFH policies or ask employees to come to offices on a scheduled based so they do not have to come to the workplace every day. However, many types of jobs cannot be done online, so they still ask their workers to come to the workplace. Therefore, the results on mobility in residential areas are significant but not for mobility in workplaces. However, this occurs only for the early period since, in the second period of observations, the government has actually been relaxing any mobility intervention policies.

Similarly, the days squared of PSBB provide intuitive results. The signs are the opposite of the number of days of PSBB, which shows that there is an optimum point of PSBB. The longer the PSBB is applied, the effect decreases. As the number of days of PSBB implemented increases, people tend to get increasingly bored and tired of staying at home and therefore stop following the government's directions.

The results for nationwide social distancing as reflected in the variable stringency index are as expected. The combined factors included in the index reduce workplace mobility and increase residential mobility.

We applied various time controls to absorb as much as possible time trends. The time trend and squared time trend coefficients are both statistically significant. While time trend has a positive coefficient in Period I (for residential mobility in Column 1 in Table 2-4), squared time trend has a negative coefficient, confirming the U-shaped nature of the changes in mobility. This suggests that people tend to increase their activities at home and reduce their activities in the workplace, but with lower speeds over time. The squared time trend suggests that people tend to get used to – and deal with issues in – the new pandemic situation. Interestingly, in the second period, the signs of those variables have been reversed. People tend to reduce their activity at home. Using face masks in their daily life may have become a habit for many people, and many have returned to their daily activities outside their homes.

People reduce their working activities during the weekends, holidays and Eid festivities. They increase their activities at home during the weekend and holiday. But, the Eid holiday variable is not significant for residential mobility because many people travelled to their hometowns during it for *mudik*. The results confirm that the efforts of the government to limit *mudik* and the spread of the virus to the rural areas may not have been effective.

Island time trend measures the time trend differences between Java and each island. All island time trends coefficients are negative and significant except for Papua. This indicates that the highest degree of mobility change occurs in Java island, with less activity change in other regions. Interestingly, for mobility in workplaces, most islands have a similar trend with Java, except for Kalimantan and Maluku.

Table 5 shows results when we change the first three rows in Table 2-4 into 17 subsectors (a to q). In the table, we only present results of the variable of the share of employment in each sector interacted with lagged daily new Covid-19 cases for each province in the first 120 days, the next 100 days and the whole observed days. In each sector in Table 5, we include the same control variables as in Table 2-4.

The coefficient for subsectors of the primary (a and b) and secondary (c to f) sectors varies, showing the heterogeneity of how workers in those sectors respond to the pandemic. As explained in Tables 2-3, most jobs in this sector cannot be done remotely. This is true in most subsectors for both the first 120 days and after. However, there are exceptions. Agriculture (a) has significant coefficients at the second period (121st to 220th day) in both mobility in the workplaces and in residential areas. The increase in residential area mobility shows the crowding into agriculture as many working-age populations have been impacted by COVID-19. BPS SAKERNAS (August 2020) found that around 29.12 million people have been affected, with 2.7 million more agricultural workers in August 2020 compared to the same period in 2019.[12] As with the Asian financial crisis, agriculture has become the buffer for the economy (Suryahadi et al., 2012).

Similarly, the construction sector (f) also has statistically significant coefficients in the model for the second period. This appears to be caused by changes in demand. Interestingly, mining and quarrying (b) has statistically significant coefficients in the model for the first period of residential area mobility, but not for workplaces. This suggests that, although jobs in this sector cannot be done remotely, people in provinces with higher employment in it reduce their mobility to other places.

The results confirm our previous findings that workers in the tertiary sector respond to new daily cases more than in other sectors. The tertiary sectors could be disaggregated into 11 subsectors (g to q in Table 5). We can see from the table that most of them, except for wholesale and retail trade and education, are significant in the models for the first 120 days. Types of jobs in subsectors j to n are most likely to be conducted via WFH because they mainly involve office work. Our results confirm the conjecture and show that, in the early stage of the pandemic, workers in the subsectors reduce their activities in workplaces and increase their activities at home when the number of new daily cases increases. This is the case for mobility both in workplaces and residential areas.

However, the statistical significance disappears in the second period for most subsectors in the tertiary sector. This suggests that the effect of sectoral employment on mobility mainly lasts during the earlier stage of the pandemic. As the pandemic

[12] Amongst the affected people, 2.56 million have become unemployed, 1.77 million temporarily unemployed, 24.03 million with reduced working hours and 0.76 million unemployed but actually not of working age (SAKERNAS BPS, August 2020).

continues and the country enters the new normal, these differences become less important. This does not necessarily mean that workers in these sectors are back in the office, but that more employment and new Covid-19 cases do not statistically correlate with changes in mobility level after the 120th day.

