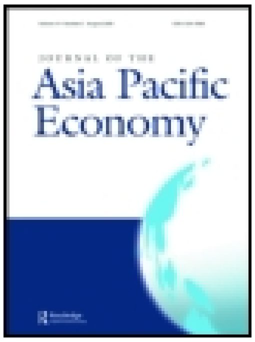

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The impact of COVID-19 on the labour market and the role of E-commerce development in developing countries: Evidence from Indonesia

Masagus M. Ridhwan[a], Asep Suryahadi[a,b], Jahen F. Rezki[a,c] and Dinda Thalia Andariesta[a]

[a]Bank Indonesia Institute, Bank Indonesia, Jakarta Pusat, DKI Jakarta, Indonesia; [b]SMERU Research Institute, Jakarta Pusat, DKI Jakarta, Indonesia; [c]Institute for Economic and Social Research (LPEM-FEB UI), Jakarta Pusat, DKI Jakarta, Indonesia

ABSTRACT

This paper assesses the impact of covid-19 pandemic, measured through work mobility reduction, and e-commerce growth on the labour market using data from Indonesian labour force surveys and e-commerce transaction values. The findings confirm that the pandemic adversely affects workers' employment prospects, work hours, total earnings, and hourly earnings. E-commerce growth does not counteract the adverse impact of the pandemic as expected, but it plays a role as an employment buffer during the crisis, although it tends to suppress workers' earnings. Our results imply that more efforts are needed to improve the productivity of workers involved in e-commerce.

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1. Introduction

One of the markets most adversely affected by the COVID-19 pandemic is the labour market. On the supply side, infected workers, fear of infection, and mobility restriction policies reduced the supply of workers. On the demand side, a decrease in goods and services markets reduced the derived demand for workers. The net effect of these pressures is a reduction in the number of available jobs (Brochu et al., 2020; Hensvik et al., 2021; Ranchhod & Daniels, 2020), fewer working hours (Anderton et al., 2020; Béland et al., 2020; Crossley et al., 2021; Lemieux et al., 2020), or increased early retirement (Anderton et al., 2020; Coibion et al., 2020).

In terms of earnings, however, there are fewer convergent findings. Using early UK and US data, Bell and Blanchflower (2020) predict that nominal earnings growth will slow down and real take-home pay will decline. However, Béland et al. (2020) found that the pandemic has, so far, had no significant impact on wages in the US. Meanwhile, Schotte et al. (2021) found that earnings only declined as an immediate impact after the imposition of the lockdown but bounced back to the normal level approximately four months after the relaxation.

CONTACT Jahen F. Rezki jahen.fr@ui.ac.id

The pandemic has disproportionate effects on parts of the labour market due to their work nature, such as hotels and restaurants, retail trade, arts, and leisure and recreation activities (Barrot et al., 2021; Borland & Charlton, 2020; Byrne et al., 2020; Lemieux et al., 2020). The ability to work remotely might have a cushioning effect (Anderton et al., 2020; Barrot et al., 2021; Lin & Meissner, 2020). However, a better cushion is the wage subsidy programmes, such as the job retention scheme in the UK (Crossley et al., 2021) and JobKeeper in Australia (Borland & Charlton, 2020).

The pandemic also has disproportionate effects on workers with specific characteristics. The most affected are the young, women, informal workers, especially the self-employed, the less-educated, the low-skilled, racial minority or immigrants, non-union or low-tenured workers, as well as workers who have jobs with temporary or zero-hours contracts, low-paid jobs, and jobs in low-productivity services (Abraham et al., 2022; Béland et al., 2020; Bell & Blanchflower, 2020; Borland & Charlton, 2020; Brochu et al., 2020; Casarico & Lattanzio, 2022; Churchill, 2021; Crossley et al., 2021; Hassink et al., 2021; Inanc, 2020; Lemieux et al., 2020; Pouliakas & Branka, 2020; Ranchhod & Daniels, 2020; Schotte et al., 2021). However, Casarico and Lattanzio (2022) did not find gender a significant predictor of job loss.

On the other hand, the COVID-19 pandemic has caused a dramatic rise in digitalisation in almost every aspect of human life (World Bank, 2021). Adopting digital technologies, such as the internet, social media, specialised apps, and digital platforms, to replace the pre-COVID-19 conventional practice of business has been one of the most highlighted strategies of firms in coping with the pandemic. Although digitalisation allows remote work, it does not do so to the same extent for all jobs. Dingel and Neiman (2020) show that remote work primarily applies to higher-educated or higher-skilled workers, who are more immune to the risk of automation and artificial intelligence.

These two strands of the literature, one on the labour market impact of COVID-19 (e.g., Abraham et al., 2022; Béland et al., 2020; Bell & Blanchflower, 2020; Borland & Charlton, 2020; Brochu et al., 2020; Casarico & Lattanzio, 2022; Churchill, 2021; Crossley et al., 2021; Hassink et al., 2021; Inanc, 2020; Lemieux et al., 2020; Pouliakas & Branka, 2020; Ranchhod & Daniels, 2020; Schotte et al., 2021) and the other on the development of e-commerce as a response to the restrictions due to the pandemic (e.g., Google et al., 2021; Park & Inocencio, 2020; World Bank, 2021), suggest that to understand the impact of COVID-19 on the labour market comprehensively, we need to assess both phenomena simultaneously. Indonesia is an ideal case to assess how far e-commerce growth can counteract the adverse effects of the COVID-19 pandemic since the country has experienced both a severe impact of the COVID-19 pandemic and the fast development of e-commerce since early 2020. Hence, this study's contribution is assessing simultaneously the impact of COVID-19 and the growth of e-commerce on workers' labour market outcomes, particularly in terms of their employment prospects, work hours, total earnings, and earnings per hour.

In Indonesia, COVID-19 was first identified in March 2020 in the capital city of Jakarta. Soon, it spread to all parts of the country. By September 2021, the virus has infected more than 4.2 million people, with more than 140,000 deaths (Ritchie et al., 2020). Like in other countries, the pandemic has severely disrupted the Indonesian economy. During 2020, the economy contracted consecutively in the last three quarters, resulting in negative economic growth of 2.07% during the whole year (Statistics Indonesia, 2021).

At the same time, Indonesia has experienced fast growth in electronic commerce (e-commerce), even before the COVID-19 pandemic. The onset of the pandemic accelerated e-commerce growth further, as people used it as an alternative strategy or solution to the mobility and activity restriction policy. As a result, the contribution of e-commerce to the trade sector's Gross Domestic Product (GDP) has jumped from around 2% in 2016 to about 20% in 2020 (Pratama, 2021). This growth of e-commerce was, hence, expected to counteract the adverse effects of COVID-19 on the labour market.

This study finds that COVID-19 indeed has adverse effects on workers' labour market outcomes. However, e-commerce growth did not counteract the adverse effects of COVID-19 as expected, but it did play a role as an employment buffer during the crisis. While e-commerce growth creates jobs, these jobs are mainly in the form of self-employment, strengthening the effect of COVID-19 on increasing the share of informal workers. Furthermore, e-commerce growth tends to suppress the earnings of workers, which does not help the efforts to improve people's welfare either.

The remainder of the paper is structured as follows. Section Two reviews the developments of the COVID-19 pandemic and the digital economy in Indonesia. Section Three presents the conceptual framework and empirical strategy used in this study. Section Four presents the descriptive analysis of mobility, e-commerce, and labour market developments during the pandemic. Section Five discusses the estimation results of the effects of COVID-19 and e-commerce on workers' outcomes. Finally, Section Six provides the conclusion and policy implication.

2. The developments of the COVID-19 pandemic and digital economy in Indonesia

2.1. The COVID-19 pandemic

The declaration of the first COVID-19 case in Indonesia took place on 2 March 2020. Since then, up until September 2021, Indonesia recorded more than 4.2 million cases, with over 140,000 deaths (Ritchie et al., 2020). The pandemic disrupted economic growth in Indonesia and brought it down from a steady 5% during the pre-COVID-19 period to a negative growth of 2.07% during the whole year of 2020 (Statistics Indonesia, 2021). The negative growth has been brought about not only by the pandemic *per se* but also by the policy responses to curb the pandemic (Iyke et al., 2021). The drop in growth was caused by, most notably, a reduction in the contribution of household consumption and gross fixed capital formation (Olivia et al., 2020; Sparrow et al., 2020).

However, the impact has not been uniformed across sectors. While the pandemic has hit some sectors harder than others, certain other sectors have grown positively. During 2020, when the GDP of the overall economy contracted by 2.07%, the GDP of several sectors actually expanded. Out of the 17 economic sectors in Indonesia, seven sectors managed to show positive GDP growth during 2020: health services and social activities by 11.60%, information and communication by 10.58%, water and recycling by 4.94%, financial services and insurance by 3.25%, education services by 2.63%, real estate by 2.32%, and agriculture by 1.75% (Statistics Indonesia, 2021).

Similarly, the impact has not been equal for all workers. Manning (2021a) finds that the distancing and mobility restriction measures have directly hit informal sectors, with two-thirds having to cease their business activities, facing cash-flow problems, thereby leading to retrenchment and lay-offs. This finding was confirmed by Prospera's business survey (Temenggung et al., 2021). On the other hand, while millions of workers have lost jobs and/or getting reduced income, some other workers have managed to increase their income (Ridhwan et al., 2023). Similarly, while most households reduced their per capita consumption during 2020, the top 5% of households managed to increase their per capita consumption, indicating a higher income during the pandemic (Suryahadi et al., 2021).

On the labour market impact, Manning (2021a) argues that while unemployment is a good measure of labour market difficulties, underemployment and informality might provide more insights into the problem. Similarly, Temenggung et al. (2021) point out that the increase in the number of unpaid family workers during the pandemic is a form of adaptation to the shock. They also suggest that labour market adjustment might disproportionately affect a particular demographic category.

COVID-19 also changed the sectoral share of employment. Agriculture experienced the most significant increase in the number of workers, with an additional 2.8 million workers from August 2019 to August 2020. Meanwhile, the sector that experienced the largest reduction in the number of workers is manufacturing, with a reduction of 1.7 million workers in the same period (Suryahadi et al., 2021). At least some of the displaced, mostly male, workers from manufacturing, transport, and construction probably moved into agriculture temporarily. The new jobs were not only in their home villages but also in urban locations where new forms of agriculture have grown during 2020 (Manning, 2021a).

2.2. The development of the digital economy

The development of digital technology is projected to have an essential contribution to Indonesian economic development. Das et al. (2016) predict that, by 2025, digitization will bring an impact of 150 billion US dollars and additional employment for 3.7 million people. The number of startups in Indonesia has grown significantly from 1,400 in 2017 to 2,200 in 2019, placing Indonesia in the second rank in Asia and fifth in the world after the US, India, UK, and Canada, as reported by the Startup Ranking website in 2020.

Indonesia has fostered a digital ecosystem that includes e-commerce. Electronic commerce, popularly known as e-commerce, is defined by Khan (2016) as buying and selling products and services through the Internet. Similarly, Das et al. (2018) define e-commerce as buying and selling physical products online. Before purchasing online or in a physical store, many people use the internet to compare prices or check out the newest products on the market. In 2022, the potential of e-commerce in Indonesia was projected to reach 55-65 billion dollars (Das et al., 2018).

Related to this development, Indonesia's internet connectivity has grown steadily over the years. The number of adults with internet connections increased almost four times, from 13% in 2011 to 51% in 2019 (World Bank, 2021). This increase was driven by significant information and communication technology (ICT) infrastructure development, such as constructing a 36,000 km Palapa Ring fibre optic project in the country, including in rural areas, to facilitate equal high-speed internet access across Indonesia.

The adaptation of digital technology has been translated to a substantial increase in e-commerce transactions. Based on the e-commerce transaction values summary provided by Bank Indonesia, total e-commerce transactions increased almost five times from 42 trillion rupiahs in 2017 to 205 trillion rupiahs in 2019. Even in the recession year of 2020, e-commerce transactions still increased to a total of 266.3 trillion rupiahs. According to Indonesian E-Commerce Association data, as of May 2021, the number of micro, small, and medium enterprises (MSMEs) that have joined the Indonesian digital ecosystem has reached 13.7 million, or about 21% of the total number of enterprises.[1] Nevertheless, connectivity gaps still exist across regions, income, generations, education, and gender (World Bank, 2021).

Digital apps such as ride-hailing services have been an integral part of Indonesians' daily activities, especially in big cities. Many startups have been popping up in Indonesia to provide digital solutions to customers in almost every aspect of life. These digital advancements have boosted consumer welfare by supplying various goods and services that were not accessible before. COVID-19 has accelerated the digitalisation of enterprises to cope with restrictions due to limited mobility and interaction. For example, many food sellers have joined food delivery platforms to still operate without providing a dine-in place. However, this adoption is disproportionately higher for larger firms (World Bank, 2021).

Besides firms that utilise digital technologies to continue their operation, digital technologies also give opportunities for people to produce and deliver services, specifically using online platforms. These types of jobs are typically known as "digital gig jobs". These digital gig workers are typically hired as "partners" without regular work time or a specific workload. One of the most typical examples of Indonesian gig workers is the driver of ride-hailing apps. Digital gig workers earn more than similar informal workers and are less likely to have second jobs (World Bank, 2021). Overall, the digital economy in Indonesia has been growing substantially over the years and has been amplified by the necessity to adopt digital technologies caused by the COVID-19 pandemic.

The COVID-19 pandemic has accelerated the growth of e-commerce. Since the pandemic, Indonesia has seen 21 million new digital consumers, where 72% are from non-metro areas, indicating a growing penetration in the region. Meanwhile, those who have already used the services have consumed an average of 3.6 more services since the pandemic began. Overall, all internet sectors rebounded strongly with double-digit growth. Indonesia's gross merchandise value (GMV) is expected to reach a total value of $70 billion in 2021, a 49% year-on-year increase. A 52% growth in e-commerce underpins this steep increase. Indonesia continues to be one of the most vibrant digital financial services markets due to its relatively open regulatory framework (Google et al., 2021).

However, the increase in digital adaptability is still unequal among various socioeconomic strata. Internet access is still uneven across regions, gender, income levels, education levels, and business sectors. For example, in 2019, only 2% of the total workforce in the agricultural sector used the internet, while the number of workers in this sector reached 27% of the total number of people working in Indonesia (Statistics Indonesia, 2019). Furthermore, the internet is still mainly considered a mere means of communication and entertainment, not yet widely considered a means of business (Bachtiar et al., 2020). Furthermore, internet availability has only a small significant effect on the female labour force participation rate and no statistically significant effect on the employment rate. It also reduces the probability of women with a low level of education working in the formal sector. However, it increases the likelihood of women having a full-time job, especially for women aged 15–45 and those with a low level of education (Kusumawardhani et al., 2021).

The World Bank survey in Indonesia in June 2020 showed that many firms had adjusted their strategy in response to COVID-19 by adopting digital technologies (World Bank, 2021). However, the uptake was higher among larger firms, although the number for medium and micro firms is not negligible. Higher-skilled workers and larger and more formal firms can easily adopt digital technologies. Overall, digitalisation has enabled firms to adapt to the new working circumstances caused by the COVID-19 pandemic. On the other hand, like in other countries, the shift to remote working might negatively affect some jobs predominantly occupied by low-skilled workers. Therefore, appropriate policies such as increasing digital readiness, developing skills for the digital economy, and strengthening social protection are needed to alleviate this trend of job polarisation (Park & Inocencio, 2020).

3. Conceptual framework and Empirical strategy

3.1. Conceptual framework

Theoretically and empirically, various studies have found that the pandemic impact on the economy does not come from the health aspect itself but rather from the mobility restrictions or the lockdown policy. Guirrieri et al. (2020) propose a theoretical framework along with possible outcomes in various market settings. Eichenbaum et al. (2021) formulated a model that captures the interaction between economic decisions and epidemiologic outcomes. Their model confirms that the virus containment might take a toll on the economy in the form of a recession.

The findings are also confirmed by Melbourne Institute Submitter, Hassink et al. (2021) in the case of the Netherlands, where the location of the policy is imposed explains the economic decline better than the number of cases. Schotte et al. (2021) found that workers in districts under lockdown had a 34.3% lower chance of working than the control group in Ghana. Further evidence is found from the analysis of European labour market data (Anderton et al., 2020), British labour market survey

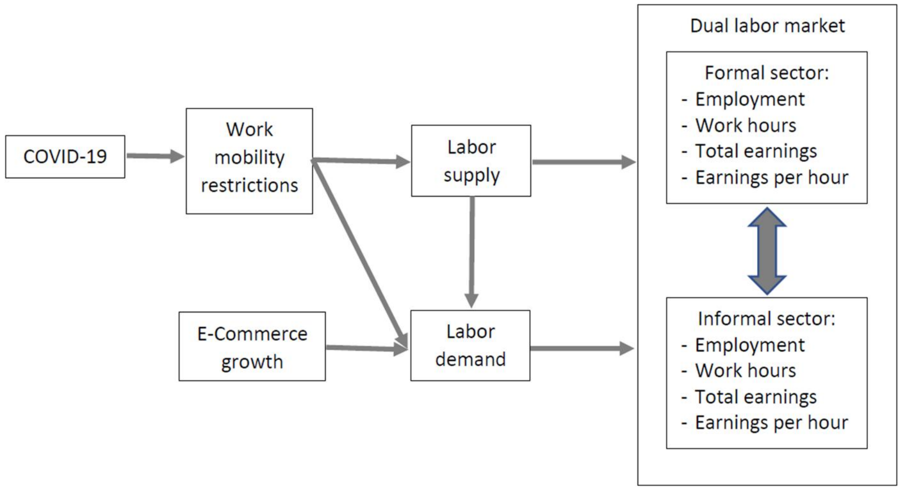


Figure 1. The framework of the Impacts of COVID-19 and e-commerce growth on labour market outcomes of workers.
Figure 1 Alt Text: The framework that explains the impact of COVID-19 on the labour market due to work mobility restrictions and the growth of e-commerce.

data (Crossley et al., 2021), and Indonesian consumer survey data (Ridhwan et al., 2023).

