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COVID-19-associated income loss and job loss: Evidence from Indonesia

Rendra A.A. Putra [a], Kostiantyn Ovsiannikov [b], Koji Kotani [c,d,e,*]

[a] Statistics Indonesia, Indonesia
[b] General Research Center, Shohoku College, Japan
[c] Research Institute for Future Design, Kochi University of Technology, Japan
[d] Urban Institute, Kyushu University, Japan
[e] College of Business, Rikkyo University, Japan

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ABSTRACT

COVID-19 pandemic has substantially altered socioeconomic conditions around the world. While numerous existing studies analyze the impact of the COVID-19 pandemic among developed states, little is known about its effects on people's lives and social discrepancies in emerging economies. To this end, we empirically analyze the 2020 Indonesian Labor Force Survey data, hypothesizing that COVID-19 has given idiosyncratic risks and impacts on people by gender, age, education, occupation and regions. We find that income loss and job loss are prominent among males, younger and less educated people as well as among self-employed and part-time non-agricultural workers. These tendencies are not pronounced for people enjoying high income and mobility, but tend to be evident for urban residents and those having dependents. Notably, self-employed people have the highest risk of losing income, while part-time urban workers face the highest probability of losing their jobs. The propensity score matching method also demonstrates that these losses are most evident for the regions susceptible to COVID-19. Overall, we suggest that socioeconomically disadvantaged groups require additional support to strengthen their resilience in the face of exogenous shocks, such as the one caused by the global coronavirus pandemic.

1. Introduction

Socioeconomic consequences of the COVID-19 pandemic have been devastating. According to ILO (2021), 114 million jobs were lost in 2020 as compared to 2019. Consequently, the number of unemployed increased by 33 million globally. Furthermore, over the same period of time, global labor income declined by 8.3%, amounting to 4.4% of the global gross domestic product (GDP). On top of these grave overall impacts, some employment cohorts have suffered disproportionate damage. For example, 80% or 1.6 billion of informal workers around the world lost 60% of their income (UNDP, 2020). Their situation has been exacerbated by the virtually absent access to social security funds. Against this background, our paper addresses the issue of the COVID-19 impact on the well-being among developing countries' citizens, concentrating on whether or not the existing socioeconomic discrepancies have widened.

A salient feature of the ongoing pandemic is the deepening of the existing socioeconomic inequalities. One of the major dividing lines in the context of the COVID-inflicted loss runs through occupational sectors and employment types. Being the case of an

* Corresponding author at: Research Institute for Future Design, Kochi University of Technology, Japan.
E-mail address: kojikotani757@gmail.com (K. Kotani).

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Nomenclature

ATE	Average treatment effect
ATT	Average treatment effect on the treated
EAP	East Asia and Pacific
FDG	Facebook Data for Good
GAM	Generalized additive model
GCMR	Google Community Mobility Report
GDP	Gross domestic product
ME	Marginal effect
PSM	Propensity score matching

exogenous economic shock, COVID-19 has jeopardized low-skill and non-regular labor (Cotofan et al., 2021). The former group has higher chances of being displaced due to automation processes, while the latter has weaker legal protection compared to regular workers, being subject to layoffs as part of corporate optimization plans. On top of that, self-employed tend to suffer from the negative income adjustments, since their profits are particularly susceptible to demand fluctuations (Parker et al., 2005). Hence, depressed consumer activity during the pandemic period has led to lower profits accruing to private entrepreneurs.

Khamis et al. (2021) provide evidence of service and manufacturing workers in the developing countries being most heavily impacted by the ongoing pandemic. They also conclude that urban employees bear the brunt of the crisis to a larger extent than rural workers who are mostly involved in agriculture. Based on the data from the U.S., the U.K., Germany and Japan, Adams-Prassl et al. (2020), Blundell et al. (2020) and Kanbayashi et al. (2021) identify self-employed and temporary employees as the groups most prone to the impacts of the crises such as COVID-19. Available scholarship provides evidence of unequal impact of lockdown on the economic well-being depending on the levels of income. In cases of the U.K. Blundell et al. (2020), Italy (Bonaccorsi et al., 2020), China (Qian & Fan, 2020), Japan (Kikuchi et al., 2021) and South Korea (Dang & Viet Nguyen, 2021), the relatively poorer inhabitants tend to lose larger portions of income. In Italy, this tendency is even more pronounced for the fiscally better-off provinces, providing an evidence of the negative effect of mobility restrictions being magnified for the regions with higher levels of inequality (Bonaccorsi et al., 2020). Additionally, Mongey et al. (2020) point at socioeconomic adversities associated with being younger, less educated and having limited access to health care. All in all, the evidence testifies to the fact that COVID-19 pandemic has disproportionately affected the most vulnerable layers of society.