Wholesale and retail trade (g) is usually the second- (or third-) largest employer in most provinces. But, interestingly, workers in this sector do not respond to the daily new Covid-19 cases as much as in other services sectors. This may suggest that wholesale and retail trade workers tend to do their activities as usual even though risks from physical interactions from Covid-19 occur. One possible explanation is that many jobs in this subsector cannot be conducted through WFH. Another explanation is because this subsector includes retail trade for essential products, the need for which does not change after the 120th day. However, the regression with the whole period shows a weak statistical significance, suggesting that the longer-term effects of the pandemic, such as through the change in demand, may have affected the mobility of provinces with higher employment share in wholesale and retail trade.

Another interesting subsector is accommodation and food service activities. This subsector is affected significantly by the pandemic due to physical distancing policies, as well as border restriction policies in many countries. The result shows that, during the first 120 days, employees in the subsector respond to the new daily cases by reducing activities in workplaces and increasing activities at home. However, most activities in the sectors cannot be conducted via WFH. Therefore, the coefficient in Table 5 may also reflect the changing situations in business activities in which many accommodation and restaurant business have closed down or have reduced their employee numbers. Similar to many other services, the statistical significance of the coefficient disappears in the model with the second period, suggesting the return of activities after the new normal. The results should be confirmed by other business surveys.

Table 5: The Results for the Interaction Variable of the Share of Employment in 17 Subsectors and New Daily Cases to People's Mobility

Sectoral impact	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Mobility in residentials			**Mobility in workplaces**		
	Period I	**Period II**	**Period Total**	**Period I**	**Period II**	**Period Total**
(a) Agriculture, forestry and fishing	–0.00112	0.0158***	0.0183***	0.0128	–0.0215**	–0.00207
	(0.0112)	(0.00494)	(0.00525)	(0.0277)	(0.00912)	(0.0116)
(b) Mining and quarrying	0.669***	0.160***	0.243***	–0.338	–0.159*	–0.282***
	(0.204)	(0.0430)	(0.0837)	(0.426)	(0.0930)	(0.0827)
(c) Manufacturing	0.0292	0.00938	0.0234***	–0.0462	–0.0149	0.00362
	(0.0363)	(0.00636)	(0.00740)	(0.0698)	(0.0114)	(0.0231)
(d) Electricity and gas	4.892**	0.825*	1.384***	–10.18**	–1.159*	–2.561***
	(2.354)	(0.419)	(0.452)	(4.132)	(0.631)	(0.767)
(e) Water supply, sewerage, waste	2.076	0.525*	1.041***	–4.106	–0.612	–0.979
management and remediation activities	(1.418)	(0.270)	(0.355)	(2.826)	(0.432)	(0.636)
(f) Construction	0.0501	0.0360**	0.0733***	–0.0655	–0.0505*	–0.00918
	(0.0710)	(0.0172)	(0.0194)	(0.138)	(0.0284)	(0.0457)
(g) Wholesale and retail trade, repair of motor	0.0606	0.00680	0.0134**	–0.118	–0.0107	–0.0234*
vehicles	(0.0374)	(0.00620)	(0.00560)	(0.0702)	(0.00990)	(0.0117)
(h) Transportation and storage	0.346***	0.00281	0.00775	–0.708***	–0.0154	–0.0693**
	(0.0369)	(0.0153)	(0.0124)	(0.0571)	(0.0283)	(0.0297)
(i) Accommodation and food service activities	0.179*	0.00764	0.0177	–0.332*	–0.0192	–0.0581**

	(0.0922)	(0.0139)	(0.0115)	(0.173)	(0.0238)	(0.0268)
(j) Information and communication	1.676***	–0.00643	0.00577	–3.581***	–0.0361	–0.288*
	(0.143)	(0.0699)	(0.0606)	(0.331)	(0.132)	(0.151)
(k) Financial and insurance activities	0.952***	0.00113	0.0152	–1.932***	–0.0456	–0.207**
	(0.185)	(0.0462)	(0.0382)	(0.313)	(0.0865)	(0.0969)
(l) Real estate activities	1.880***	–0.0492	–0.0402	–4.088***	–0.00362	–0.300*
	(0.195)	(0.0727)	(0.0715)	(0.568)	(0.146)	(0.165)
(m) Business activities	0.809***	0.00247	0.00908	–1.674***	–0.0294	–0.160**
	(0.0936)	(0.0375)	(0.0309)	(0.159)	(0.0679)	(0.0755)
(n) Public administration and defense,	0.408***	0.0373	0.0586**	–0.796***	–0.0808*	–0.192***
compulsory social security	(0.147)	(0.0277)	(0.0249)	(0.239)	(0.0475)	(0.0477)
(o) Education	0.184	0.0532*	0.101***	–0.347	–0.0761*	–0.126***
	(0.133)	(0.0269)	(0.0268)	(0.255)	(0.0416)	(0.0408)
(p) Human health and social work activities	0.849*	0.0706	0.135**	–1.644**	–0.167	–0.396***
	(0.433)	(0.0714)	(0.0610)	(0.780)	(0.125)	(0.121)
(q) Other service activities	0.258***	0.00229	0.0105	–0.507***	–0.0148	–0.0618*
	(0.0894)	(0.0152)	(0.0129)	(0.168)	(0.0280)	(0.0319)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each field of results represents different estimations. All estimations include all variables as in Table 2.
Source: Authors.