Based on these literatures, Figure 1 depicts the framework of the impact of COVID-19 and e-commerce growth on workers' labour market outcomes used in this study. To contain the spread of COVID-19, the government imposes mobility and activity restrictions, including mobility to the workplace (Ridhwan et al., 2023; Suryahadi et al., 2021). In addition, several workers are infected, thereby reducing production capacity (Hausmann, 2020). Furthermore, the fear of being infected also reduced the labour supply, as people choose to stay at home rather than go to work, and this causes a negative labour supply shock.

These factors have led to a demand shock. As people lost jobs or faced shortened working hours, their earnings declined, resulting in lower household income and reduced consumption. Hence, the demand for goods and services declines. Moreover, in countries with incomplete markets and liquidity-constrained consumers, the initial supply shock leads to amplified demand shocks (Guirrieri et al., 2020).

Developing countries, including Indonesia, lack unemployment benefits, and the social protection system is weak and insufficient. Hence, workers cannot remain unemployed for long, thereby they have to return to the labour market to earn income. Since the formal sector has shrunk, they have to enter the informal sector, increasing the informalisation of the economy. The existence of a dual labour market, which consists of the formal and informal sectors[2], makes this mechanism possible. The informal sector provides a buffer for workers who lost jobs and cannot find one in the formal sector. The expectation is that they will return to the formal sector after the recovery.

The importance of the informal sector as a buffer during the Asian Financial Crisis (AFC) of 1997–1998 in Indonesia is well documented (Booth, 2000; Feridhanusetyawan, 1999; Manning, 1999, 2000; Papanek & Handoko, 1999; Potter, 2000). Manning (2000) summarises this phenomenon by arguing that the Indonesian labour market had not shed its 'traditional' features on the eve of the AFC, despite three decades of rapid economic growth. The agricultural and urban informal sectors remained large. This structure supported labour market adaptation to the crisis through flexible real wages, although this contributed to a considerable loss of income for most workers.

Like many other countries globally, Indonesia has experienced fast growth in e-commerce, which accelerated during the COVID-19 pandemic. People use e-commerce as an alternative strategy or solution to the mobility and activity restrictions policy imposed by the government. This increases the labour demand, potentially offsetting the adverse effects of COVID-19 on the labour market. This means that to understand the impact of COVID-19 on the labour market comprehensively, we need to look at the impact of both COVID-19 and e-commerce growth on individual workers' employment prospects, work hours, total earnings, and earnings per hour in both the formal and informal sectors of the labour markets.

3.2. Empirical method and data description

3.2.1. Method

In this study, the COVID-19 pandemic is measured through its impact on reducing work mobility, which is defined as people's mobility in workplaces relative to the baseline of the 3 January – 6 February 2020 period, measured at the province level average, which is obtained from the Google Mobility Report.[3] Meanwhile, the e-commerce transaction values summary provided by Bank Indonesia becomes the proxy for e-commerce growth.[4]

To assess the impact of work mobility and e-commerce growth on the probability to work, work hours, total earnings, and earnings per hour in the formal and informal sectors for individual workers during the COVID-19 pandemic, we estimate the following Instrumental Variable (IV) regression models with province and time fixed-effects:

$$M_{jt} = \vartheta' + \beta' Z_{jt} + \pi' W_{ijt} + \rho' X_{jt} + \varphi'_j + \tau'_t + \varepsilon'_{ijt} \quad (1)$$

$$E_{jt} = \vartheta'' + \beta'' Z_{jt} + \pi'' W_{ijt} + \rho'' X_{jt} + \varphi''_j + \tau''_t + \varepsilon''_{ijt} \quad (2)$$

$$U_{ijt} = \vartheta + \sigma \widehat{M_{jt}} + \omega \widehat{E_{jt}} + \pi W_{ijt} + \rho X_{jt} + \varphi_j + \tau_t + \varepsilon_{ijt} \quad (3)$$

Where U is an outcome variable to measure employment prospects (i.e., $0 =$ not working, $1 =$ working), work hours, total earnings, and earnings per hour, M is mobility index, E is e-commerce growth, Z is the instrumental variable (i.e., change in hospitalisation rate, and the number of villages with base transceiver station (BTS)), W is a vector of worker characteristics variable (i.e., gender, education level, years of experience, training attendance, using the internet for work, working from home, disability status, working in essential sectors, and urban–rural location),

X is province characteristics (i.e., employment rate, labour force growth, population density, the share of manufacturing in GDP, the share of services in GDP, the proportion of the higher educated population, the proportion of villages with paved road, and degree of openness ((export + import)/GDP)), φ is province fixed-effect, and τ is time fixed-effect.

The individual and province-level control variables exploit within-province variation over time to remove omitted variable bias. The province and time fixed-effect controls for unobserved time-invariant province characteristics, as well as eliminate bias from unobservable confounding that are constant across provinces but vary over time. Furthermore, i indexes an individual worker, j indexes province, and t indexes time. The unit of observation is individual workers (i), with the time period (t) being four rounds of Indonesia's national labour force survey conducted twice a year (i.e., August 2019, February 2020, August 2020, and February 2021) throughout the provinces (j). The detailed process of data merging is explained in the following data section.[5]

For the model with employment prospects as the outcome variable, the model is estimated using the IV Probit method.[6] Meanwhile, for work hours, total earnings, and earnings per hour, the model is estimated using the Two-stage Least Squares (2SLS) method. Furthermore, the model for each outcome variable is estimated for overall samples and estimated separately for both the formal and informal sectors. Since work mobility declined during the COVID-19 period compared to the pre-pandemic period, a positive coefficient of the work mobility (M) variable indicates a negative effect of COVID-19 on the outcome variable.

We use change in hospitalisation rate and the number of villages with BTS as the instrumental variables for this study due to the endogeneity issues with our main explanatory variables (i.e., work mobility index and e-commerce growth). Our work mobility index variable may have measurement error problems because the data obtained to measure mobility may have selection issues–the information is only for people who have access to google maps or have google accounts. Moreover, omitted variables may also bias our estimations. The work mobility index may also be correlated with other unobserved factors, such as people's preferences to keep travelling around even though COVID-19 cases have spiked up.

Our second main explanatory variable (i.e., e-commerce growth) may also suffer from an endogeneity issue, where the variable is potentially correlated with the unobserved factors. For instance, people tend to use e-commerce for daily transactions due to some promotions strategies offered by e-commerce, which may increase total transactions. Moreover, e-commerce growth may be correlated with the expansion of e-commerce investment or collaboration between e-commerce and their sellers, which may also affect total workers and working hours. Therefore, we expect an upward bias for our ω parameter.

We employ instrumental variables techniques to address the endogeneity issues from the two main explanatory variables that may bias our estimates. We use the change in hospitalisation rate and the number of villages with BTS as two instrumental variables in the estimations. The change in hospitalisation rate in our study refers to the changes in both hospitalisation and self-isolation at home. We argue that the change in the hospitalisation rate is exogenous because the growth of the hospitalisation rate is random due to the spread of the virus, which is also exogenous. Furthermore, since the work-from-home policy allows asymptomatic people to continue their activities at home, we argue that the change in hospitalisation rate only influences labour market outcomes through work mobility and hence meets the exclusion restriction requirement. We expect this variable will negatively affect the mobility index. A higher hospitalisation rate will reduce people's mobility. Indeed, the hospitalisation rate may also correlate with other factors, such as the urbanisation rate. Therefore, we include an urban dummy variable and province-fixed effects as control variables in the estimations.

To address the endogeneity issue coming from the e-commerce growth, we use the number of villages with BTS in each province. The number of villages with BTS will affect access to e-commerce, and hence a higher number of villages with BTS will increase e-commerce growth. Again, BTS may also be correlated with other factors that may bias our results, like economic activities, locations, and the decision by telecommunication providers to build BTS. Economic activities and locations may affect our IV's validity because both variables potentially correlate with the number of villages with BTS. Therefore, similar to what we did to the change in hospitalisation rate, we also include urban dummy and province-fixed effects to deal with the potential exclusion restriction violation. Henceforth, using our instruments for this study will be valid after controlling for other factors that may affect our main explanatory and outcome variables.

3.2.2. Data

We construct a combined dataset from Indonesia's National Labour Force Survey (*Survei Angkatan Kerja Nasional*, SAKERNAS) at the individual level and national accounts at the provincial level, both from Statistics Indonesia (*Badan Pusat Statistik*, BPS) and other provincial-level datasets, including the Google Mobility Report and e-commerce transaction values summary provided by Bank Indonesia, and several other data from various sources for control variables. Our study has the advantage of using the e-commerce transaction values provided by the Bank Indonesia, which is not publicly available, to delve deeper and gain insights into the role of e-commerce in the labour market dynamics during the pandemic. Table A1 in the Appendix provides the descriptive statistics of the provincial-level dataset, and Table A2 provides the descriptive statistics of the individual-level dataset.

The SAKERNAS data contains information on activities during the week before the survey and other work-related information on individuals aged 15 years old and older. The data source is used for calculating labour force participation, unemployment rates, and other Indonesian labour market statistics. The national accounts provide data on the Gross Domestic Product and its components at the expenditure and production sides at the national and province levels. Meanwhile, the Google Mobility Report provides data on people's mobility in six activity categories—retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential—relative to the baseline of the 3 January – 6 February 2020 period at the province level. The e-commerce transaction value data from Bank Indonesia is also at the province level.

In merging the data from different sources, we need to do several alignments to make the merging possible. First, there are differences in the economic sectors in the structure of GDP and the structure of the labour force survey (SAKERNAS). Hence, we need to make a concordance between the two structures of economic sectors. Second, there are differences in the period of GDP, e-commerce transactions, mobility, and employment data. The GDP is measured quarterly (i.e., there are four observations of GDP every year), the labour force survey is conducted twice a year (i.e., each in February and August), the e-commerce transactions data is measured monthly, while the mobility and COVID-19 data are measured daily. To align GDP and labour force data, we collapse the four quarterly GDP data into two semesterly GDP data by adding the previous year's fourth-quarter GDP data to the current year's first-quarter GDP data and then merging the combined GDP data with the February labour force data. Second, we add the second and third-quarter GDP data of a given year and integrate the combined GDP data with the August labour force data.

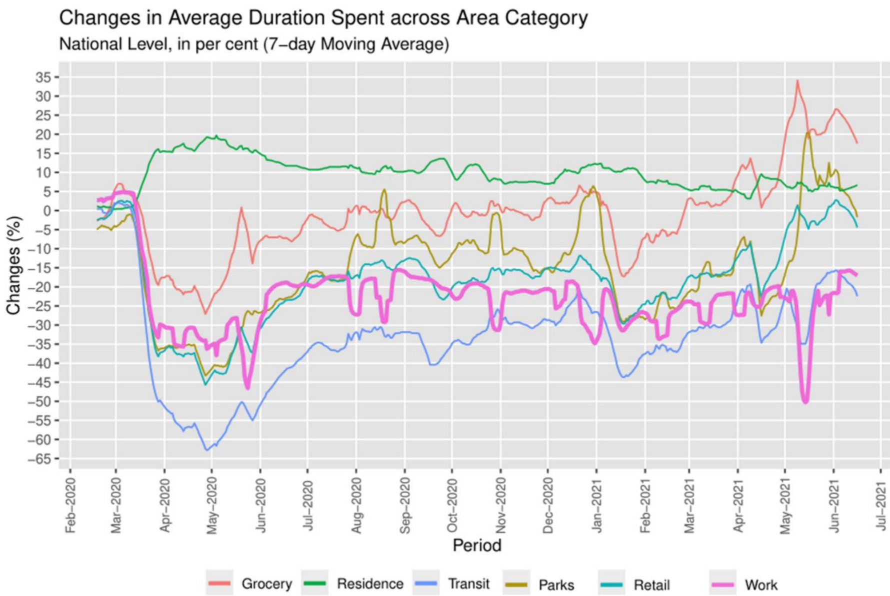
Likewise, to align e-commerce and labour force data, we collapse the twelve-monthly e-commerce transactions data into two semesterly e-commerce transactions data by first adding the previous year's ninth-month e-commerce data until the current year's second-month e-commerce data and merging it with the February labour force data. Second, we add the third until eighth-month e-commerce transactions data of a given year and then integrate the e-commerce growth data with the August labour force data. Lastly, we first average the daily data into monthly data to align work mobility and COVID-19 data with employment data. We then merged the second-month mobility and COVID-19 data with the February labour force data and the eighth-month mobility data with the August labour force data. All the data mergings are conducted at the province-level.

4. Descriptive analysis of mobility, e-commerce, and labour market indicators

4.1. People's mobility during the COVID-19 pandemic

Like many other countries, Indonesia has experienced a significant change in mobility due to the pandemic. Using data from Google Mobility Report, Figure 2 depicts the 7-day moving average change of mobility from February 2020 to June 2021 for the six different categories at the national level. Following the implementation of a lockdown policy called *Pembatasan Sosial Skala Besar* (PSBB), or large-scale social restriction, in April 2020, people's mobility outside residential areas categories (i.e., parks, transit, work, retail, and grocery) decreased by around 25-65%. The categories that experienced the steepest decrease in mobility are transit and retail. On the other hand, mobility within residential areas increased by approximately 20%.

In June 2021, more than one year after the first COVID-19 case, mobility to groceries, parks, and retail almost returned to the pre-pandemic level. However, mobility to work and transit areas are still near the pre-pandemic condition. This indicates that a significant proportion of workers work remotely from home rather than in the workplace due to government regulations restricting companies from having the total capacity and requiring workers to work from home, except for several essential sectors.



Source: Google Mobility Report

Figure 2. Average change of mobility in Indonesia during February 2020–June 2021 Relative to January–February 2020.
Figure 2 Alt Text: Figure of the average change of mobility in Indonesia between February 2020 and June 2021. Each line represents a different type of mobility. Mobility to work and transit have not recovered yet.

Figure A1 in the Appendix shows the changes in work mobility at the province level. In February 2020, before the first case of COVID-19 was discovered in Indonesia, the Bali province, the main tourist destination, had already suffered a decline in work mobility by 17.40%. This reflects the fact that the outbreak of COVID-19 in other countries has already significantly reduced tourist arrivals in Bali. Meanwhile, work mobility in the other provinces was still not affected. However, in August 2020 and February 2021, all provinces had already suffered a very significant decline in work mobility due to the lockdown policy. Bali still suffered the largest decline in work mobility, which decreased to just 41.36% in February 2021. Notably, Jakarta and West Java provinces, the centres of COVID-19 infections in Indonesia, also suffered from large declines in work mobility by 32.46% and 26.25%, respectively, in February 2021.

4.2. Development of e-commerce during the COVID-19 pandemic

To understand the development of e-commerce in Indonesia and how significant the impact of COVID-19 is in accelerating the growth of e-commerce, we need to see the trend in this sector even before Indonesia faced the pandemic. Figure 3 illustrates the ratio between the total transaction value of the top-4 marketplace in Indonesia relative to the trade sector's GDP and the country's e-commerce growth.[7] The contribution of e-commerce to the trade sector's GDP shows a significant increase from 4.41% in June 2018 to 16.94% in December 2020. The contribution of e-commerce to

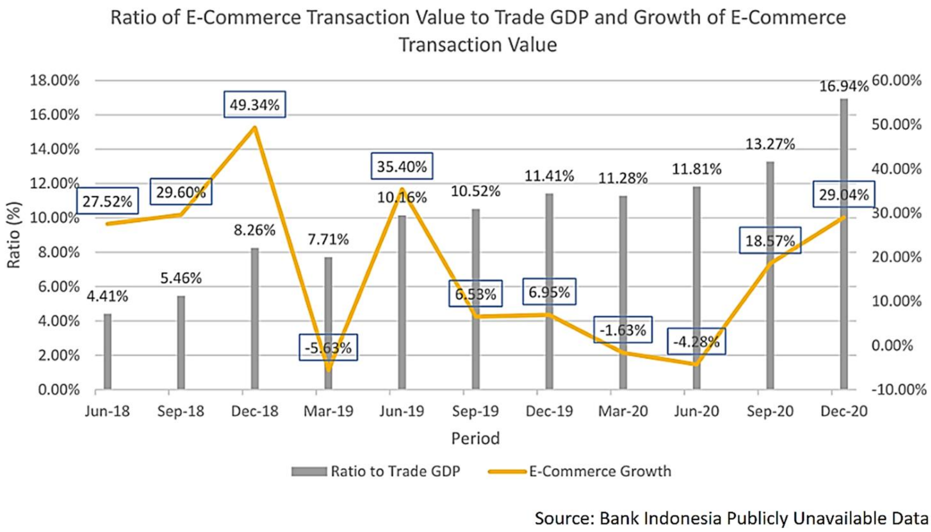


Figure 3. The ratio of transaction value of top-4 marketplace to GDP of trade sector and growth of transaction value of top-4 marketplace in Indonesia, Q2 2018–Q4 2020.
Figure 3 Alt Text: The trend of e-commerce transactions to GDP and e-commerce growth. The figure suggests there have been some fluctuations for both indicators.

the GDP of the trade sector in December 2020 was the highest compared to all the previous periods. After facing a slowing down during the early pandemic period in March to June 2020, the growth of e-commerce in Indonesia found its pace in September to December 2020, with a growth rate of around 18.56% and 29.04%, respectively.