Despite the extensive coverage of the gender-related impacts of economic shocks, the findings appear inconclusive. While Hoynes et al. (2012) and Bredemeier et al. (2017) argue that males are more likely to be victims of cyclical crises than females, Adams-Prassl et al. (2020) and Dang and Viet Nguyen (2021) find out that females in the developed countries have felt the impacts of the COVID-19 more severely than males. According to Alon et al. (2020), this tendency results from the fact that female-dominated service industries suffered most from the pandemic. Furthermore, the closures of childcare facilities have substantially increased the workload of mothers who often do not have any choice other than to quit their jobs in order to concentrate on parenting (Albanesi & Kim, 2021; Fisher & Ryan, 2021). Kalenkoski and Pabilonia (2020) approach this issue by additionally modeling income and working hours' loss for the men involved in childcare, documenting their resulting vulnerability. Moreover, Gallacher and Hossain (2020) conclude that males have lower chances of performing work duties remotely, which leads to a higher probability of job loss among them. In this context, Adams-Prassl et al. (2020) suggest that provision of telework infrastructure can remedy these negative effects.

While literature analyzes the impact of the COVID-19 pandemic among developed states, little is known about its effects on people's lives and social discrepancies in emerging economies. Our paper aims at identifying socioeconomic groups most heavily impacted by income loss and job loss in Indonesia — a country that epitomizes the challenges faced by developing countries. To this end, we analyze the 2020 Indonesian Labor Force Survey data, hypothesizing that COVID-19 has given idiosyncratic risks and impacts on people by gender, age, education, occupation and regions. We find that income loss and job loss are prominent among males, younger and less educated people as well as among self-employed and part-time workers. These tendencies are not pronounced for people enjoying high income, mobility and for those being able to work remotely, but are severe for urban residents and for those having dependents. Notably, self-employed people have the highest risk of losing income, while part-time urban workers face the highest probability of losing their jobs. Finally, through the implementation of propensity score matching (PSM) we determine that substantial drop in Facebook mobility characterizing COVID-19-impacted sub-provinces leads to high probabilities of income loss and job loss. Our study is therefore novel for (i) identifying crisis-inflicted perils associated with urban residency, especially for temporary employees, (ii) demonstrating the challenges that exist for breadwinners in the context of a community-oriented society and (iii) assessing the impact of mobility and teleworking on the socioeconomic resilience against the pandemic.

2. Indonesia and COVID-19

Previous studies have mostly attempted to address the impact of COVID-19 pandemic on labor market outcomes among developed countries, with the study by Qian and Fan (2020) based on the sample from China and cross-country World Bank report by Khamis et al. (2021) being among the few exceptions. Khamis et al. (2021) demonstrate that among the developing states, the highest rate (57%) of people receiving partial or no payment for their work during the COVID-19 pandemic has been observed in Indonesia. Moreover, withing the East Asia and Pacific (EAP) region, Indonesia has registered the highest proportions of self-employed (28%) and employees who lost their jobs (23%) between April and July 2020. Finally, from a sectorial standpoint, Indonesia experienced the heaviest regional job loss among service workers (24%) as well as the second-largest (35%) job loss among industrial employees. These findings invite further attention to the analysis of income loss and job loss in this country.