The coefficients of the share of employment in education subsector (o) are not significant for both workplace and residential mobility. One possible explanation is, even though the pandemic has massively impacted the education subsector, it may have mostly affected students, not the workers. In some schools, teachers still have to go to school to prepare the teaching materials. This, however, changes in the second period, indicating that the pattern in the education sector is the reverse of most other sectors. Whereas other sectors appear to be returning to a sense of normality in the second period, this is not true for the education sector, as schooling continues to be done remotely when possible.

6. Conclusion

This study explores the role of sectoral employment within a province in determining mobility changes in workplaces and residential areas during the early period (the first 120 days) and the following period (121st–220th day) of the COVID-19 pandemic using the case of Indonesia. We also consider the effect of mobility restrictions' stringency, such as the PSBB, and public holidays, as variables that also explain mobility changes during the pandemic.

To do this, we interact the number of new confirmed COVID-19 cases with the share of sectoral employment in the province. Since the number of provincial new confirmed cases is released daily, we interpret it as a proxy for the perception of the severity of the pandemic in the province, which, in turn, affects mobility levels. Its interactions with the share of sectoral employment represent how this perception affects each sector differently. To measure mobility in workplaces and residential areas, we use Google mobility data that record the changes in the number of people in a certain location and time spent there as compared to a benchmark day in February 2020.

Using panel fixed-effects regressions, we find that, during the first 120 days of the observation, the number of new COVID-19 cases did not significantly affect mobility in workplaces in provinces that have a large share of primary and secondary sector employment. The primary sector, which includes agriculture and mining, is mainly located in rural areas and is less affected by mobility restrictions, including the PSBB. Interestingly, the results are statistically significant in the model with the second period (121st–220th day). The secondary sector, which includes manufacturing, construction, and utilities, may have also been less affected by mobility restrictions because manufacturing continued to operate on-site throughout the pandemic. These results are also confirmed by the more detailed 17-sector model.

In contrast, the same effect is statistically significant in provinces that have a larger share of employment in the tertiary sector. We find that, during the same period, provinces with a higher share of tertiary sector employment reduced their mobility in workplaces and increased their mobility in residential areas as the number of COVID-19 cases in the province increased. The tertiary sector is composed mainly of services sector jobs, which tend to require higher social interaction and thus are more affected by mobility restrictions. Parts of the sector also mainly involve office work, which can transition into a WFH arrangement smoothly.

However, we find that the effect of new COVID-19 cases in provinces with a high proportion of employment in the tertiary sector is temporary. The coefficient becomes statistically insignificant in the second period, suggesting a transition to the new normal, where sectoral characteristics become less important in determining mobility.

These results highlight the role of provincial sectoral employment in responding to the pandemic. We find a statistically significant effect of PSBB on mobility in residential areas but not in workplaces during the first 120 days of the observation. This suggests that while the policy failed to limit people's activity in the workplace, it was successful in limiting other kinds of activities, thus increasing the number of people at home and the time spent there. This may be because of the WFH limitations for most workers, especially in areas outside of the capital, such as the type of jobs or sectors that they are in (as some jobs can only be done on-site), the informal nature of some employments, or internet and technology access. Without a WFH option, and limited government support for workers in the informal sectors, many workers have to keep working on-site. These results raise doubts about the effectiveness of large-scale social restrictions, especially when WFH is not an option for many workers.

We also find that the effect of PSBB on mobility declines the longer it is implemented. We confirm this by adding a variable of the squared number of days of PSBB. The other measure of mobility restrictions, the stringency index, has a negative and significant effect on mobility in workplaces, and a positive and significant effect on mobility in residential areas in both the first and second periods. This shows that the more stringent physical and social restriction measures are, the stronger their impacts on mobility.

We also find that time-trend and its squared form, as well as holidays and Eid celebrations, day of week fixed effects, and month fixed effects, to significantly affect both workplace and residential mobility. We find that people worked less on the weekend, holidays and during the Eid festive days. They increased the time they spent at home during the weekend and holidays.