4.3. Changes in the labour market during the COVID-19 pandemic

Using the SAKERNAS data from February 2018 until February 2021, Figure 4 depicts the labour market indicators in Indonesia and suggests that employment outcomes (e.g., labour force participation rate (LFPR), the share of informal workers, and unemployment rate) tend to fluctuate between February and August each year, indicating seasonal effects. The labour force participation rate has been stable between 70% in February 2018 and 69.5% in February 2020. However, the pandemic reduced the labour force participation rate to 64.61% in August 2020, which recovered slightly in February 2021 to 68.08%. This indicates that the COVID-19 pandemic has caused some workers to quit the labour force by returning to school, taking early retirement, or simply staying idle and waiting for the labour market condition to improve.

The reduction in labour force participation was also followed by an increase in the unemployment rate. The rate was relatively stable between February 2018 and February 2020. However, the pandemic boosted the unemployment rate from 4.51% in February 2020 to 6.79% in August 2020. The pandemic has also shifted the structure of the economy, indicated by the increasing share of informal workers from 56.64% in February 2020 to 60.47% in August 2020.[8]

Figure A2 in the Appendix shows the probability to work at the province level over time. In August 2019 and February 2020, before the COVID-19 pandemic, there

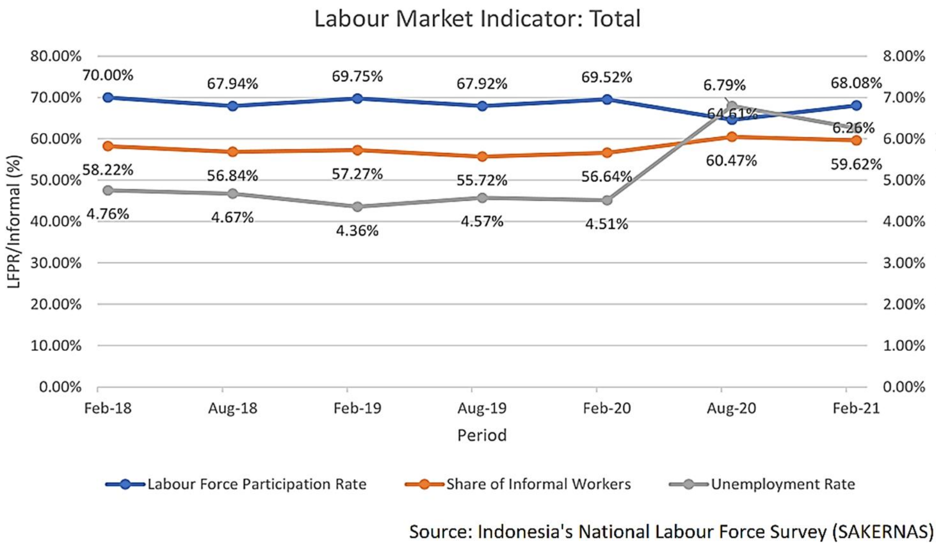


Figure 4. Labour market indicators in Indonesia, February 2018–February 2021.
Figure 4 Alt Text: Three lines indicate the trend of labour force participation, the share of informal workers and the unemployment rate.

were few changes in employment prospects across the provinces. However, by August 2020, the employment prospects in all provinces have declined significantly. The lowest employment prospects in August 2020 were found in Jakarta and West Java provinces, with only 53.86% and 53.83%, respectively. These lower employment prospects remained until February 2021, except in the provinces of East Nusa Tenggara (65.94%) and Papua (66.50%), where the probability to work has recovered although not yet returned to the pre-pandemic levels. Similar patterns of COVID-19 impact across provinces are also observed for work hours, total earnings, and earnings per hour.

Finally, Figure A3 in the Appendix shows the scatterplots between work mobility and the average of the four labour market outcomes at the province level from August 2019 - February 2021. The scatterplot between work mobility and probability to work shows a positive correlation of 0.0013, indicating that provinces with higher work mobility have higher employment prospects. Since COVID-19 reduces work mobility significantly, this indicates that COVID-19 lowers employment prospects. The same positive correlations are also observed for correlations between work mobility with total earnings and earnings per hour with 0.0024 and 0.001, respectively. However, the scatterplot between work mobility and work hours indicates they have no correlation.

5. Estimation results

5.1. Effects of COVID-19 and e-commerce on workers' outcomes

This section presents the results of estimations of Equation (3) on the effects of changes in work mobility and e-commerce growth on the four labour market outcomes for individual workers: employment prospects (Table 1), work hours (Table 2), total earnings (Table 3), and earnings per hour (Table 4). The estimations for each

Table 1. Estimation results of probability to work using probit and IV probit models, August 2019–February 2021.

	Overall				Formal				Informal			
	(1) Probit	(2) Probit	(3) IV Probit	(4) IV Probit	(5) Probit	(6) Probit	(7) IV Probit	(8) IV Probit	(9) Probit	(10) Probit	(11) IV Probit	(12) IV Probit
Work mobility	0.108***	0.0475	−4.847***	−1.593***	0.308***	0.158***	0.352	1.517***	−0.158***	−0.148***	−5.026***	−2.100***
	(0.0378)	(0.0522)	(0.671)	(0.345)	(0.0409)	(0.0527)	(0.732)	(0.339)	(0.0378)	(0.0438)	(0.666)	(0.290)
E-commerce growth	0.0197***	0.0539***	1.210***	0.227**	−0.00584	0.00235	−0.0256	−0.506***	0.0165***	0.0290***	1.181***	0.480***
	(0.00578)	(0.00824)	(0.164)	(0.114)	(0.00617)	(0.00821)	(0.179)	(0.111)	(0.00575)	(0.00694)	(0.164)	(0.0950)
Workers Characteristics:												
Male		0.797***		0.796***		0.470***		0.469***		0.304***		0.304***
		(0.00237)		(0.00239)		(0.00234)		(0.00239)		(0.00197)		(0.00199)
Work experience		0.0179***		0.0178***		−0.00251***		−0.00250***		0.0164***		0.0163***
		(0.0000832)		(0.0000835)		(0.0000790)		(0.0000789)		(0.0000696)		(0.0000710)
Secondary education		−0.286***		−0.286***		0.0945***		0.0944***		−0.274***		−0.273***
		(0.00294)		(0.00294)		(0.00310)		(0.00310)		(0.00251)		(0.00251)
Tertiary education		0.0456***		0.0451***		0.872***		0.871***		−0.786***		−0.785***
		(0.00593)		(0.00593)		(0.00481)		(0.00486)		(0.00498)		(0.00500)
On-the-job training		0.0355***		0.0350***		0.261***		0.260***		−0.203***		−0.203***
		(0.00487)		(0.00487)		(0.00380)		(0.00381)		(0.00396)		(0.00396)
Training for unemployed		0.0711***		0.0804***		0.127***		0.119***		−0.0112		−0.0000154
		(0.00885)		(0.00905)		(0.00784)		(0.00810)		(0.00693)		(0.00714)
Using internet for work		1.538***		1.538***		0.905***		0.903***		−0.221***		−0.220***
		(0.00820)		(0.00821)		(0.00328)		(0.00346)		(0.00352)		(0.00353)
Work from home		0.847***		0.844***		0.743***		0.741***		−0.183***		−0.184***
		(0.0206)		(0.0206)		(0.00879)		(0.00884)		(0.00879)		(0.00879)
Moderate disability		−0.679***		−0.679***		−0.244***		−0.244***		−0.431***		−0.429***
		(0.00424)		(0.00426)		(0.00507)		(0.00506)		(0.00379)		(0.00381)
Severe disability		−1.923***		−1.922***		−0.805***		−0.803***		−1.570***		−1.566***
		(0.0128)		(0.0129)		(0.0190)		(0.0190)		(0.0126)		(0.0126)
Essential sector		1.968***		1.967***		0.801***		0.799***		0.725***		0.723***
		(0.00409)		(0.00417)		(0.00245)		(0.00259)		(0.00238)		(0.00246)
Urban		−0.591***		−0.590***		0.0792***		0.0788***		−0.500***		−0.499***
		(0.00267)		(0.00268)		(0.00249)		(0.00249)		(0.00217)		(0.00221)
Constant	−0.226	−1.072***	−31.90***	−6.227**	−0.505***	−1.954***	0.0207	9.245***	−0.790***	−0.255	−31.76***	−11.02***
	(0.154)	(0.278)	(4.373)	(2.476)	(0.164)	(0.276)	(4.778)	(2.417)	(0.153)	(0.239)	(4.367)	(2.068)
Province Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956	1,982,956
Pseudo R^2	0.006	0.395			0.011	0.298			0.014	0.162		
Wald chi^2	16,488.640***	3.70e + 05***	17,488.364***	3.70e + 05***	23,393.188***	4.58e + 05***	23,279.818***	4.60e + 05***	37,160.314***	3.39e + 05***	39,179.698***	3.41e + 05***

Robust standard errors in parentheses $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2. Estimation results of work hours using OLS and 2SLS, August 2019–February 2021.

	Overall				Formal				Informal			
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) OLS	(10) OLS	(11) 2SLS	(12) 2SLS
Work mobility	0.0128	−0.111***	−2.525***	−0.685***	0.0165	0.0181	−27.19	0.735**	−0.0856***	−0.219***	−4.084***	−1.439***
	(0.0222)	(0.0229)	(0.357)	(0.145)	(0.0297)	(0.0320)	(16.93)	(0.312)	(0.0304)	(0.0309)	(0.396)	(0.164)
E-commerce growth	0.0144***	0.0230***	0.448***	−0.0290	0.00254	0.00486	7.097	−0.319***	0.0195***	0.0311***	0.728***	0.155***
	(0.00335)	(0.00358)	(0.0863)	(0.0484)	(0.00430)	(0.00474)	(4.481)	(0.0924)	(0.00464)	(0.00493)	(0.0741)	(0.0537)
Workers Characteristics:												
Male		0.179***		0.179***		0.126***		0.126***		0.204***		0.204***
		(0.00109)		(0.00109)		(0.00154)		(0.00155)		(0.00145)		(0.00145)
Work experience		−0.000341***		−0.000340***		−0.00284***		−0.00285***		0.00201***		0.00201***
		(0.0000459)		(0.0000459)		(0.0000649)		(0.0000653)		(0.0000610)		(0.0000610)
Secondary education		−0.00673***		−0.00683***		−0.0294***		−0.0293***		−0.0119***		−0.0122***
		(0.00137)		(0.00137)		(0.00215)		(0.00216)		(0.00173)		(0.00173)
Tertiary education		−0.000762		−0.000657		−0.113***		−0.113***		−0.0330***		−0.0334***
		(0.00216)		(0.00216)		(0.00270)		(0.00271)		(0.00485)		(0.00485)
On-the-job training		−0.0314***		−0.0317***		−0.0261***		−0.0259***		−0.0651***		−0.0657***
		(0.00175)		(0.00175)		(0.00182)		(0.00182)		(0.00356)		(0.00356)
Training for unemployed		−0.0124***		−0.00841**		−0.00938**		−0.00953**		0.0135***		0.0199***
		(0.00334)		(0.00346)		(0.00471)		(0.00479)		(0.00518)		(0.00527)
Using internet for work		0.0678***		0.0680***		0.0365***		0.0364***		0.0194***		0.0198***
		(0.00143)		(0.00143)		(0.00156)		(0.00157)		(0.00267)		(0.00267)
Work from home		−0.171***		−0.173***		−0.235***		−0.235***		−0.0499***		−0.0524***
		(0.00331)		(0.00332)		(0.00349)		(0.00351)		(0.00906)		(0.00908)
Moderate disability		−0.0970***		−0.0970***		−0.0663***		−0.0669***		−0.112***		−0.111***
		(0.00232)		(0.00232)		(0.00424)		(0.00426)		(0.00274)		(0.00275)
Severe disability		−0.189***		−0.190***		−0.159***		−0.160***		−0.204***		−0.206***
		(0.0138)		(0.0138)		(0.0299)		(0.0299)		(0.0155)		(0.0155)
Essential sector		0.299***		0.299***		0.164***		0.164***		0.367***		0.367***
		(0.00117)		(0.00117)		(0.00163)		(0.00164)		(0.00165)		(0.00165)
Urban		0.0864***		0.0864***		0.0833***		0.0831***		0.0457***		0.0459***
		(0.00120)		(0.00120)		(0.00148)		(0.00149)		(0.00177)		(0.00177)
Constant	4.430***	3.881***	−7.088***	4.225***	4.874***	5.201***	−184.0	11.82***	4.208***	3.317***	−14.62***	−0.570
	(0.0893)	(0.124)	(2.297)	(1.061)	(0.115)	(0.156)	(119.3)	(1.975)	(0.124)	(0.179)	(1.971)	(1.190)
Province Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1,214,732	1,214,732	1,214,732	1,214,732	458,762	458,762	458,762	458,762	755,970	755,970	755,970	755,970
R^2	0.021	0.129			0.026	0.128			0.018	0.115		
First Stage F-stats			453.117	2,108.708			1.353	441.536			778.640	2,168.930

Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3. Estimation results of total earnings using OLS and 2SLS, August 2019–February 2021.

	Overall				Formal				Informal			
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) OLS	(10) OLS	(11) 2SLS	(12) 2SLS
Work mobility	0.311***	0.156***	−0.380	1.967***	0.377***	0.203***	4.382	2.368***	0.252***	0.107	1.068	0.962**
	(0.0425)	(0.0408)	(3.499)	(0.352)	(0.0509)	(0.0496)	(2.837)	(0.548)	(0.0644)	(0.0649)	(1.745)	(0.449)
E-commerce growth	−0.0127**	−0.0154**	0.117	−0.496***	−0.00758	−0.0207***	−1.112	−0.500***	−0.00831	−0.00261	−0.209	−0.324***
	(0.00617)	(0.00614)	(0.842)	(0.0950)	(0.00757)	(0.00758)	(0.723)	(0.148)	(0.00922)	(0.00957)	(0.350)	(0.115)
Workers Characteristics:												
Male		0.493***		0.492***		0.428***		0.428***		0.535***		0.534***
		(0.00192)		(0.00193)		(0.00247)		(0.00248)		(0.00294)		(0.00295)
Work experience		0.00575***		0.00577***		0.0137***		0.0137***		0.00141***		0.00143***
		(0.0000790)		(0.0000793)		(0.000106)		(0.000106)		(0.000119)		(0.000120)
Secondary education		0.245***		0.246***		0.326***		0.326***		0.121***		0.121***
		(0.00234)		(0.00235)		(0.00324)		(0.00326)		(0.00328)		(0.00329)
Tertiary education		0.679***		0.680***		0.713***		0.713***		0.375***		0.375***
		(0.00379)		(0.00381)		(0.00442)		(0.00444)		(0.00918)		(0.00919)
On-the-job training		0.162***		0.162***		0.178***		0.178***		−0.0387***		−0.0387***
		(0.00290)		(0.00291)		(0.00314)		(0.00315)		(0.00621)		(0.00622)
Training for unemployed		0.0397***		0.0359***		0.0276***		0.0235***		0.00769		0.00830
		(0.00569)		(0.00582)		(0.00705)		(0.00725)		(0.00953)		(0.00966)
Using internet for work		0.296***		0.296***		0.262***		0.261***		0.228***		0.228***
		(0.00227)		(0.00228)		(0.00259)		(0.00261)		(0.00430)		(0.00431)
Work from home		0.0971***		0.0976***		0.0281***		0.0296***		−0.0354**		−0.0367**
		(0.00504)		(0.00508)		(0.00522)		(0.00526)		(0.0147)		(0.0147)
Moderate disability		−0.206***		−0.207***		−0.135***		−0.136***		−0.198***		−0.198***
		(0.00427)		(0.00429)		(0.00658)		(0.00661)		(0.00541)		(0.00542)
Severe disability		−0.377***		−0.375***		−0.188***		−0.190***		−0.412***		−0.410***
		(0.0221)		(0.0222)		(0.0344)		(0.0345)		(0.0270)		(0.0270)
Essential sector		0.261***		0.261***		0.221***		0.220***		0.318***		0.318***
		(0.00196)		(0.00197)		(0.00260)		(0.00261)		(0.00293)		(0.00293)
Urban		0.133***		0.132***		0.113***		0.113***		0.114***		0.114***
		(0.00192)		(0.00193)		(0.00241)		(0.00243)		(0.00301)		(0.00302)
Constant	14.54***	13.21***	11.09	24.02***	14.56***	12.77***	43.95**	23.61***	14.23***	13.55***	19.58**	20.66***
	(0.165)	(0.204)	(22.40)	(2.109)	(0.202)	(0.246)	(19.24)	(3.229)	(0.246)	(0.329)	(9.320)	(2.611)
Province Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	793,325	793,325	793,325	793,325	429,120	429,120	429,120	429,120	364,205	364,205	364,205	364,205
R^2	0.054	0.279			0.059	0.288			0.047	0.193		
First Stage F-stats			10.517	919.509			12.785	332.281			63.838	656.756

Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. Estimation results of earnings per hour using OLS and 2SLS, August 2019–February 2021.