According to the 2020 National Census, Indonesia's population stood at 270.2 million, which is the fourth-highest figure in the world (BPS, 2021). Indonesia has been experiencing a demographic boom resulting in the growth of active population (15–64 years) that currently encompasses 70.72%. To illustrate this positive dynamics: overall labor force stood at 138.22 million as of August 2020, representing an increase of about 2.36 million people compared to August 2019. Furthermore, during the same period, the working-age population in Indonesia increased from 201.19 to 203.97 million people. In terms of educational attainment, workers with incomplete high-school education are the most dominant group (38.89%), while the employees with higher education (diploma or university) constitute only 12.33% (BPS, 2020).

Glancing at the employment composition, "agriculture, forestry and fisheries" dominate with 29.76% of the workforce, followed by trade and processing industries that employ 19.23% and 13.61% respectively (BPS, 2020). Mass involvement in agriculture presents the following challenges for the Indonesian economy.[1] First, the value added of "agriculture, forestry and fisheries" expressed as the share of GDP has been steadily declining: from 24% in 1983 to 14% in 2020 (World Bank, 2020). Second, on par with the construction industry, agriculture is known for accommodating the largest fraction of informal workers (Cuevas et al., 2009). In fact, about 60.5% of the Indonesian working population is employed informally (BPS, 2020). While constituting a substantial improvement compared to the respective figure of 80% during the late-1980s (Nazara, 2010), informal employment is still viewed as one of the major problems for the local economy (Rothenberg et al., 2016).

Indonesia's labor market has been severely affected by the COVID-19 pandemic. Its impact has caused job loss, working hours' reduction, falling wages as well as relegation from formal to informal employment status. The damage has materialized in 2.56 million or 7.07% of unemployed, 1.77 million of those temporarily out of job, and 24.03 million of working people who experienced a reduction in working hours. An annual wage decrease constituted 5.2%, representing a drop from 2.91 to 2.76 million Indonesian rupiahs. Moreover, the share of informally employed increased by 4.59%. Finally, the proportion of underemployed as well as part-time workers increased by 3.77% and 3.42% respectively (BPS, 2020).[2]

The socioeconomic impact of COVID-19 on the well-being of Indonesians has been uneven, as demonstrated in BPS (2020). First, higher unemployment rates have been recorded among men (an increase from 5.24% to 7.46%) as compared to women (an increase from 5.22% to 6.46%). Second, urban unemployment rates have reached 8.98%, which is almost twice as much as in rural areas (4.71%). Third, pronounced geographic differences exist in regard to the income loss and job loss. The provinces with the highest decline in labor wages are Bali, Bangka Belitung Islands, West Nusa Tenggara and Gorontalo at 17.91%, 16.98%, 8.95% and 8.68% respectively. Overall, it is notable that these four provinces are among the smallest ones, occupying, respectively: 32nd, 27th, 25th, 29th area ranks out of 32 administrative units (excluding the Special Regions of Jakarta and Yogyakarta). Additionally, these regions are highly dependent on agriculture.[3] In West Nusa Tenggara, for instance, as a result of the significant drop in demand due to the pandemic-inflicted economic crisis, prices' collapse triggered significant income loss for the farmers (Rozaki, 2020).

3. Analysis

The 2020 Indonesia's National Labor Force Survey (Sakernas), which is the source for our statistical analysis, includes 291 919 observations. It encompasses the households based in each of the country's 34 provinces and in 511 out of 514 sub-provinces.[4] The respondents of the survey that was conducted in August 2020 were asked to compare their current economic situation to the one prior to the pandemic that was first registered in February 2020. Concentrating on economic deprivations caused by the COVID-19 pandemic, we pose the following hypothesis: informally employed workers, such as "self-employed" and "temps", have suffered higher magnitudes of income loss and job loss than formally employed workers. In order to capture spatial patterns of the COVID-19 in Indonesia, we additionally incorporate the following socio-demographic indices into our analysis:

1. *Google Community Mobility Report (GCMR)* aggregated on a provincial level. It measures daily visitor numbers to specific location types vis-à-vis pre-pandemic baseline expressed as the median value over the period from January 3rd to February 6th 2020 for each respective day of the week. While GCMR contains 6 categories, we excluded the "residential mobility" and combined the remaining 5 groups ("retail", "grocery", "parks", "transit" and "workplace") to obtain a unified metric from February till September 2020. GCMR has been utilized in the related studies such as the ones by Ossimetha et al. (2021), Saha et al. (2020) and Sulyok and Walker (2020).