Our findings provide important lessons for policymakers on the underlying economic structure when applying mobility restrictions in the face of a pandemic. Indonesia was only able to limit mobility during the early stages of the pandemic, with varying effectiveness of these policies due to the provincial employment structure. Limiting mobility during the early stage of a pandemic is crucial and can determine its trajectory and recovery. This is especially important in the case of developing countries, where strict restrictions are hard to enforce and the economic implications of economic shut down can have a detrimental effect on people's welfare.

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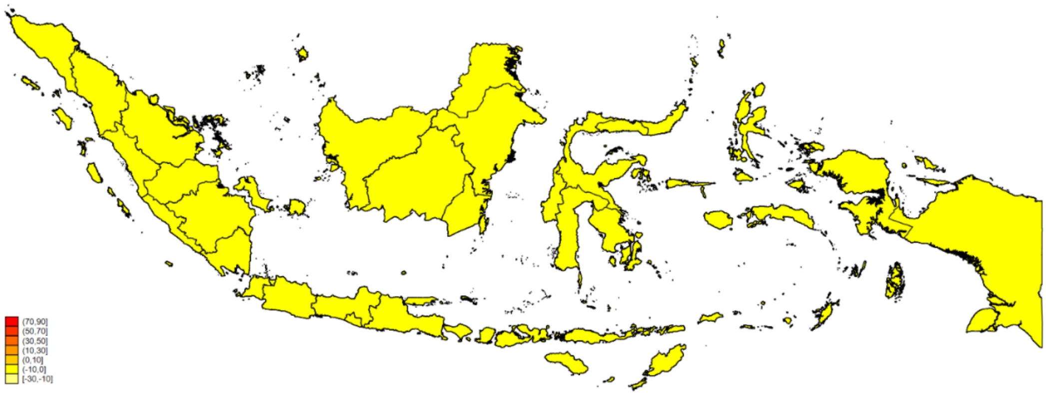
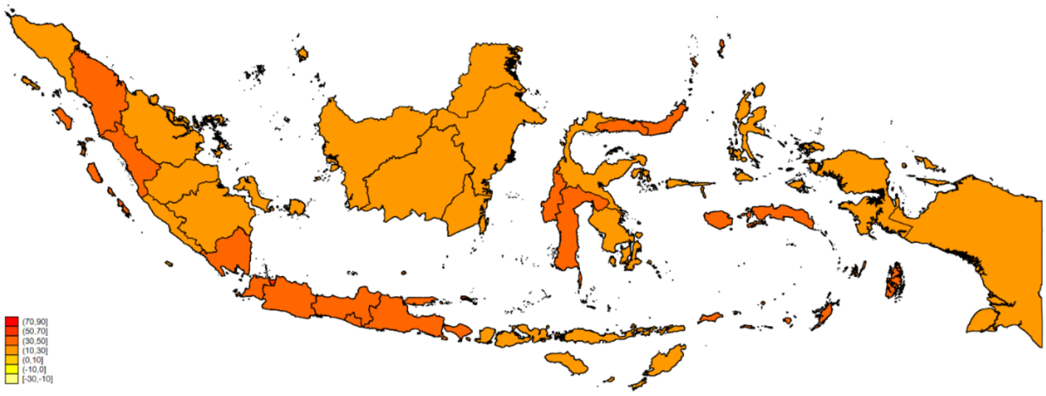
Appendix

Figure A.1. Changes in Mobility Level At Workplaces Compared to the Benchmark Period (Every 30 Days)

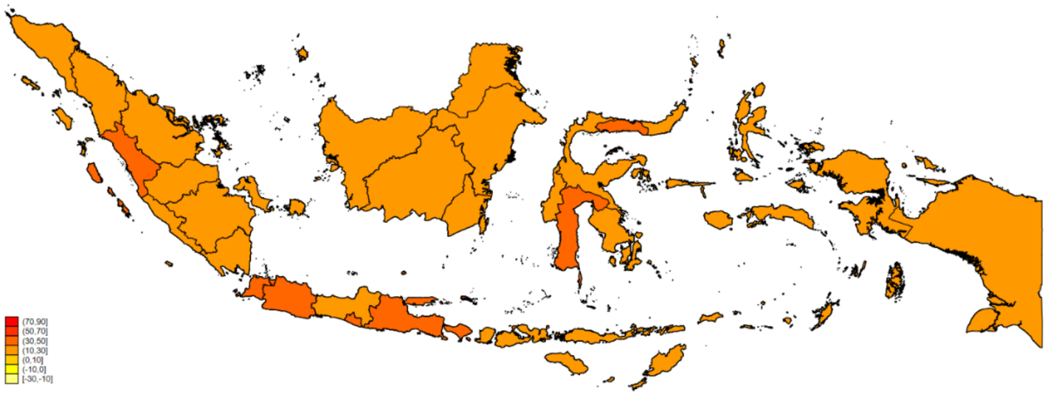
a. Day 30 (15 March 2020)