	Overall				Formal				Informal			
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) OLS	(10) OLS	(11) 2SLS	(12) 2SLS
Work mobility	0.243***	0.124***	−1.347	1.650***	0.340***	0.147***	20.83***	1.135**	0.187***	0.120*	5.697***	1.551***
	(0.0424)	(0.0419)	(2.155)	(0.338)	(0.0524)	(0.0507)	(7.291)	(0.515)	(0.0650)	(0.0682)	(1.479)	(0.451)
E-commerce growth	−0.0196***	−0.0256***	0.520	−0.285***	−0.00722	−0.0229***	−5.330***	−0.0840	−0.0186**	−0.0217**	−1.016***	−0.298**
	(0.00598)	(0.00616)	(0.534)	(0.0971)	(0.00758)	(0.00753)	(1.910)	(0.147)	(0.00906)	(0.00993)	(0.303)	(0.124)
Workers Characteristics:												
Male		0.321***		0.321***		0.292***		0.292***		0.315***		0.315***
		(0.00192)		(0.00193)		(0.00240)		(0.00240)		(0.00307)		(0.00309)
Work experience		0.00902***		0.00903***		0.0160***		0.0160***		0.00364***		0.00365***
		(0.0000786)		(0.0000788)		(0.000103)		(0.000103)		(0.000122)		(0.000122)
Secondary education		0.252***		0.252***		0.349***		0.349***		0.142***		0.142***
		(0.00237)		(0.00237)		(0.00319)		(0.00319)		(0.00343)		(0.00344)
Tertiary education		0.711***		0.711***		0.817***		0.818***		0.455***		0.455***
		(0.00379)		(0.00379)		(0.00435)		(0.00435)		(0.0102)		(0.0102)
On-the-job training		0.188***		0.188***		0.200***		0.200***		0.0516***		0.0520***
		(0.00288)		(0.00289)		(0.00307)		(0.00308)		(0.00667)		(0.00668)
Training for unemployed		0.0567***		0.0525***		0.0415***		0.0385***		0.0126		0.0102
		(0.00583)		(0.00590)		(0.00712)		(0.00718)		(0.0104)		(0.0105)
Using internet for work		0.270***		0.269***		0.223***		0.223***		0.293***		0.293***
		(0.00228)		(0.00228)		(0.00256)		(0.00256)		(0.00460)		(0.00460)
Work from home		0.292***		0.293***		0.275***		0.277***		0.0415***		0.0419***
		(0.00524)		(0.00525)		(0.00539)		(0.00540)		(0.0157)		(0.0157)
Moderate disability		−0.122***		−0.122***		−0.0806***		−0.0809***		−0.108***		−0.108***
		(0.00438)		(0.00439)		(0.00650)		(0.00651)		(0.00573)		(0.00574)
Severe disability		−0.222***		−0.220***		−0.121***		−0.121***		−0.217***		−0.213***
		(0.0233)		(0.0233)		(0.0365)		(0.0366)		(0.0289)		(0.0289)
Essential sector		0.0470***		0.0472***		0.0800***		0.0800***		0.0193***		0.0195***
		(0.00196)		(0.00196)		(0.00252)		(0.00252)		(0.00305)		(0.00306)
Urban		0.0531***		0.0528***		0.0336***		0.0335***		0.0640***		0.0636***
		(0.00192)		(0.00192)		(0.00237)		(0.00238)		(0.00311)		(0.00312)
Constant	9.857***	8.753***	−4.505	15.15***	9.627***	7.437***	151.3***	9.501***	9.705***	10.04***	36.21***	16.90***
	(0.159)	(0.206)	(14.22)	(2.129)	(0.202)	(0.245)	(50.84)	(3.157)	(0.242)	(0.347)	(8.055)	(2.791)
Province Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	773,816	773,816	773,816	773,816	418,179	418,179	418,179	418,179	355,637	355,637	355,637	355,637
R^2	0.043	0.222			0.052	0.295			0.039	0.103		
First Stage F-stats			25.159	971.291			5.526	355.998			87.555	686.550

Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

outcome are separated into formal and informal sector workers as well as for the overall sample. The data used for the estimations cover the period from August 2019 to February 2021. We show the results of estimations using instrumental variables (IV) as well as without IV, but our preferred method is using IV.

Figures A6 and A7 in the Appendix provide regional variation over time for changes in hospitalisation rate and the number of villages with BTS. It shows variations of our instruments across provinces and periods, which indicate further the relevance of the instruments used in this study. Table A3 in the Appendix provides the results from our first stage regression following equations (1) and (2), which validates the use of change in hospitalisation rate and the number of villages with BTS as an instrument for our main independent variable (i.e., work mobility and e-commerce growth). We can see that the relationship from the first stage is negatively significant for the change in hospitalisation rate and positively significant for the number of villages with BTS. An increase in the hospitalisation rate decreases work mobility and e-commerce growth. Meanwhile, an increase in the number of villages with BTS increases work mobility and e-commerce growth. This adequately suggests statistical evidence for the change in hospitalisation rate and the number of villages with BTS as good instruments for the variation of work mobility and e-commerce growth in Indonesia.

Additionally, the first stage F-statistics for our IV shows that we do not have any issue with the weak instruments problem. We also perform the exogeneity test proposed by Nevo and Rosen (2012) in Table A7 in the Appendix. The result suggests that we do not have any issue with the exogeneity from the use of our instrumental variables. Similarly, for the monotonicity assumptions, Figure A8 in the Appendix suggests that the relationship between our instrumental variables with the main independent variables has a consistent sign with the result from the first stage regression.

The point estimates in our 2SLS estimation results are larger if we do not control for the covariates. This implies that increasing our instruments' validity requires us to include control variables in our estimations. We also find that the point estimates from OLS estimations are generally higher than the 2SLS estimations. These results suggest a potential omitted variable issue that will bias our OLS estimates upward. This can happen when the $COV(U,X) > 0$ and $COV(U,Y) > 0$, which makes the results from our OLS estimation larger than the actual values. This vindicates the use of the instrumental variable method in our analysis.

5.1.1. Employment prospects

Table 1 shows the estimation results on employment prospects, measured by the probability to work using Probit and IV Probit models. For these estimations, the number of observations is the total number of samples in the four rounds of SAKERNAS (i.e., August 2019, February 2020, August 2020, and February 2021). In the formal column, the dependent variable is 1 if a worker worked in the formal sector and 0 otherwise. Likewise, in the informal column, the dependent variable is 1 if a worker worked in the informal sector and 0 otherwise. Meanwhile, in the overall column, the dependent variable is 1 if a worker worked in either the formal or informal sector and 0 otherwise. All samples are used in all estimations.

The IV Probit estimation results show that our variables of interest, work mobility and e-commerce growth, are both statistically significant. The coefficient of work mobility is positive in the formal sector but negative in the informal sector and overall samples. Since COVID-19 has caused work mobility to decline (Figure 2), these coefficients indicate that COVID-19 reduces the probability for workers to find jobs in the formal sector and, on the other hand, increases it in the informal sector and also in the full sample. An increase in one standard deviation in mobility will increase the probability to work in the full sample by 21% ($=0.137 \times 1.593 \times 100$) or an increase of 45% ($=0.218/0.483 \times 100$) of a standard deviation in the probability work, which is a sizable in terms of the magnitude.

Similarly, an increase in one standard deviation in mobility will reduce the probability to work in the formal sector by 20% ($=0.137 \times 1.517 \times 100$) or a decrease of 49% of a standard deviation in the probability to work in the formal sector. Finally, COVID-19 has increased the probability to work in the informal sector by 29% or 59% of a standard deviation in our main explanatory variable. These results suggest that, as workers who lost jobs cannot find other jobs in the shrinking formal sector, they join the informal sector by creating self-employment jobs. Hence, the informal sector plays a role as a buffer of employment for many job seekers.

Meanwhile, the e-commerce growth coefficient is positively significant in the informal sector and overall samples but negatively significant in the formal sector. The magnitude of the impact of e-commerce growth for each sector is substantial. For instance, one standard deviation of an increase in e-commerce growth will increase the probability to work in the full sample by 41.6% ($=0.227 \times 1.832 \times 100$). However, it reduces the probability of people who work in the formal sector by 93% ($=0.506 \times 1.832 \times 100$), while most of it may shift their work into the informal sector because it increases the probability of people who work in the informal sector by 88% ($=0.480 \times 1.832 \times 100$). These results suggest that e-commerce growth decreases employment prospects in the formal sector but increases in the informal sector. This indicates that most jobs created by the growth of e-commerce are self-employment, such as opening an online shop to sell goods.

The employment prospects of individual workers are also affected by their characteristics. Male workers have significantly higher employment prospects than female workers in both the formal and informal sectors. More experienced workers have fewer employment prospects in the formal sector but are more likely to work in the informal sector, indicating that more experienced workers tend to start their own businesses. The education variables indicate that workers with higher educational attainment are more likely to work in the formal sector and less likely to work in the informal sector. Workers with disabilities have lower employment prospects in both the formal and informal sectors, and the more severe the disability, the less likely their chance of employment.

There are also other workers' attributes that affect their employment prospects. Attending on-the-job training and training for the unemployed increases the formal sector's employment prospects and reduces the probability of working in the informal sector.[9] As expected, workers who use the internet for work and can work from home have higher prospects of working in the formal sector and a lower probability of working in the informal sector. Workers in the essential sectors, i.e. the sectors that are allowed to continue operating during the pandemic, have positive employment prospects in both the formal and informal sectors. Workers in urban areas have higher employment prospects in the formal sector and a lower probability of working in the informal sector than workers in rural areas, indicating that most formal jobs are available in urban areas.

5.1.2. Work hours

The 2SLS estimation results on work hours in Table 2 show that work mobility has a positive significant coefficient in the formal sector but a significant negative coefficient in the informal sector and overall samples. This means that COVID-19 decreases work hours in the formal sector but increases it in the informal sector and overall sample. An increase in one standard deviation of work mobility will increase work hours in the full sample by 9% ($=0.137 \times 0.685 \times 100$) and in the informal sector by 20% ($=0.137 \times 1.439 \times 100$). However, it reduces the work hours in the formal sector by 10% ($=0.137 \times 0.735 \times 100$). Similarly, e-commerce growth decreases work hours in the formal sector by 58% ($=1.832 \times 0.319 \times 100$) but increases it in the informal sector by 28% ($=1.832 \times 0.155 \times 100$). However, the impact is not significant overall. This means that informal workers work longer hours due to the effects of both COVID-19 and e-commerce growth.

Workers' characteristics also affect their work hours. On average, male workers tend to have longer work hours than female workers. Workers with more experience have shorter work hours in the formal sector but longer work hours in the informal sector. Higher education level is associated with shorter work hours in both formal and informal sectors. Workers with disabilities have shorter work hours in both formal and informal sectors, and the more severe the disability, the shorter the work hours.

Other workers' attributes also affect their work hours. Workers who have attended training tend to have shorter work hours, except for informal workers who attend training for the unemployed. Workers who use the internet for work have longer work hours in both formal and informal sectors. However, workers who work from home have shorter work hours in both formal and informal sectors. Workers who work in the essential sectors have longer work hours in both formal and informal sectors since such sectors continued to operate normally during the pandemic. Finally, in both the formal and informal sectors, workers in urban areas work longer hours than those in rural areas.

5.1.3. Total earnings

The 2SLS estimation results on total earnings in Table 3 show that work mobility has positive significant coefficients in the overall sample, formal, and informal sectors, indicating that COVID-19 reduces the total earnings of workers in both the formal and informal sectors. The impact of COVID-19 on total earnings would be a decrease in earnings in the formal sector by around 32% ($=0.137 \times 2.368 \times 100$) and around 13% ($=0.137 \times 0.962 \times 100$) for the informal sector. Meanwhile, e-commerce growth has significant negative coefficients in the overall sample, formal, and informal sectors. In terms of magnitude, an increase in one standard deviation in e-commerce growth will shrink total earnings by 91% (=$1.832 \times 0.496 \times 100$) in the total sample, 92% (=$1.832 \times 0.500 \times 100$) in the formal sector, and 60% (=$1.832 \times 0.324 \times 100$) in the informal sector. This means that e-commerce growth also suppresses workers' earnings in both the formal and informal sectors.

Workers' earnings are also affected by their characteristics. Both in the formal and informal sectors, male workers earn much higher than female workers. Work experience is also associated with higher total earnings in the formal and informal sectors. Higher education attainment boosts total earnings in both the formal and informal sectors. The higher the education level, the higher the earnings premium. On the other hand, having a disability reduces workers' total earnings both in the formal and informal sectors. The more severe the disability, the lower the total earnings.

Other workers' attributes also affect their total earnings. Attending training increases total earnings in the formal sector. However, on-the-job training is associated with lower total earnings in the informal sector, while training for the unemployed has no effect. Workers who use the internet for work have higher total earnings in the formal and informal sectors. Workers in the formal sector who work from home earn higher total earnings. However, informal sector workers who work from home earn lower total earnings. Workers who work in the essential sectors earn higher total earnings. Finally, on average, workers in urban areas have higher total earnings than rural workers.

5.1.4. Earnings per hour

The 2SLS estimation results on earnings per hour in Table 4 show that work mobility has positive significant coefficients in the overall sample, formal and informal sectors, which means that COVID-19 reduces the earnings per hour of workers in both the formal and informal sectors. In terms of the magnitude, a one standard deviation increase in worker mobility will reduce earnings per hour by 23% (=$0.137 \times 1.650 \times 100$) in the full sample, 15.5% (=$0.137 \times 1.135 \times 100$) for the formal sector, and 21.2% (=$0.137 \times 1.551 \times 100$). Meanwhile, e-commerce growth suppresses the earnings per hour of workers in the overall sample and the informal sector by approximately 52.2% (=$1.832 \times 0.285 \times 100$) and 54% (=$1.832 \times 0.298 \times 100$).

Workers' characteristics also affect their hourly earnings. On average, male workers receive higher earnings per hour than female workers in the formal sector and more so in the informal sector. Every additional year of working experience leads to higher earnings per hour for workers in the informal sector and more so in the formal sector. Like experience, education attainment increases earnings per hour in the informal sector and more so in the formal sector. As expected, workers with a disability have lower earnings per hour in the formal sector and more so in the informal sector. More severe disability is associated with a larger hourly earnings penalty.

Other workers' attributes also affect their hourly earnings. On-the-job training increases earnings per hour of workers, especially in the formal sector, indicating that training increases workers' productivity. Training for the unemployed also increases the earnings per hour of workers in the formal sector. The workers who use the internet and those who work from home have higher earnings per hour in both the formal and informal sectors. Workers in the essential sectors earn higher hourly earnings than workers in other sectors. Finally, workers in urban areas receive higher earnings per hour than rural workers, particularly in the informal sector.

5.2. Robustness test

We use the Oster (2019) approach to evaluate the robustness of our results with regard to omitted variable bias by observing coefficient stability after the inclusion of controls.[10] The results of the coefficient stability test approach are presented in Table A4 in the Appendix. The results show that all identified sets exclude zero. It suggests that the signs and coefficients of our estimates, which indicate the links between work mobility and e-commerce growth with labour market outcomes, are robust to the substantial selection of the unobservables.

5.3. Heterogeneity analysis

5.3.1. Heterogeneity by gender

Labour market outcomes have always been different for male and female workers. Figure A4 in the Appendix shows the labour market indicators disaggregated by gender. There is a marked difference in the labour force participation rates between males and females, with the rate for males more than 80%, while for females less than 55%. The share of informal workers is slightly higher among females than males, with the share among females more than 65% and around 60% among males. Meanwhile, the unemployment rates among males and females are similar, at around 5%. The changes in these labour market indicators during the COVID-19 pandemic across gender are similar, where labour participation rates slightly decrease while the share of informal workers and unemployment rates increase.

The results of estimations of the four outcomes for the main explanatory variables, i.e., work mobility and e-commerce growth, disaggregated by gender, are shown in Table A5 in the Appendix. For probability to work, the results indicate that COVID-19 reduces the employment prospects in the formal sector for both male and female workers. However, it increases the probability to work in the informal sector for females but not so for males. Meanwhile, e-commerce growth has shown similar effects for males and females in increasing their employment prospects in the informal sector but not so in the formal sector.

There were notable differences identified in terms of the effects of COVID-19 and e-commerce growth on work hours between male and female workers. COVID-19 increases the work hours of males and females in the informal sector but decreases the work hours of females in the formal sector. Similarly, e-commerce growth also increases the work hours of males in the informal sector but decreases the work hours of females in the formal sector.

In terms of total earnings, both COVID-19 and e-commerce growth have notable differences in their effects on male and female workers. COVID-19 has no impact on the total earnings of males in the informal sector but reduces them in the formal sector. However, it reduces the total earnings of females in both the formal and informal sectors. Similarly, e-commerce growth reduces the total earnings of males in both the formal and informal sectors. However, it has no effect on the total earnings of females in both formal and informal sectors, but it reduces the total earnings overall.

In terms of hourly earnings, COVID-19 and e-commerce growth have significant differences in their effects on male and female workers. COVID-19 reduces the hourly earnings of males in both formal and informal sectors. However, it does not affect the hourly earnings of females in both formal and informal sectors. Meanwhile, e-commerce growth reduces the hourly earnings of males in both formal and informal sectors. For females, e-commerce growth has no effect on hourly earnings in both formal and informal sectors.

5.3.2. Heterogeneity by age group

Labour market outcomes are different for workers across age groups. Figure A5 in the Appendix shows the labour market indicators for youth workers (15–24 years old), adult workers (25–59 years old), and older workers (60+ years old). The labour force participation rate is highest among adult workers, with around 80%, but much lower among the youth and older workers, with around 45% and 50%, respectively. Slightly over one-half of the youth workers work in the informal sector, while informal workers among adult workers are higher at around 60%. Still, the highest share of informal workers is among older workers, at more than 85%. The highest unemployment rate was found among the youth workers, at around 15%, while unemployment rates among the adult and older workers were found to be much lower, at only about 3% and 1%, respectively.

The changes in the labour market indicators during the COVID-19 pandemic across age groups are similar, where labour force participation rates decrease while the share of informal workers and unemployment rates increase. However, the effects seemed more pronounced among the youth workers. The older workers' participation in the labour force does not seem to be much impacted. The youth workers experience a hike in their share of informal workers and remain at that level. The other categories only see a small upward nudge. Lastly, the unemployment trend seems similar across the three categories, with a spike in August 2020 and a partial recovery in February 2021. Meanwhile, the recovery in the participation rate is observed only among adult workers.

The results of the estimations of the four labour market outcomes for work mobility and e-commerce growth disaggregated by age group are shown in Table A6 in the Appendix. For probability to work, the results indicate that COVID-19 reduces the employment prospects in the formal sector for youth and adult workers, but it does not affect older workers. However, COVID-19 increases the employment prospects of adult and youth workers in the informal sector but not so for older workers. This means that the employment prospects of older workers in both the formal and informal sectors are unaffected by COVID-19. Meanwhile, e-commerce growth increases the employment prospects of only youth and adult workers in the informal sector but decreases it in the formal sector. Furthermore, e-commerce growth has no effect on the employment prospects of older workers in both formal and informal sectors.

COVID-19 unanimously increases the work hours of all categories of workers in the informal sector but decreases the work hours of adult workers in the formal sector. Similarly, e-commerce growth also increases the work hours of adult and older workers in the informal sector but decreases them in the formal sector. E-commerce growth has shown no effects on work hours of older workers in both the formal and informal sectors.

COVID-19 reduces the total earnings of all categories of workers in the formal sector but only reduces the total earnings of adult workers in the informal sector. It does not have any effect on the total earnings of youth and older workers in the informal sector. Meanwhile, e-commerce growth significantly reduces the total earnings of adult workers in both formal and informal sectors. Furthermore, e-commerce growth significantly reduces the total earnings of youth workers in the informal sector but not in the formal sector. However, the total earnings of older workers in both the formal and informal sectors are not affected by e-commerce growth.

The hourly earnings of adult workers in the informal sector and youth workers in the formal sector are reduced by COVID-19. However, it does not have any effect on the hourly earnings of older workers in both formal and informal sectors. Similarly, e-commerce growth also reduces the hourly earnings of adult workers in the informal sectors. For youth and older workers, e-commerce growth does not affect their hourly earnings in both formal and informal sectors.

6. Conclusion

This study assesses the impact of COVID-19 and e-commerce growth on employment prospects, work hours, total earnings, and earnings of workers in the formal and informal sectors in Indonesia. The findings confirm the adverse effects of COVID-19 on workers' labour market outcomes. However, this study finds that e-commerce growth does not counteract the adverse effects of COVID-19 as expected. Although e-commerce growth creates jobs, those jobs are primarily in the form of self-employment, which further strengthens the effect of COVID-19 on the informalisation of the economy. This indicates that, although e-commerce plays a role as an employment buffer during the COVID-19 crisis, it suppresses the earnings of workers, which does not help with the efforts to maintain people's welfare during the crisis.

The results from heterogeneity analysis indicate that female and youth workers are, in general, more adversely affected by the COVID-19 pandemic. For female workers, the pandemic increases the probability to work in the informal sector, decreases the work hours in the formal sector, and reduces their total earnings in both the formal and informal sectors. For youth workers, there is a more pronounced decrease in labour force participation rates and a more pronounced increase in informalisation and unemployment than other workers.

In addition, this study finds that workers who use the internet for work have higher employment prospects in the formal sector and a lower probability of working in the informal sector. Moreover, in both the formal and informal sectors, workers who use the internet for work have longer work hours and earn higher total earnings as well as earnings per hour.

There are several policy implications from the findings of this study. Since e-commerce growth does not counteract the adverse effects of COVID-19 on the labour market, this means that e-commerce cannot be solely used as a policy tool to assist workers who are adversely affected by the pandemic. However, to realise the potential benefits of e-commerce in order for it to contribute to improving labour market conditions beyond job creation in the informal sector, efforts are needed to increase the productivity of workers involved in e-commerce activities, such as through skills enhancement and capacity building programmes.

Considering the heterogeneous effects of COVID-19 on workers, where female and youth workers are more adversely affected by the pandemic, specific assistance for female and youth workers is needed. Female workers face higher burdens during the pandemic as, for example, they also have to assist their children to study from home. This implies that there is a need for a gender-parity policy to achieve a more equitable distribution of household tasks between males and females who work in both the public and private sectors as well as providing extra support for childcare.

Meanwhile, youth workers face higher risk of losing their jobs during the pandemic as they are often the ones who are laid off first when companies face difficulties. Therefore, training, reskilling, and mentorship programmes for unemployed youths are needed to equip them with work relevant skills and assist them to diversify their opportunities and regain employment.

Finally, since workers who use the internet for work have better outcomes, improving digital skills of workers is crucial to improve their productivity and work performance. This should be implemented through both pre-employment and on the job training, utilising both face to face and online courses.

Notes

1. Indonesian E-commerce Association (idEA) is a communication forum for Indonesian E-commerce industry players. For further details, see: https://idea.or.id
2. Statistics Indonesia (BPS) defines formal sector workers as consisting of employers assisted by permanent/paid workers, and employees, while informal sector workers as consisting of own-account workers, employers assisted by temporary/unpaid workers, casual employees in agriculture and non-agriculture, and family/unpaid workers. For further details, see: https://sirusa.bps.go.id/sirusa/index.php/variabel/8482 (definition of formal sector) and https://sirusa.bps.go.id/sirusa/index.php/variabel/8483 (definition of informal sector).
3. For further details of Google Mobility Report, see: https://www.google.com/covid19/mobility
4. This data is publicly unavailable.
5. According to Abadie et al. (2017), three factors determine the correct clustering strategy for the standard error. First, the data should have enough variation across samples in each cluster. Second, there is enough variation in different units being observed. Finally, the treatment assignment across units has enough variation. In our case, we rely on the variation of the mobility index at the province levels. Nonetheless, across provinces, the variation in the mobility index is not substantial. Because all provinces faced a similar mobility restriction during the COVID-19 pandemic, thus if we clustered at the province levels, it would reduce the variation in our dataset. Moreover, we only have 34 provinces, and henceforth, we have a problem with a small degree of freedom. Therefore, we use

the robust standard error to overcome the potential heteroscedasticity in our data due to these issues.

6. During the normal situation, workers have a choice whether to work in the formal sector, to work in the informal sector, or to be unemployed. In such a situation, the choice of where to work is endogenous and hence the appropriate estimation method is the Multinomial Probit. However, the period of analysis in this paper is during a crisis situation, where the formal sector was shrinking and hence workers did not really have a choice where to work. Therefore, we estimate the model for the formal and the informal sectors separately using the Probit method.
7. The share of the top-4 marketplace is almost 80% of the total market capitalisation of e-commerce in Indonesia.
8. These indicators were calculated from the SAKERNAS microdata. There are some slight differences from the official figures published by BPS.
9. Training for the unemployed represents the Prakerja (Pre-employment) Programme. This is part of the National Economic Recovery (PEN) Programme launched by the Government of Indonesia to counter the adverse effect of the pandemic on the economy (https://pen.kemenkeu.go.id/in/post/mengapa-program-pen). The PEN Programme includes many specific programmes in six clusters: health, social protection, business incentives, support to micro, small, and medium enterprises (MSME), corporate financing, and regional governments and sectoral ministries. Information on participation in the Prakerja Programme is available in the SAKERNAS data. For the PEN-MSME programme, however, we did not find data that is suitable to be merged with the data analysed in this study as most of the benefits of this programme were distributed through banks.
10. We use some bounding assumptions on Rmax and develop a set of bounds for δ. According to Oster (2019), the appropriate upper bound for δ is 1, which indicates that the unobservables are equally important as the observables. We define some bounds for δ: one side of the bound is $R_{max} = R$, $\delta = 0$ and the other bound is $R_{max} = 1.3R$, $\delta = 1$.

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Notes on contributors

Masagus M. Ridhwan, Ph.D is a deputy director at the Bank Indonesia Institute, Bank Indonesia. He holds a doctorate in economics from Vrije Universiteit Amsterdam in the Netherlands.

Asep Suryahadi, Ph.D is a senior research fellow at the SMERU Research Institute, Indonesia. He holds a doctorate in economics from the Australian National University in Australia.

Jahen F. Rezki, PhD is a lecturer at the University of Indonesia and the Vice Director for Research at the Institute for Economic and Social Research (LPEM-FEB UI). He holds a doctorate in economics from the University of York, United Kingdom.

Dinda Thalia Andariesta, MSM is a researcher at the Bank Indonesia Institute, Bank Indonesia. She holds a master degree in management science from Institut Teknologi Bandung, Indonesia.

References

Abadie, A., S. Athey, G. W. Imbens, and J. Wooldridge. 2017. *When Should You Adjust Standard Errors for Clustering? (No. w24003)*. Cambridge, USA: National Bureau of Economic Research.

Abraham, R., A. Basole, and S. Kesar. 2022. "Down and out? The Gendered Impact of the Covid-19 Pandemic on India's Labour Market." *Economia Politica* 39 (1): 101–128. doi:10.1007/s40888-021-00234-8.

Anderton, R., V. Botelho, A. Consolo, A. D. da Silva, C. Foroni, M. Mohr, and L. Vivian. 2020. "The Impact of the COVID-19 Crisis on the Euro Area Labour Market." *ECB Economic Bulletin* (8). doi:10.46914/1562-2959-2021-1-1-186-190.

Bachtiar, P. P., R. A. Diningrat, A. Z. D. Kusuma, and A. Diandra. 2020. "Who is Digital Economy for? Toward an Inclusive Digital Economy." *SMERU Policy Brief*. 1 (Aug, 2020): 1–3. https://www.smeru.or.id.

Barrot, J. N., B. Grassi, and J. Sauvagnat. 2021. "Sectoral effects of social distancing." *InAEA Papers and Proceedings* 111: 277–81. doi:10.1257/pandp.20211108.

Béland, L.-P., A. Brodeur, and Wright Taylor. 2020. *The short-term economic consequences of COVID-19: Exposure to disease, remote work and government response* (Issue IZA DP No. 13159). https://www.iza.org/publications/dp/13159/the-short-term-economic-consequences-of-covid-19-exposure-to-disease-remote-work-and-government-response

Bell, D. N. F., and D. G. Blanchflower. 2020. "US and UK Labour Market before and during the COVID-19 Crash." *National Institute Economic Review* 252 (252): R52–R69. doi:10.1017/nie.2020.14.

Booth, A. 2000. "The Impact of the Economic Crisis on Welfare: What Do we Know Two Years on." In *Indonesia in Transition: Social Dimensions of Reformasi and Crisis*, edited by Chris Manning and Peter van Diermen, 145–162. Institute of Southeast Asian Studies, Singapore.

Borland, J., and A. Charlton. 2020. "The Australian Labour Market and the Early Impact of COVID-19: An Assessment." *Australian Economic Review* 53 (3): 297–324. (doi:10.1111/1467-8462.12386.

Brochu, P., J. Crechet, and Z. Deng. 2020. "*Labour Market Flows and Worker Trajectories in Canada during COVID-19*." (Working Paper Series, Issue 32).

Byrne, S., D. Coates, E. Keenan, and T. McIndoe-Calder. 2020. "*The Initial Labour Market: Impact of COVID-19*." (Economic Letter, Vol. 2020, Issue 4). https://publicpolicy.ie/digest/the-initial-labour-market-impact-of-covid-19/.

Casarico, A., and S. Lattanzio. 2022. "The Heterogeneous Effects of COVID-19 on Labor Market Flows: Evidence from Administrative Data." *The Journal of Economic Inequality* 20 (3): 537–558. doi:10.1007/s10888-021-09522-6.

Churchill, B. 2021. "COVID-19 and the Immediate Impact on Young People and Employment in Australia: A Gendered Analysis." *Gender, Work & Organization* 28 (2): 783–794. doi:10.1111/gwao.12563.

Coibion, O., Y. Gorodnichenko, and M. Weber. 2020. "*Labor Markets during the COVID-19 Crisis: A Preliminary View*." (No. 27017; NBER Working Paper Series, Issue 27017).

Crossley, T. F., P. Fisher, and H. Low. 2021. "The Heterogeneous and Regressive Consequences of COVID-19: Evidence from High Quality Panel Data." *Journal of Public Economics* 193: 104334. doi:10.1016/j.jpubeco.2020.104334.

Das, K., M. Gryseels, P. Sudhir, and K. T. Tan. 2016. "*Unlocking Indonesia's Digital Opportunity*." McKinsey & Company (Issue October). https://www.mckinsey.com/~/media/McKinsey/Locations/Asia/Indonesia/Our%20Insights/Unlocking%20Indonesias%20digital%20opportunity/Unlocking_Indonesias_digital_opportunity.ashx

Das, K., T. Tamhane, B. Vatterott, P. Wibowo, and S. Wintels. 2018. "The Digital Archipelago: How Online Commerce is Driving Indonesia's Economic Development." *McKinsey & Company* (Issue August). www.mckinsey.com/featured-insights/asia-pacific/the-digital-archipelago-how-online-.

Dingel, J. I., and B. Neiman. 2020. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189: 104235. doi:10.1016/j.jpubeco.2020.104235.

Eichenbaum, M. S., S. Rebelo, and M. Tranbandt. 2021. *The macroeconomics of epidemics* (No. 26882; NBER Working Paper Series). http://www.nber.org/papers/w26882

Feridhanusetyawan, T. 1999. "The Impact of the Crisis on the Labor Market in Indonesia." Report prepared for the Asian Development Bank, Manila.

Google, Temasek, & Bain & Company. 2021. *The SEA digital decade*. Economy SEA. https://economysea.withgoogle.com/

Guirrieri, V., G. Lorenzoni, L. Straub, and I. Werning. 2020. *Macroeconomics Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortage?* (No. 26918; NBER Working Paper Series). http://www.nber.org/papers/w26918

Hausmann, R. 2020. *Flattening the COVID-19 Curve in Developing Countries*. Project Syndicate. https://www.project-syndicate.org/commentary/flattening-covid19-curve-in-developing-countries-by-ricardo-hausmann-2020-03?barrier=accesspaylog

Hassink, W. H., Kalb, G., and J. Meekes. 2021. "Regional coronavirus hotspots during the COVID-19 outbreak in the Netherlands." *De Economist* 169 (2): 127–140.

Hensvik, L., T. Le Barbanchon, and R. Rathelot. 2021. "Job Search during the COVID-19 Crisis." *Journal of Public Economics* 194: 104349. doi:10.1016/j.jpubeco.2020.104349.

Inanc, H. 2020. Breaking Down the Numbers: What Does COVID-19 Mean for Youth Unemployment? *Mathematica*. https://www.mathematica.org/our-publications-and-findings/publications/breaking-down-the-numbers-what-does-covid-19-mean-for-youth-unemployment

Iyke, B. N., S. S. Sharma, and I. Gunadi. 2021. "COVID-19 Policy Responses and Industrial Productivity around the Globe." *Buletin Ekonomi Moneter Dan Perbankan* 24 (3): 365–382. doi:10.21098/bemp.v24i3.1691.