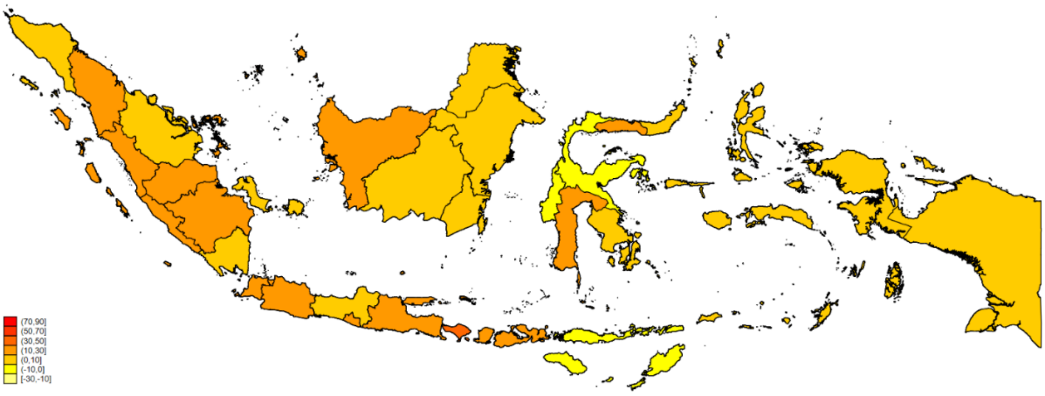
b. Day 60 (14 April 2020)



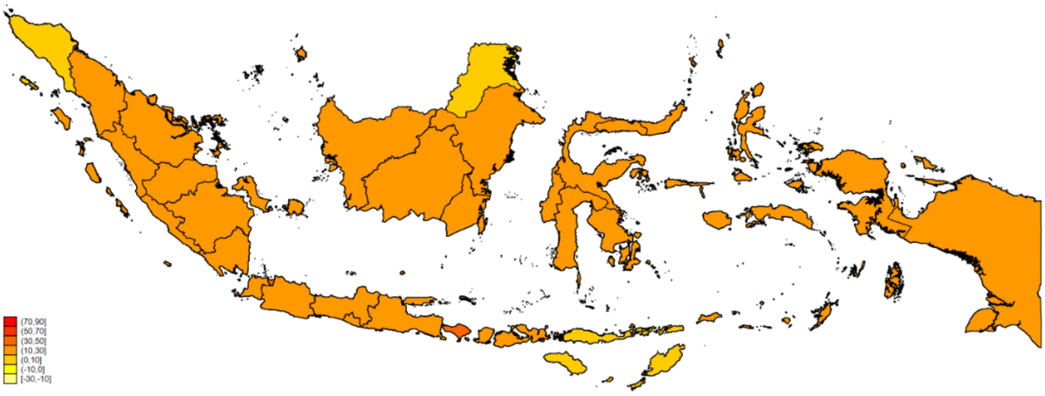
c. Day 90 (14 May 2020)



d. Day 120 (13 June 2020)



e. Day 150 (13 July 2020)



f. Day 180 (12 August 2020)

g. Day 210 (11 September 2020)

Note: The colors correspond to difference (in percentages) in mobility at workplaces compared to a baseline day in the benchmark period (3 January–6 February). Higher values (red and orange) mean a steeper decline in mobility, while lower values (yellow) mean a modest decline or an increase in mobility at workplaces.
Source: Authors' calculations based on Google mobility data.

Table A.1. Robustness Check: The Impact of the Share of Employment in the Primary Sector On People Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Simplified Mobility in Residentials**			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Primary	0.000487	0.0149***	0.0183***	0.0108	–0.0200**	–0.00301
Sectors x Lagged Daily New	(0.0110)	(0.00448)	(0.00487)	(0.0261)	(0.00829)	(0.0109)
COVID Cases						
Lagged Total Accumulated	0.000283*	2.02e-05	–1.65e-06	–0.00100*	–5.32e-05	–5.41e-05
Cases	(0.000148)	(1.52e-05)	(1.95e-05)	(0.000585)	(4.50e-05)	(7.84e-05)
PSBB (days)	0.0816***	0.00128	0.0163	–0.116	0.0140	–0.0563*
	(0.0296)	(0.0111)	(0.0131)	(0.0772)	(0.0180)	(0.0300)
PSBB (days squared)	–0.00136***	7.10e-05	–0.000121	0.00148	–8.73e-05	0.000406*
	(0.000403)	(6.44e-05)	(9.57e-05)	(0.00126)	(0.000121)	(0.000206)
Stringency Index	0.0829***	0.0650***	0.155***	–0.0425**	–0.0558***	–0.174***
	(0.00847)	(0.00870)	(0.00834)	(0.0192)	(0.0180)	(0.0118)
Time (days)	0.614***	–0.202***	0.226***	–1.562***	0.00392	–0.677***
	(0.0254)	(0.0283)	(0.00971)	(0.0590)	(0.0498)	(0.0267)
Time (days squared)	–0.00392***	0.000560***	–0.000776***	0.0101***	0.000272	0.00234***
	(0.000151)	(8.12e-05)	(3.30e-05)	(0.000335)	(0.000167)	(7.17e-05)
Weekend and Holiday	3.943***	4.265***	4.595***	–21.18***	–34.02***	–25.70***
	(0.138)	(0.276)	(0.161)	(0.338)	(0.692)	(0.399)
Eid Week	0.00844		–2.481***	–6.800***		0.294

	(0.182)		(0.242)	(0.296)		(0.325)
Time x Sumatera	–0.0433***	0.0125*	–0.0102***	0.0316	–0.0122	0.0116
	(0.0102)	(0.00636)	(0.00320)	(0.0330)	(0.0194)	(0.0131)
Time x Kalimantan	–0.0389***	–0.00125	–0.00583	0.0654**	–0.0281	0.0105
	(0.00840)	(0.00828)	(0.00362)	(0.0321)	(0.0199)	(0.0126)
Time x Sulawesi	–0.0258**	-0.00521	–0.00878**	0.0664*	–0.000929	0.0295*
	(0.0125)	(0.00695)	(0.00364)	(0.0388)	(0.0207)	(0.0152)
Time x Maluku	–0.0304***	–0.0152	–0.00895	0.0784**	0.00546	0.0294
	(0.00841)	(0.0112)	(0.00553)	(0.0385)	(0.0246)	(0.0190)
Time x Papua	–0.0132	–0.0182***	–0.0138***	0.0315	–0.0209	0.0162
	(0.00899)	(0.00520)	(0.00469)	(0.0329)	(0.0193)	(0.0135)
Constant	89.17***	116.5***	88.63***	148.1***	134.4***	152.7***
	(0.524)	(2.217)	(0.698)	(0.946)	(4.715)	(1.082)
Province fixed effects	yes	yes	yes	yes	yes	yes
Monthly fixed effects	yes	yes	yes	yes	yes	yes
Daily dummy	yes	yes	yes	yes	yes	yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.839	0.583	0.765	0.799	0.849	0.770
Number of id_region	34	34	34	34	34	34

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Labour data using SAKERNAS February 2020.
Source: Authors' calculations.

Table A.2. Robustness Check: The Impact of the Share of Employment in the Secondary Sector on People Mobility

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Simplified Mobility in Residentials			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Secondary Sectors x Lagged Daily New COVID Cases	0.0165	0.00839*	0.0189***	–0.0229	–0.0122	0.000563
	(0.0241)	(0.00495)	(0.00559)	(0.0453)	(0.00836)	(0.0148)
Lagged Total Accumulated Cases	0.000202*	1.11e-05	–1.04e-05	-0.000821	–3.91e-05	–6.14e-05
	(0.000113)	(1.65e-05)	(2.05e-05)	(0.000502)	(4.73e-05)	(8.48e-05)
PSBB (days)	0.0766***	0.00880	0.0236	–0.104	0.00366	–0.0568*
	(0.0262)	(0.0143)	(0.0147)	(0.0674)	(0.0222)	(0.0294)
PSBB (days squared)	–0.00124***	1.58e-05	–0.000207*	0.00119	–1.04e-05	0.000414**
	(0.000373)	(8.39e-05)	(0.000115)	(0.00105)	(0.000138)	(0.000197)
Stringency Index	0.0829***	0.0654***	0.155***	–0.0428**	–0.0565***	–0.173***
	(0.00846)	(0.00850)	(0.00831)	(0.0191)	(0.0180)	(0.0119)
Time (days)	0.613***	–0.206***	0.225***	–1.562***	0.00887	–0.678***
	(0.0253)	(0.0303)	(0.00989)	(0.0589)	(0.0516)	(0.0264)
Time (days squared)	–0.00392***	0.000581***	–0.000768***	0.0101***	0.000246	0.00234***
	(0.000151)	(8.82e-05)	(3.37e-05)	(0.000339)	(0.000169)	(7.26e-05)
Weekend and Holiday	3.943***	4.260***	4.593***	–21.18***	–34.02***	–25.70***