Khan, A. G. 2016. "Electronic Electronic Commerce: A Study on Benefits and Challenges in an Emerging Economy." *Global Journal of Management and Business Research: B Economics and Commerce* 16 (1): 1–5. https://5y1.org/download/a654f321cd56479ddbac15a48b349d39.pdf.

Kusumawardhani, N., R. Pramana, N. Saputri, and D. Suryadarma. 2021. *Heterogeneous Impact of Internet Availability on Female Labour Market Outcomes in an Emerging Economy: Evidence from Indonesia* (2021/49; WIDER Working Paper, Issue March). https://www.wider.unu.edu/sites/default/files/Publications/Working-paper/PDF/wp2021-49-impact-internet-availability-female-labour-market-outcomes-Indonesia.pdf%0Ahttps://www.wider.unu.edu/node/238359

Lemieux, T., K. Milligan, T. Schirle, and M. Skuterud. 2020. "Initial Impacts of the COVID-19 Pandemic on the Canadian Labour Market." *Canadian Public Policy* 46 (S1): S55–S65. doi:10.3138/cpp.2020-049.

Lin, Z., and C. M. Meissner. 2020. "*Health vs. wealth? Public Health Policies and the Economy during COVID-19*." (No. 27099; NBER WORKING PAPER SERIES HEALTH).

Manning, C. 1999. "Poverty Decline and Labour Market Change in Indonesia: Lessons from the Soeharto Era." *Indonesian Quarterly* 27 (2): 122–145.

Manning, C. 2000. "Labour Market Adjustment to Indonesia's Economic Crisis: Context, Trends and Implications." *Bulletin of Indonesian Economic Studies* 36 (1): 105–136. doi:10.1080/00074910012331337803.

Manning, C. 2021a. "COVID-19 and Jobs: Implications for Indonesia's on-Going Rural Transformation." Presentation at the Mubyarto Public Policy Forum. ANU, Australia.

Manning, C. 2021b. "The Labour Market Shock and Policy Responses to the Coronavirus Pandemic." In *Economic Dimensions of COVID-19 in Indonesia: Responding to the Crisis*, edited by B. D. Lewis and F. Witoelar, 94–113. Singapore: ISEAS Yusof Ishak Institute.

Nevo, A., and A. M. Rosen. 2012. "Identification with Imperfect Instruments." *Review of Economics and Statistics* 94 (3): 659–671. doi:10.1162/REST_a_00171.

Olivia, S., J. Gibson, and R. Nasrudin. 2020. "Indonesia in the Time of COVID-19." *Bulletin of Indonesian Economic Studies* 56 (2): 143–174. doi:10.1080/00074918.2020.1798581.

Oster, E. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37 (2): 187–204. doi:10.1080/07350015.2016.1227711.

Papanek, G., and B. S. Handoko. 1999. "The Impact on the Poor of Growth and Crisis: Evidence from Real Wage Data. Paper Presented at the Conference 'Economic Issues Facing the New Government." Jakarta, 18–20 August.

Park, C.-Y, and A. M. Inocencio. 2020. "COVID-19, Technology, and Polarizing Jobs." *ADB Briefs* 147. 1–10. doi:10.22617/BRF200217-2.

Potter, L. 2000. "Rural Livelihoods and the Environment at a Time of Uncertainty: The Situation outside Java." In *Indonesia in Transition: Social Dimensions of Reformasi and Crisis*, edited by Chris Manning and Peter van Diermen, 239–252. Singapore: Institute of Southeast Asian Studies.

Pouliakas, K., and J. Branka. 2020. "*EU Jobs at Highest Risk of COVID-19 Social Distancing: Will the Pandemic Exacerbate Labour Market Divide?*." (IZA DP No. 13281; Discussion Paper Series, Issue 13281).

Pratama, A. H. 2021. *Report: Ecommerce Penetration in Indonesia Higher than in the US, France*. Tech in Asia. https://www.techinasia.com/indonesia-ecommerce-40b-market

Ranchhod, V., and R. Daniels. 2020. *Labour Market Dynamics in South Africa in the Time of COVID-19: Evidence from Wave 1 of the NIDS-CRAM Survey* (Issue July). http://www.statssa.gov.za/publications/Report-02-11-02/Report-02-11-022020.pdf

Ridhwan, M. M., J. F. Rezki, A. Suryahadi, A. Ramayandi, and A. Ismail. 2023. "The Impact of COVID-19 Lockdowns on Household Income, Consumption, and Expectation: Evidence from High-Frequency Data in Indonesia." *Bulletin of Indonesian Economic Studies*: 1–42. accepted author version posted online: 19 Jan 2023. doi:10.1080/00074918.2023.2167930.

Ritchie, H., E. Mathieu, L. Rodés-Guirao, C. Appel, C. Giattino, E. Ortiz-Ospina, J. Hasell, B. Macdonald, D. Beltekian, and M. Roser. 2020. *Coronavirus Pandemic (COVID-19)*. OurWorldInData.Org. https://ourworldindata.org/coronavirus

Schotte, S., M. Danquah, R. D. Osei, and K. Sen. 2021. "The Labour Market Impact of COVID-19 Lockdowns: Evidence from Ghana." IZA Discussion Paper Series (No. 14692; Discussion Paper Series, Issue 14692). doi:10.2139/ssrn.3917307.

Sparrow, R., T. Dartanto, and R. Hartwig. 2020. "Indonesia under the New Normal: Challenges and the Way Ahead." *Bulletin of Indonesian Economic Studies* 56 (3): 269–299. doi:10.1080/00074918.2020.1854079.

Statistics Indonesia. 2019. Keadaan Tenaga Kerja Indonesia Agustus 2019. *Berita Resmi Statistik*. https://www.bps.go.id/publication/2019/11/29/96138ece33ccc220007acbdd/keadaan-angkatan-kerja-di-indonesia-agustus-2019.html

Statistics Indonesia. 2021. Pertumbuhan Ekonomi Indonesia Triwulan IV-2020. *Berita Resmi Statistik*. (Issue 13). https://www.bps.go.id/pressrelease/2021/02/05/1811/ekonomi-indonesia-2020-turun-sebesar-2-07-persen–c-to-c-.html

Suryahadi, A., R. Al Izzati, and A. Yumna. 2021. "The Impact of COVID-19 and Social Protection Programs on Poverty in Indonesia." *Bulletin of Indonesian Economic Studies* 57 (3): 267–296. doi:10.1080/00074918.2021.2005519.

Temenggung, D., A. Saputro, R. Rinaldi, and D. Pane. 2021. "Managing Recovery and Seizing Reform Opportunities." *Bulletin of Indonesian Economic Studies* 57 (1): 1–28. doi:10.1080/00074918.2021.1908207.

World Bank. 2021. *Beyond Unicorns: Harnessing Digital Technologies for Inclusion in Indonesia*. Jakarta, ID: World Bank Jakarta Office.

Appendix

Table A1. Summary statistics of provincial-level dataset.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Source: Google Mobility Report						
Google mobility index for workplaces	Proportion	136	−0.104	0.137	−0.414	0.076
Source: Bank Indonesia publicly unavailable data						
Log e-commerce transaction	NA	136	27.699	1.832	24.617	32.071
Source: Statistics Indonesia (*Badan Pusat Statistik*, BPS)						
Employment rate	Proportion	136	0.978	0.024	0.918	1.036
Labour force growth	Proportion	136	−0.002	0.036	−0.112	0.097
Population density	Population per km^2	136	741.191	2,681.642	9.000	15,978.000
Proportion of higher educated population	Proportion	136	0.471	0.088	0.317	0.699
GRDP growth	Proportion	136	0.012	0.046	−0.194	0.114
Share of manufacturing in GRDP	Proportion	136	0.160	0.112	0.012	0.432
Share of services in GRDP	Proportion	136	0.137	0.064	0.028	0.320
Degree of openness	Proportion	136	0.334	0.404	0.000	2.031
Source: Village Potential Statistics (PODES)						
Proportion of villages with paved road	Proportion	136	0.913	0.141	0.230	1.000
Number of villages with BTS	Thousand	136	1.098	1.164	0.196	4.826
Source: *Satuan Tugas Penanganan* COVID-19 (covid19.go.id)						
Change in hospitalisation rate	Change in hospitalisation per thousand population	136	−0.001	0.005	−0.042	0.011

Note: The data consists of 34 provinces in Indonesia, covering the period of four rounds of the Labour Force Survey from August 2019 to February 2021.

Table A2. Summary statistics of individual-level dataset.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Source: Labour Force Survey (SAKERNAS)						
Employed	Proportion	1,982,956	0.629	0.483	0.000	1.000
Formal worker	Proportion	1,982,956	0.238	0.426	0.000	1.000
Informal worker	Proportion	1,982,956	0.391	0.488	0.000	1.000
Unemployed	Proportion	1,982,956	0.037	0.189	0.000	1.000
Non-labour force	Proportion	1,982,956	0.334	0.472	0.000	1.000
Log hours worked	NA	1,266,454	4.838	0.627	1.386	6.510
Log total earnings	NA	803,054	14.206	0.916	−0.049	19.082
Log earning per hour	NA	782,997	9.275	0.874	−4.462	15.579
Male	Proportion	1,982,956	0.495	0.500	0.000	1.000
Secondary education	Proportion	1,982,956	0.494	0.500	0.000	1.000
Tertiary education	Proportion	1,982,956	0.100	0.300	0.000	1.000
On-the-job training	Proportion	1,982,956	0.104	0.305	0.000	1.000
Training for unemployed	Proportion	1,982,956	0.031	0.174	0.000	1.000
Using internet for work	Proportion	1,982,956	0.158	0.364	0.000	1.000
Work from home	Proportion	1,982,956	0.021	0.142	0.000	1.000
Moderate disability	Proportion	1,982,956	0.086	0.281	0.000	1.000
Severe disability	Proportion	1,982,956	0.013	0.112	0.000	1.000
Work in the essential sector	Proportion	1,982,956	0.331	0.471	0.000	1.000
Urban	Proportion	1,982,956	0.436	0.496	0.000	1.000

Note: The data period covers four rounds of the Labour Force Survey from August 2019 to February 2021, where the observation unit is individual workers.

Table A3. First-stage Regression Results, August 2019–February 2021.

	Work Mobility		E-commerce Growth	
	(1) OLS	(2) OLS	(1) OLS	(2) OLS
Change in hospitalisation rate	−1.364***	−1.206***	−5.570***	−5.590***
	(0.00769)	(0.00696)	(0.0570)	(0.0360)
Number of villages with BTS	0.0233***	0.0865***	0.00629**	0.105***
	(0.000282)	(0.000330)	(0.00273)	(0.00302)
Constant	−0.00986***	−1.302***	26.70***	18.67***
	(0.000399)	(0.00357)	(0.00408)	(0.0186)
Worker Control	No	Yes	No	Yes
Province Control	No	Yes	No	Yes
Province Dummies	Yes	Yes	Yes	Yes
Period Dummies	Yes	Yes	Yes	Yes
Observation	1,982,956	1,982,956	1,982,956	1,982,956
R^2	0.945	0.956	0.993	0.994

Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4. Bounding statement β of IV regressions using Oster approach, August 2019–February 2021.

	Overall			Formal			Informal		
	Baseline effect (Std. Error), [R^2]	Controlled effect (Std. Error), [R^2]	Identified Set	Baseline effect (Std. Error), [R^2]	Controlled effect (Std. Error), [R^2]	Identified Set	Baseline effect (Std. Error), [R^2]	Controlled effect (Std. Error), [R^2]	Identified Set
Panel A: Log Hours Worked									
Work mobility	−2.525***	−0.685***	[-1,612.23,	−27.19	0.735**	[0.735,	−4.084***	−1.439***	[-606.41,
	(0.357) [0.021]	(0.145) [0.129]	−0.685]+	(16.93) [0.026]	(0.312) [0.128]	4,474.76]+	(0.396) [0.018]	(0.164) [0.115]	−1.439]+
E-commerce growth	0.448***	−0.029	[-2,209.67,	7.097	−0.319***	[-445.05,	0.728***	0.155***	[0.155,
	(0.086) [0.021]	(0.048) [0.129]	−0.029]+	(4.481) [0.026]	(0.092) [0.128]	−0.319]+	(0.074) [0.018]	(0.054) [0.115]	581.57]+
Panel B: Log Total Earnings									
Work mobility	−0.380	1.967***	[1.967,	4.382	2.368***	[2.368,	1.068	0.962**	[0.962,
	(3.499) [0.054]	(0.352) [0.279]	7,506.17]+	(2.837) [0.059]	(0.548) [0.287]	7,955.66]+	(1.745) [0.047]	(0.449) [0.193]	11,695.25]+
E-commerce growth	0.117	−0.496***	[-1,759.76,	−1.112	−0.500***	[-2,540.91,	−0.209	−0.324***	[-1,047.26,
	(0.842) [0.054]	(0.095) [0.279]	−0.496]+	(0.723) [0.059]	(0.148) [0.287]	−0.500]+	(0.350) [0.047]	(0.115) [0.193]	−0.324]+
Panel C: Log Earning per Hour									
Work mobility	−1.347	1.650***	[1.650,	20.83***	1.135**	[1.135,	5.697***	1.551***	[1.551,
	(2.155) [0.043]	(0.338) [0.222]	5,304.97]+	(7.291) [0.052]	(0.515) [0.295]	11,780.09]+	(1.479) [0.039]	(0.451) [0.103]	2,369.95]+
E-commerce growth	0.520	−0.285***	[-2,256.15,	−5.330***	−0.084	[-19,081.47,	−1.016***	−0.298**	[-0.298,
	(0.534) [0.043]	(0.097) [0.222]	−0.285]+	(1.910) [0.052]	(0.147) [0.295]	−0.084]+	(0.303) [0.039]	(0.124) [0.103]	−0.085]+

Note: This table shows the validation results for the analysis of the impact of work mobility and e-commerce growth on work hours, total earnings, and earnings per hour. Baseline effects include only province and time dummies. Full controls: worker characteristics and province characteristics. The identified set was calculated based on 2SLS with full controls. The identified set is bounded by $\tilde{\beta}$ calculated based on $R_{max} = \tilde{R}$ and $\tilde{\delta} = 0$, and the other is bounded by β^* calculated based on $R_{max} = 1.3\tilde{R}$ and $\tilde{\delta} = 1$. Robust standard errors in parentheses $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. $^+$ identified set excludes zero.

Table A5. Labour market outcome effects of mobility restrictions and e-commerce growth by gender, August 2019–February 2021.

	Work Mobility						E-commerce Growth					
	Overall		Formal		Informal		Overall		Formal		Informal	
	(1) OLS/Probit	(2) 2SLS/IV Probit	(3) OLS/Probit	(4) 2SLS/IV Probit	(5) OLS/Probit	(6) 2SLS/IV Probit	(1) OLS/Probit	(2) 2SLS/IV Probit	(3) OLS/Probit	(4) 2SLS/IV Probit	(5) OLS/Probit	(6) 2SLS/IV Probit
Panel A: Probability to Work												
Male	0.00496	−1.470***	0.0508	1.303***	−0.0746	−1.920***	0.0660***	0.157	0.0167	−0.550***	0.0194**	0.506***
	(0.0767)	(0.517)	(0.0683)	(0.443)	(0.0610)	(0.403)	(0.0123)	(0.167)	(0.0107)	(0.143)	(0.00968)	(0.130)
Female	0.0442	−1.651***	0.295***	1.850***	−0.236***	−2.578***	0.0401***	0.238	−0.0174	−0.441**	0.0429***	0.480***
	(0.0709)	(0.463)	(0.0826)	(0.522)	(0.0658)	(0.439)	(0.0110)	(0.155)	(0.0128)	(0.173)	(0.0104)	(0.147)
Panel B: Log Hours Worked												
Male	−0.0960***	−1.058***	−0.0158	0.116	−0.152***	−1.843***	0.0264***	0.0800	0.00408	−0.125	0.0349***	0.205***
	(0.0278)	(0.176)	(0.0374)	(0.348)	(0.0386)	(0.215)	(0.00433)	(0.0577)	(0.00555)	(0.111)	(0.00615)	(0.0649)
Female	−0.138***	−0.250	0.0648	1.888***	−0.309***	−1.077***	0.0195***	−0.184**	0.00835	−0.628***	0.0295***	0.0936
	(0.0388)	(0.247)	(0.0582)	(0.604)	(0.0501)	(0.253)	(0.00607)	(0.0846)	(0.00859)	(0.160)	(0.00797)	(0.0919)
Panel C: Log Total Earnings												
Male	0.0697	1.558***	0.0975*	2.344***	0.0817	0.172	−0.0147**	−0.526***	−0.0259***	−0.574***	−0.00142	−0.294**
	(0.0494)	(0.401)	(0.0590)	(0.645)	(0.0794)	(0.537)	(0.00729)	(0.110)	(0.00890)	(0.185)	(0.0114)	(0.128)
Female	0.285***	2.452***	0.361***	2.283**	0.159	2.039**	−0.0143	−0.433**	−0.0127	−0.379	−0.00555	−0.379
	(0.0704)	(0.666)	(0.0862)	(0.956)	(0.111)	(0.835)	(0.0109)	(0.175)	(0.0134)	(0.236)	(0.0170)	(0.234)
Panel D: Log Earning per Hour												
Male	0.0553	1.917***	0.0663	1.760***	0.0731	1.524***	−0.0292***	−0.498***	−0.0276***	−0.374**	−0.0260**	−0.390***
	(0.0511)	(0.393)	(0.0614)	(0.623)	(0.0834)	(0.542)	(0.00740)	(0.116)	(0.00907)	(0.190)	(0.0118)	(0.141)
Female	0.233***	0.848	0.277***	0.0345	0.230*	1.312	−0.0182*	0.127	−0.0181	0.338	−0.0161	−0.0646
	(0.0717)	(0.631)	(0.0867)	(0.883)	(0.117)	(0.832)	(0.0108)	(0.174)	(0.0130)	(0.226)	(0.0177)	(0.248)

Note: Worker characteristics, province characteristics, province dummies, and time dummies are included in the model. Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A6. Labour market outcome effects of mobility restrictions and e-commerce growth by age groups, August 2019–February 2021.

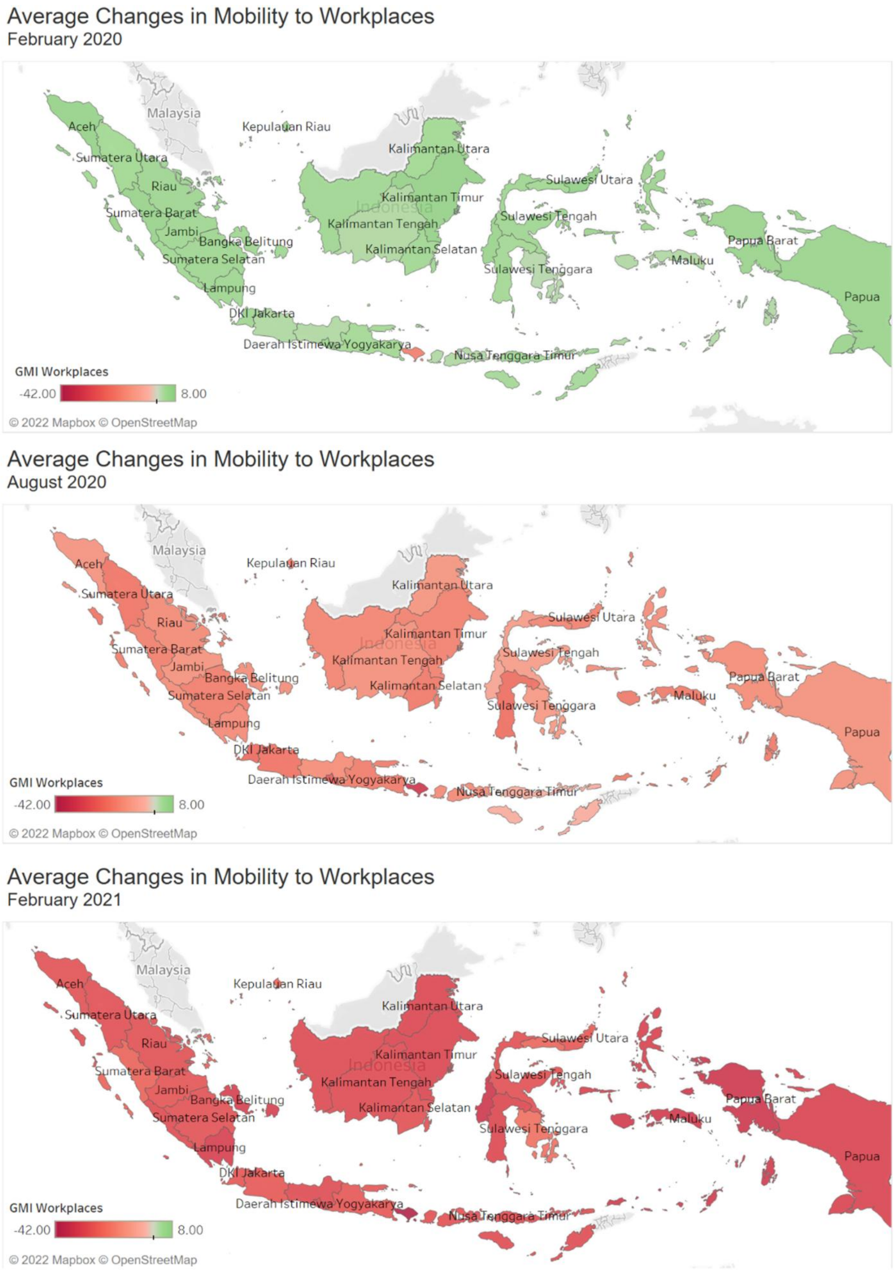
	Work Mobility						E-commerce Growth					
	Overall		Formal		Informal		Overall		Formal		Informal	
	(1) OLS/Probit	(2) 2SLS/IV Probit	(3) OLS/Probit	(4) 2SLS/IV Probit	(5) OLS/Probit	(6) 2SLS/IV Probit	(1) OLS/Probit	(2) 2SLS/IV Probit	(3) OLS/Probit	(4) 2SLS/IV Probit	(5) OLS/Probit	(6) 2SLS/IV Probit
Panel A: Probability to Work												
Youth	0.439***	−2.532***	0.176	1.870**	0.0933	−2.689***	0.00900	0.907***	0.00998	−0.676**	−0.0103	0.901***
(15-24)	(0.121)	(0.819)	(0.142)	(0.865)	(0.110)	(0.786)	(0.0195)	(0.319)	(0.0216)	(0.344)	(0.0180)	(0.304)
Adult	0.0128	−3.640***	0.167***	1.246***	−0.189***	−2.894***	0.0875***	0.673***	0.00722	−0.419***	0.0358***	0.671***
(25-60)	(0.0714)	(0.486)	(0.0616)	(0.429)	(0.0540)	(0.378)	(0.0110)	(0.157)	(0.00963)	(0.137)	(0.00847)	(0.121)
Older	−0.0610	−0.455	0.260	0.219	−0.186	−0.377	0.0295	−0.0339	−0.0598**	−0.0396	0.0405**	−0.0435
(60+)	(0.129)	(0.680)	(0.192)	(0.909)	(0.118)	(0.628)	(0.0204)	(0.194)	(0.0279)	(0.248)	(0.0187)	(0.179)
Panel B: Log Hours Worked												
Youth	−0.0518	−1.187**	0.0196	−0.562	−0.156	−3.173***	0.00612	0.106	−0.00414	0.105	−0.0186	0.351
(15-24)	(0.0738)	(0.545)	(0.0843)	(0.742)	(0.113)	(0.992)	(0.0114)	(0.201)	(0.0120)	(0.187)	(0.0179)	(0.256)
Adult	−0.103***	−0.661***	0.0216	0.794**	−0.211***	−1.402***	0.0202***	−0.0384	0.00359	−0.362***	0.0299***	0.148**
(25-60)	(0.0248)	(0.170)	(0.0347)	(0.353)	(0.0342)	(0.196)	(0.00387)	(0.0566)	(0.00514)	(0.108)	(0.00543)	(0.0633)
Older	−0.164**	−0.799**	−0.0325	2.064	−0.182**	−1.120***	0.0559***	0.0637	0.0627**	−0.651*	0.0557***	0.194*
(60+)	(0.0738)	(0.329)	(0.229)	(1.355)	(0.0782)	(0.333)	(0.0117)	(0.0998)	(0.0316)	(0.367)	(0.0126)	(0.101)
Panel C: Log Total Earnings												
Youth	0.123	3.499***	0.104	2.570**	0.129	0.630	−0.0275*	−0.666**	−0.000503	−0.320	−0.103***	−0.756*
(15-24)	(0.108)	(1.002)	(0.116)	(1.100)	(0.236)	(1.754)	(0.0163)	(0.266)	(0.0171)	(0.265)	(0.0364)	(0.459)
Adult	0.147***	1.891***	0.203***	2.061***	0.0962	1.109**	−0.0166**	−0.501***	−0.0268***	−0.473***	−0.00106	−0.352***
(25-60)	(0.0446)	(0.409)	(0.0544)	(0.636)	(0.0711)	(0.523)	(0.00673)	(0.112)	(0.00838)	(0.177)	(0.0105)	(0.134)
Older	0.0636	0.650	0.310	4.722**	0.0440	−0.437	0.0356	−0.180	0.0277	−0.901	0.0411	0.0721
(60+)	(0.164)	(0.917)	(0.344)	(2.362)	(0.184)	(0.998)	(0.0237)	(0.219)	(0.0464)	(0.550)	(0.0272)	(0.235)
Panel D: Log Earning per Hour												
Youth	0.0520	3.573***	0.0596	2.947***	0.0696	2.130	−0.0183	−0.625**	−0.000264	−0.387	−0.0456	−0.688
(15-24)	(0.108)	(0.951)	(0.119)	(1.095)	(0.237)	(1.742)	(0.0159)	(0.262)	(0.0173)	(0.272)	(0.0361)	(0.466)
Adult	0.141***	1.558***	0.142**	0.685	0.166**	1.766***	−0.0295***	−0.281**	−0.0279***	0.00847	−0.0275**	−0.358**
(25-60)	(0.0462)	(0.395)	(0.0559)	(0.595)	(0.0759)	(0.534)	(0.00680)	(0.115)	(0.00834)	(0.175)	(0.0110)	(0.146)
Older	−0.0439	0.280	0.559	1.166	−0.119	−0.0929	0.0136	0.112	−0.0346	0.0450	0.0231	0.175
(60+)	(0.172)	(0.919)	(0.353)	(2.053)	(0.196)	(1.018)	(0.0250)	(0.241)	(0.0474)	(0.484)	(0.0290)	(0.269)

Note: Worker characteristics, province characteristics, province dummies, and time dummies are included in the model. Robust standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7. Exogeneity test using Nevo and Rosen (2012) approach.

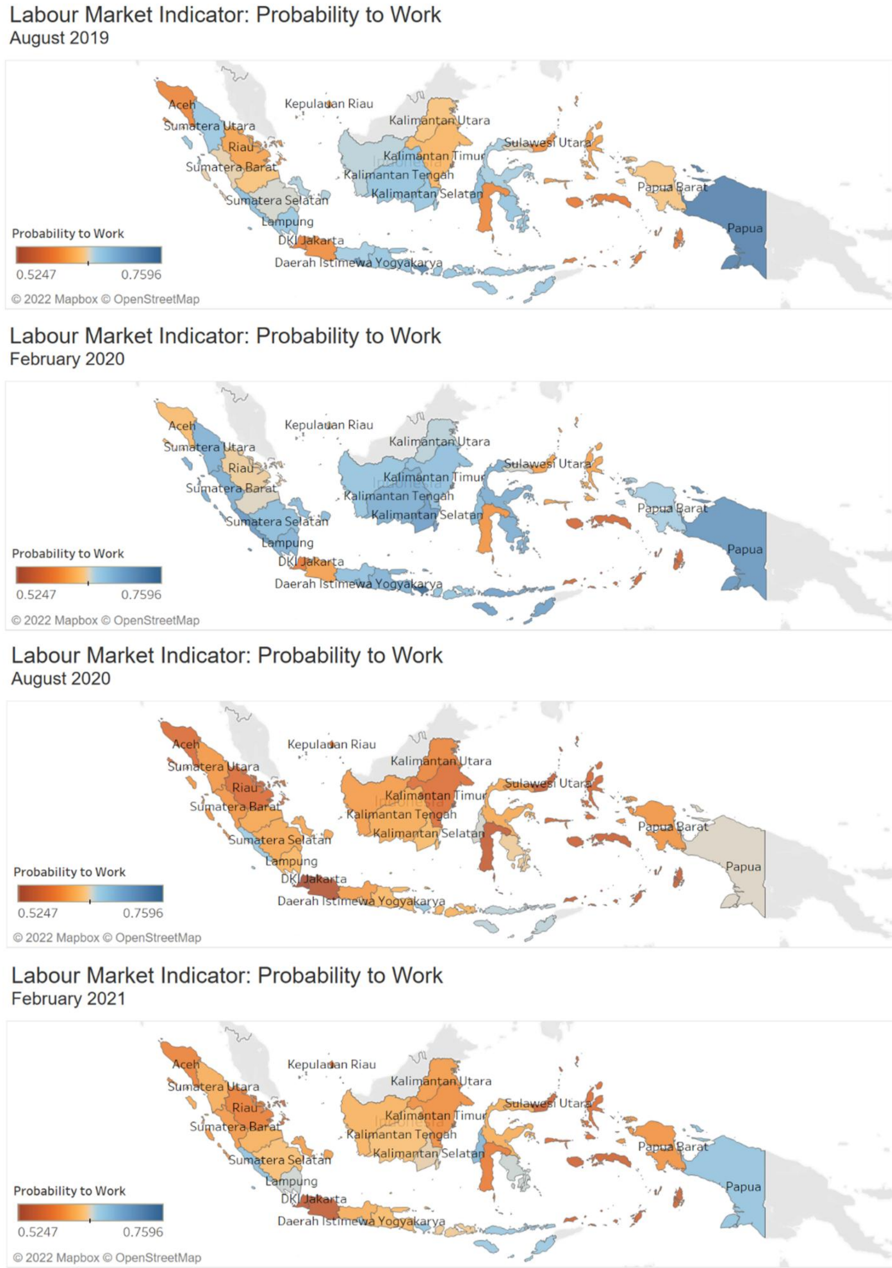
	Log Hours Worked		Log Total Earnings		Log Earning per Hour	
	Estimator [LB, UB]	CI [LB, UB]	Estimator [LB, UB]	CI [LB, UB]	Estimator [LB, UB]	CI [LB, UB]
Panel A						
Work mobility	[0.084, 1.264]	[0.038, 1.821]	[−1.407, 0.175]	[−2.018, 0.253]	[−2.290, 0.074]	[−2.926, 0.153]
Panel B						
E-commerce growth	[0.017, .]	[0.015, .]	[0.089, .]	[0.085, .]	[0.069, .]	[0.066, .]

Note: LB Lower Bound, UB Upper Bound. The correlation between e-commerce growth as an endogenous variable and the number of villages with BTS as the instrument is positive so that only one-sided bounds can be produced. The result for work mobility shows that lower and upper bounds are not crossing, this suggests that the maintained assumptions in the IIV procedure are consistent, and the model should be accepted.



Source: Google Mobility Report

Figure A1. Average changes in mobility to workplaces by Province, February 2020–February 2021.
Figure A1 Alt Text: Three images indicate the average changes of work mobility at the province level. Each image indicates different period. There are three time periods, including February 2020 on the top, August 2020 on the center, and February 2021 on the bottom.



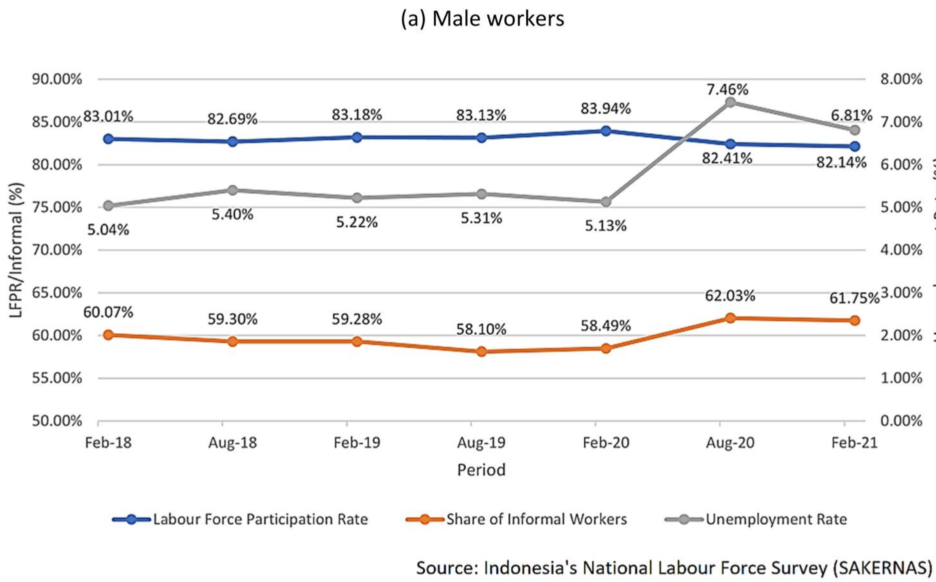
Source: Indonesia's National Labour Force Survey (SAKERNAS)

Figure A2. Labour market indicator - probability to work by Province, August 2019–February 2021. Figure A2 Alt Text: Four images indicate the cross-sectional variations of probability to work at the province level. Each image indicates a different round of the survey period. There are four rounds of survey periods, including August 2019 on the first row, February 2020 on the second row, August 2020 on the third row, and February 2021 on the last row.