	(0.138)	(0.276)	(0.163)	(0.338)	(0.692)	(0.400)
Eid Week	0.00502		–2.487***	–6.791***		0.292
	(0.181)		(0.245)	(0.292)		(0.325)
Time x Sumatera	–0.0428***	0.0121*	–0.00959***	0.0313	–0.0117	0.0117
	(0.0102)	(0.00697)	(0.00351)	(0.0331)	(0.0195)	(0.0128)
Time x Kalimantan	–0.0385***	–0.00158	–0.00471	0.0652**	–0.0277	0.0107
	(0.00835)	(0.00900)	(0.00445)	(0.0320)	(0.0204)	(0.0124)
Time x Sulawesi	–0.0253**	–0.00809	–0.00846**	0.0662*	0.00286	0.0299*
	(0.0124)	(0.00706)	(0.00372)	(0.0387)	(0.0203)	(0.0149)
Time x Maluku	–0.0301***	–0.0182	–0.00899	0.0784**	0.00944	0.0298
	(0.00842)	(0.0110)	(0.00579)	(0.0385)	(0.0241)	(0.0187)
Time x Papua	–0.0127	–0.0190***	–0.0125***	0.0318	–0.0198	0.0164
	(0.00890)	(0.00524)	(0.00409)	(0.0327)	(0.0193)	(0.0132)
Constant	89.17***	116.9***	88.64***	148.1***	133.9***	152.7***
	(0.528)	(2.375)	(0.692)	(0.946)	(4.859)	(1.086)
Province fixed effects	yes	yes	yes	yes	yes	yes
Monthly fixed effects	yes	yes	yes	yes	yes	yes
Daily dummy	yes	yes	yes	yes	yes	yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.839	0.578	0.764	0.799	0.848	0.770
Number of id_region	34	34	34	34	34	34

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Labour data using SAKERNAS February 2020.
Source: Authors' calculations.

Table A.3. Robustness Check: The Impact of the Share of Employment in the Tertiary Sector on People Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Simplified Mobility in Residentials**			**Simplified Mobility in Workplaces**		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(%) Employment in Tertiary Sectors x	0.0295**	0.00146	0.00279	–0.0585**	–0.00315	–0.00910**
Lagged Daily New COVID Cases	(0.0119)	(0.00207)	(0.00174)	(0.0218)	(0.00351)	(0.00377)
Lagged Total Accumulated Cases	–0.000156	1.16e-05	7.35e-06	–5.95e-05	–2.79e-05	2.89e-05
	(0.000104)	(2.45e-05)	(2.55e-05)	(0.000459)	(6.61e-05)	(7.31e-05)
PSBB (days)	0.0588**	0.00869	0.0225	–0.0660	0.00225	–0.0650**
	(0.0222)	(0.0154)	(0.0154)	(0.0541)	(0.0234)	(0.0311)
PSBB (days squared)	–0.000833*	1.92e-05	–0.000206	0.000305	–5.95e-07	0.000517**
	(0.000413)	(9.35e-05)	(0.000125)	(0.000891)	(0.000151)	(0.000225)
Stringency Index	0.0829***	0.0650***	0.155***	–0.0429**	–0.0559***	–0.173***
	(0.00852)	(0.00846)	(0.00840)	(0.0191)	(0.0181)	(0.0119)
Time (days)	0.613***	–0.207***	0.227***	–1.561***	0.00958	–0.677***
	(0.0246)	(0.0312)	(0.00972)	(0.0576)	(0.0522)	(0.0260)
Time (days squared)	–0.00391***	0.000589***	–0.000767***	0.0101***	0.000234	0.00233***
	(0.000144)	(8.83e-05)	(3.49e-05)	(0.000327)	(0.000167)	(7.02e-05)
Weekend and Holiday	3.936***	4.256***	4.590***	–21.16***	–34.02***	–25.71***
	(0.136)	(0.275)	(0.162)	(0.341)	(0.691)	(0.399)

Eid Week	0.0114		–2.480***	–6.801***		0.314
	(0.182)		(0.246)	(0.290)		(0.323)
Time x Sumatera	–0.0435***	0.0109	–0.0116***	0.0324	–0.00899	0.0135
	(0.00991)	(0.00753)	(0.00398)	(0.0328)	(0.0206)	(0.0130)
Time x Kalimantan	–0.0394***	–0.00305	–0.00668	0.0668**	–0.0252	0.0112
	(0.00771)	(0.00919)	(0.00479)	(0.0314)	(0.0207)	(0.0128)
Time x Sulawesi	–0.0262**	–0.00962	–0.0106**	0.0677*	0.00565	0.0308*
	(0.0120)	(0.00743)	(0.00400)	(0.0381)	(0.0206)	(0.0152)
Time x Maluku	–0.0313***	–0.0197*	–0.0112*	0.0808**	0.0124	0.0310
	(0.00797)	(0.0113)	(0.00600)	(0.0380)	(0.0249)	(0.0188)
Time x Papua	–0.0135	–0.0204***	–0.0148***	0.0331	–0.0169	0.0174
	(0.00867)	(0.00598)	(0.00451)	(0.0323)	(0.0203)	(0.0131)
Constant	89.18***	117.1***	88.65***	148.1***	133.7***	152.7***
	(0.513)	(2.402)	(0.687)	(0.939)	(4.821)	(1.074)
Province fixed effects	yes	yes	yes	yes	yes	yes
Monthly fixed effects	yes	yes	yes	yes	yes	yes
Daily dummy	yes	yes	yes	yes	yes	yes
Observations	4,046	3,468	7,514	4,046	3,468	7,514
R-squared	0.840	0.577	0.764	0.800	0.848	0.770
Number of id_region	34	34	34	34	34	34

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Labour data using SAKERNAS February 2020.
Source: Authors' calculations.