Source: Google Mobility Report and Indonesia's National Labour Force Survey (SAKERNAS)

Figure A3. Association between Mobility and Labour Market Indicators at the Province Level, August 2019–February 2021.

Figure A3 Alt Text: Four graphs indicate the association between work mobility and labour market indicators at the province level in four rounds of survey periods (i.e., August 2019, February 2020, August 2020, and February 2021). There are four labour market indicators in this graph, including probability to work (on the upper left), log work hours (on the upper right), log total earnings (on the bottom left), and log earnings per hour (on the bottom right).



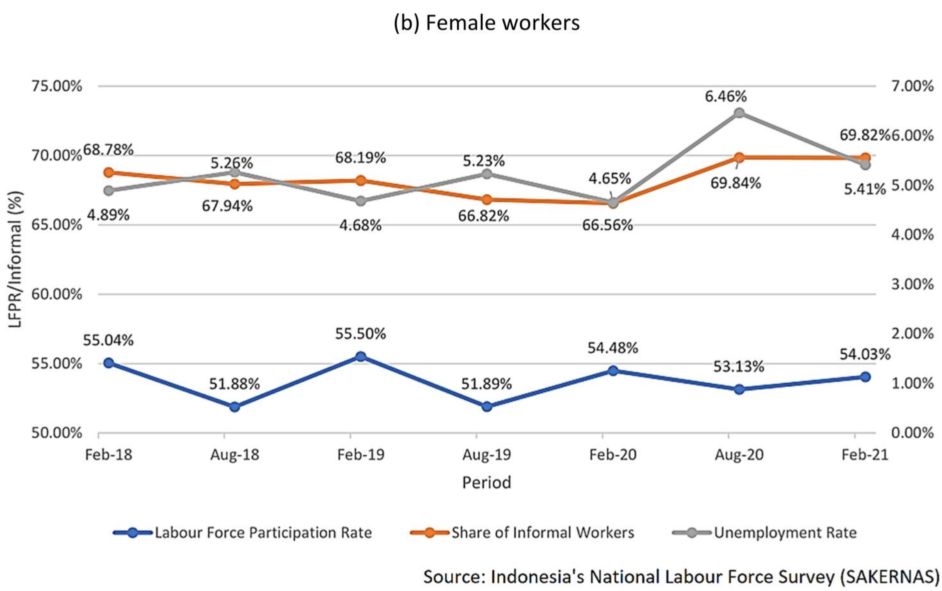


Figure A4. Labour market indicators by gender, February 2018–February 2021.

Figure A4 Alt Text: Two graphs indicate the heterogeneity of the labour market indicators by gender (male workers on the top and female workers on the bottom). There are three labour market indicators in this graph, labour force participation, the share of informal workers, and the unemployment rate.

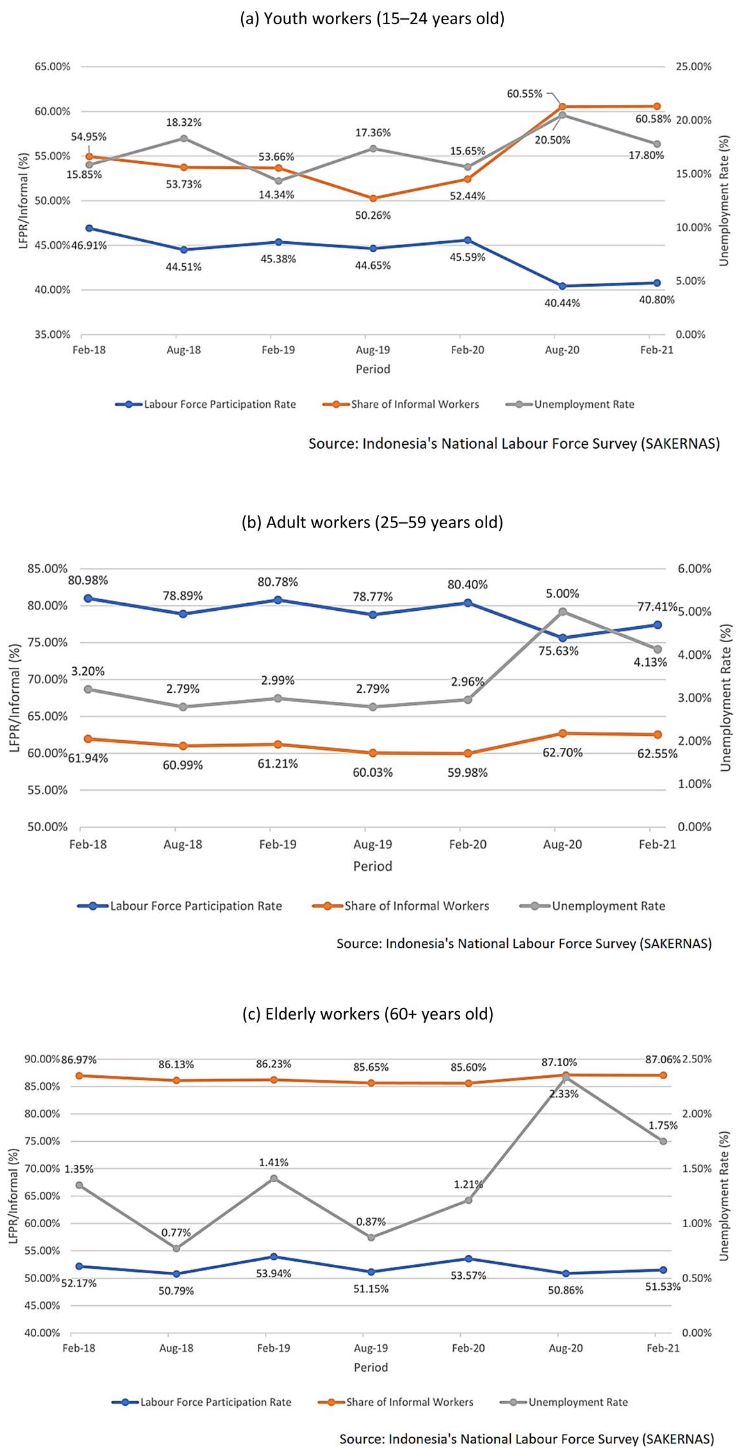


Figure A5. Labour market indicators by age group, February 2018–February 2021.

Figure A5 Alt Text: Three graphs indicate the heterogeneity of the labour market indicators by age (15–24 years on the top, 25–59 years old on the center, and above 60+ years on the bottom). There are three labour market indicators in this graph, labour force participation, the share of informal workers, and the unemployment rate.

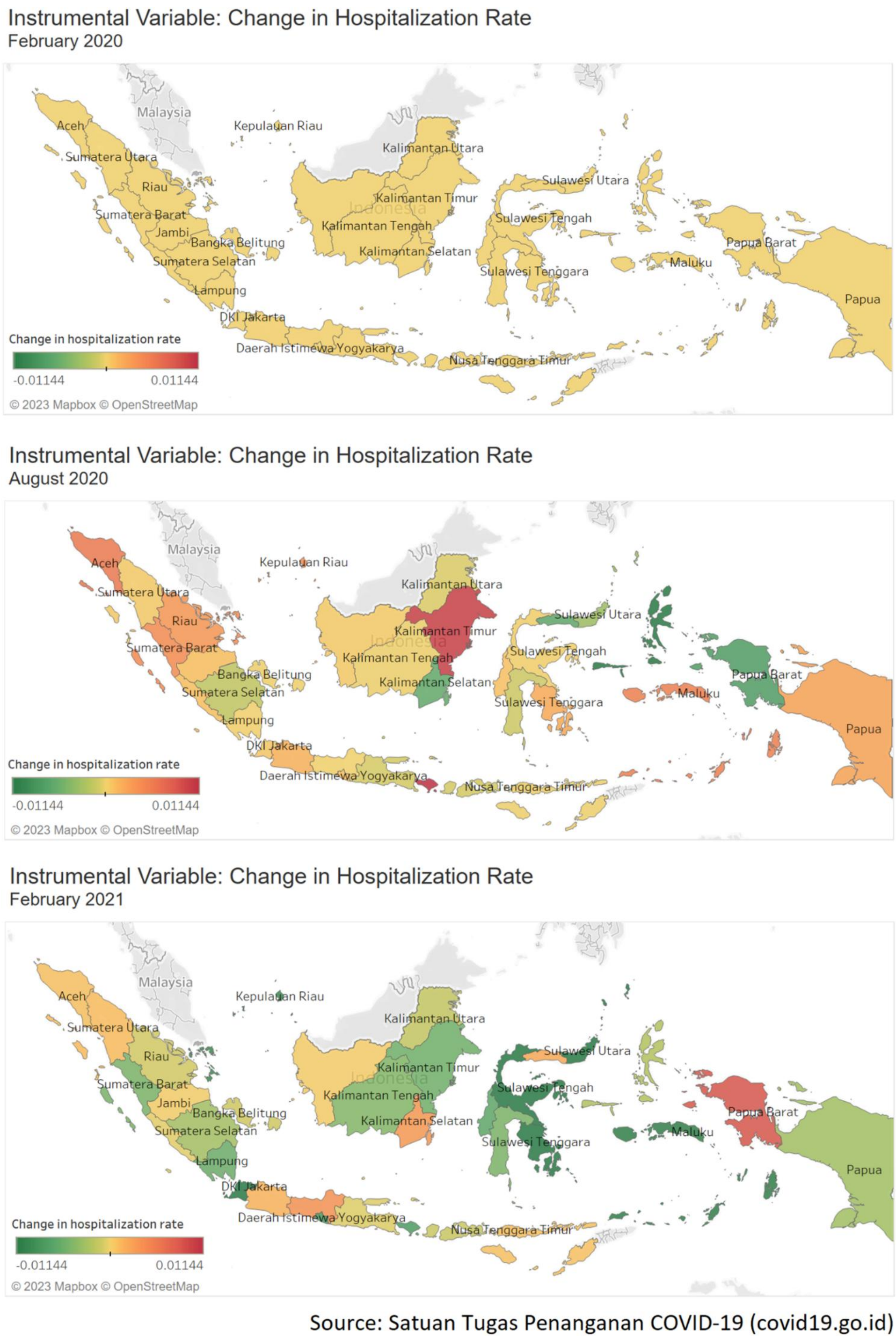


Figure A6. Instrumental variable: change in hospitalisation rate by province, February 2020–February 2021.

Figure A6 Alt Text: Three images indicate the cross-sectional variations of hospitalisation rate at the province level. Each image indicates a different period, including February 2020 on the first row, August 2020 on the second row, and February 2021 on the last row.

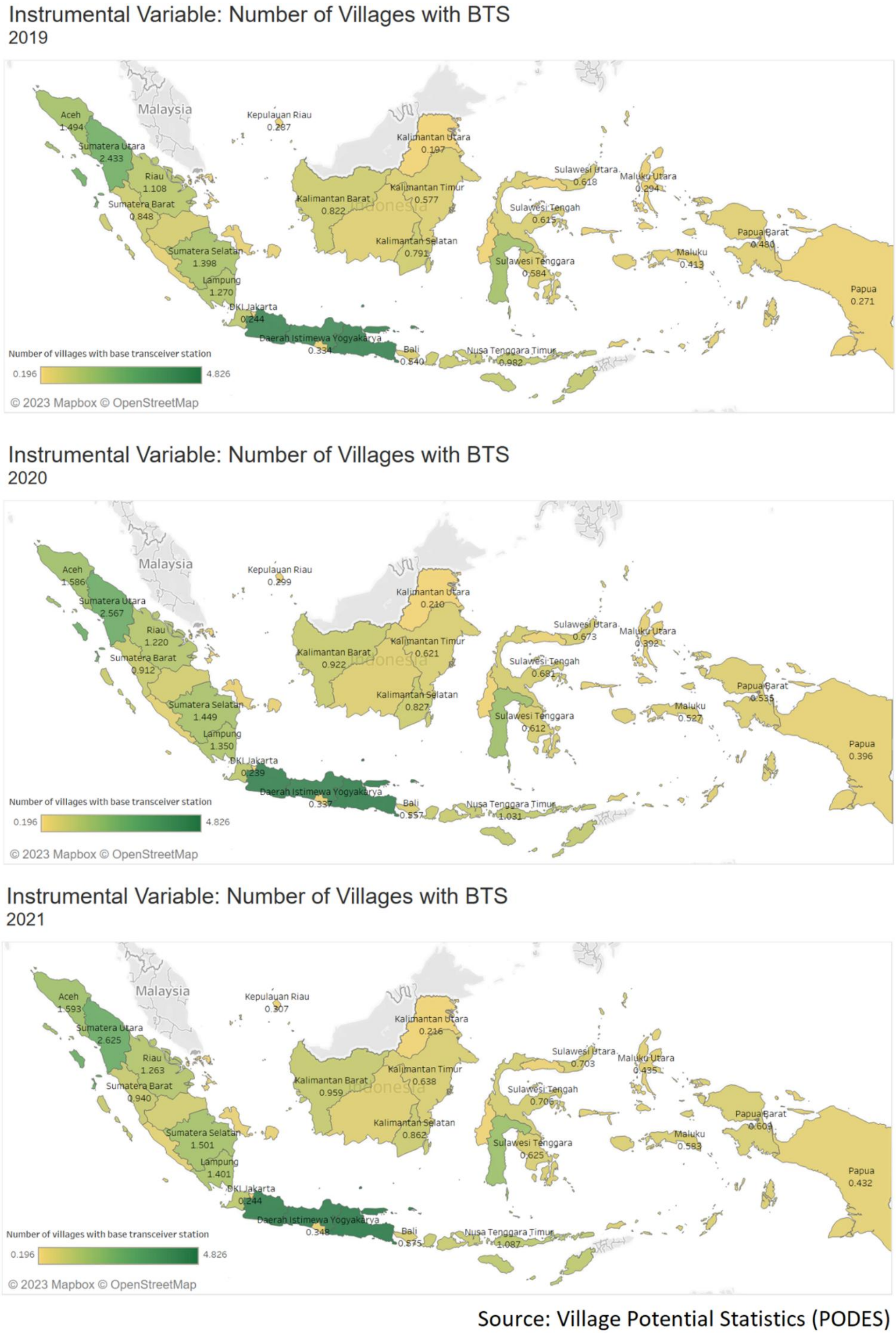
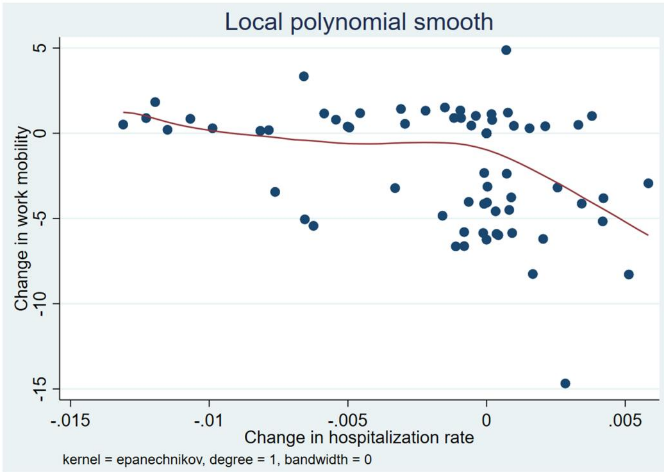


Figure A7. Instrumental variable: number of villages with base transceiver station by province, 2019–2021.

Figure A7 Alt Text: The three images indicate the cross-sectional variations of the number of villages with BTS at the province level. Each image indicates a different year period, including 2019 on the first row, 2020 on the second row, and 2021 on the last row.

(a) Hospitalisation Rate and Work Mobility



(b) Number of Villages with BTS and E-commerce Growth

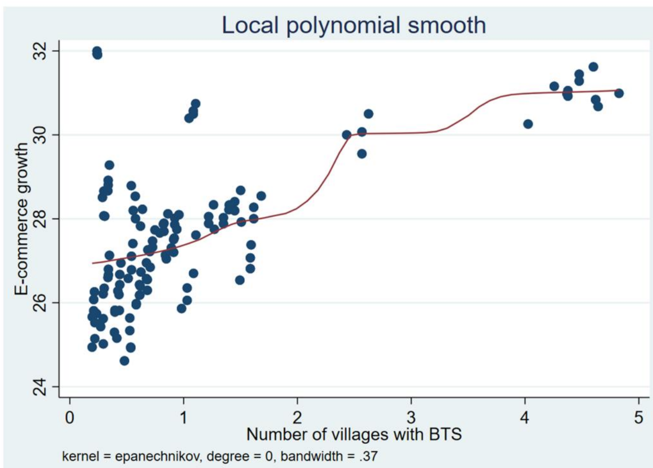


Figure A8. Monotonicity assumptions.

Figure A8 Alt Text: Two images indicate the monotonicity between the endogenous variables and instrumental variables. The top image indicates the monotonicity (negative effect) between the change in hospitalisation rate and the change in work mobility. The bottom image indicates the monotonicity (positive effect) between the number of villages with BTS and e-commerce growth.