Table A.4. The Results for the Interaction Variable of the Share of Employment in 17 Subsectors and New Daily Cases to People's Mobility

Sectoral impact	(1)	(2)	(3)	(4)	(5)	(6)
	Mobility in residentials			Mobility in workplaces		
	Period I	Period II	Period Total	Period I	Period II	Period Total
(a) Agriculture, forestry and fishing	–0.000751	0.0151***	0.0182***	0.0119	–0.0205**	–0.00166
	(0.0109)	(0.00475)	(0.00503)	(0.0270)	(0.00879)	(0.0113)
(b) Mining and quarrying	0.651***	0.161***	0.257***	–0.295	–0.178*	–0.337***
	(0.199)	(0.0361)	(0.0767)	(0.354)	(0.0999)	(0.104)
(c) Manufacturing	0.0269	0.00977	0.0236***	–0.0382	–0.0146	0.00479
	(0.0372)	(0.00677)	(0.00752)	(0.0696)	(0.0116)	(0.0236)
(d) Electricity and gas	4.224	0.581	1.203**	–7.550	–1.188	–2.759***
	(2.881)	(0.469)	(0.458)	(5.366)	(0.779)	(0.841)
(e) Water supply, sewerage, waste management	2.810	0.593*	1.234***	–4.613	–0.706	–0.712
and remediation activities	(1.780)	(0.324)	(0.403)	(3.164)	(0.524)	(0.713)
(f) Construction	0.0306	0.0428**	0.0809***	–0.0326	–0.0599*	–0.0130
	(0.0660)	(0.0189)	(0.0215)	(0.136)	(0.0322)	(0.0400)
(g) Wholesale and retail trade, repair of motor	0.0616	0.00718	0.0143**	–0.120*	–0.0110	–0.0245**
vehicles	(0.0378)	(0.00637)	(0.00575)	(0.0709)	(0.0101)	(0.0118)
(h) Transportation and storage	0.372***	0.00250	0.00793	–0.763***	–0.0165	–0.0728**
	(0.0355)	(0.0159)	(0.0128)	(0.0563)	(0.0298)	(0.0314)

(i) Accommodation and food service activities	0.178**	0.00645	0.0140	–0.340**	–0.0159	–0.0497*
	(0.0840)	(0.0129)	(0.0107)	(0.158)	(0.0222)	(0.0257)
(j) Information and communication	1.380***	–0.0149	–0.0108	–2.992***	–0.0127	–0.223*
	(0.133)	(0.0575)	(0.0533)	(0.307)	(0.110)	(0.125)
(k) Financial and insurance activities	0.952***	–0.00297	0.0103	–1.975***	–0.0340	–0.193*
	(0.185)	(0.0453)	(0.0396)	(0.301)	(0.0850)	(0.101)
(l) Real estate activities	2.067***	–0.0603	–0.0474	–4.571***	0.0124	–0.311
	(0.192)	(0.0815)	(0.0836)	(0.589)	(0.164)	(0.201)
(m) Business activities	0.860***	0.000611	0.00556	–1.791***	–0.0321	–0.173**
	(0.0830)	(0.0380)	(0.0306)	(0.161)	(0.0695)	(0.0746)
(n) Public administration and defense,	0.364**	0.0505*	0.0837***	–0.721***	–0.0984**	–0.225***
compulsory social security	(0.141)	(0.0281)	(0.0274)	(0.224)	(0.0464)	(0.0481)
(o) Education	0.167	0.0484*	0.0941***	–0.308	–0.0762*	–0.114***
	(0.123)	(0.0246)	(0.0248)	(0.235)	(0.0399)	(0.0388)
(p) Human health and social work activities	0.901**	0.0534	0.0900*	–1.893***	–0.122	–0.331***
	(0.360)	(0.0633)	(0.0522)	(0.585)	(0.110)	(0.111)
(q) Other service activities	0.273***	0.000585	0.00676	–0.537***	–0.0147	–0.0605*
	(0.0761)	(0.0146)	(0.0124)	(0.142)	(0.0277)	(0.0307)

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each field of results represents different estimations. Labour data using SAKERNAS February 2020.
Source: Authors' calculations.

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