[1] Importantly, however, according to the disaggregated picture by main sectors, agricultural employment almost halved during the last three decades: from 55.5% in 1991 to 28.5% in 2019. Concurrently, employment in services grew from 29.3% to 49.2% (World Bank, 2019).

[2] In view of a possible terminological overlap, we apply the Indonesia's National Labor Force Survey definition of informal employment, which is also incorporated in Section 3. According to it, informal employment encompasses both self-employment and temporary wage employment, categorized here as "part-time" (Cuevas et al., 2009).

[3] Additionally, one of the main sources of Bali's municipal revenues is tourism — an industry greatly affected by the pandemic.

[4] Sub-provinces include 416 regencies ("kabupaten" in Indonesian) and 98 cities.

Table 1
Descriptive statistics.

	Definition	N	Mean	Median	Min	Max	St. Dev.
Urban (Rural)	A dummy variable that takes 1 if a respondent lives in an urban area, otherwise 0.	307,329	0.489	0	0	1	0.500
Gender	A dummy variable that takes 1 if a respondent is male, otherwise 0.	307,329	0.644	1	0	1	0.479
Age	A variable that represents the age of a respondent.	307,329	40.949	40	15	98	13.108
Income	A variable that represents an annual salary of a respondent.	307,329	2,127,748	1,500,000	0	105,000,000	2,298,455
Google mobility	A variable that shows the change in people's movement throughout the pandemic on a provincial level according to GCMR.	307,329	−19.805	−18.945	−39.743	−12.730	5.148
FB mobility	A variable that shows the change in people's movement throughout the pandemic on a sub-provincial level according to FDG.	307,329	−0.126	−0.120	−0.316	0.012	0.059
COVID per 1000	A variable that corresponds to the infection rate of COVID-19 per 1000 people on a provincial level.	303,545	0.670	0.461	0.032	3.790	0.653
Using internet	A dummy variable that takes 1 if a respondent has internet connection, otherwise 0.	307,329	0.342	0	0	1	0.475
Work from home	A dummy variable that takes 1 if a respondent works from home, otherwise 0.	307,329	0.096	0	0	1	0.295
Education	A variable that shows a respondent's educational level. It takes the following values: "less than high school" (base group), "high school/vocational high school," "diploma I/II/III" and "bachelor/diploma IV".	307,329	1.793	1	1	4	1.027
Household head	A dummy variable that takes 1 if a respondent is a household head, otherwise 0.	307,329	0.541	1	0	1	0.498
Informal	A variable that shows a respondent's working status. "Formal" equals to "regular" (base group), "informal" includes "temporary" and "self-employed".	307,329	0.482	0	0	1	0.500
Married	A dummy variable that takes 1 if a respondent is married, otherwise 0.	307,329	0.819	1	0	1	0.385
Income lost	A dummy variable that takes 1 if a respondent experienced job loss, otherwise 0.	291,919	0.421	0	0	1	0.494
Job lost	A dummy variable that takes 1 if a respondent experienced job loss, otherwise 0.	295,956	0.035	0	0	1	0.183

2. *Facebook Data for Good (FDG)* aggregated on a sub-provincial level. It reflects daily movement changes measured by Facebook throughout March to August 2020 versus the baseline recorded during February 2020. The methodology of the index is based on comparing the daily number of 600 m^2 tiles a person visited on the same day of the week before and during the pandemic (Herdağdelen et al., 2020). Following the suggestions of Chang et al. (2021) and Kissler et al. (2020) we implement it as a proxy for measuring regional COVID-19 levels. While the COVID-19 infection-rates data exists *only* on a provincial level, FDG allows for capturing more nuanced sub-provincial differences.

Our dependent variables are "income loss" and "job loss", being specified as dummy ones. The "income loss" ("job loss") variable takes unity when a respondent suffers from income loss (job loss), otherwise zero. That is, the base group is a group of respondents who do not suffer from income loss (job loss). Regarding the "income loss", Sakernas survey conducted in August 2020 asked (question 14.b) whether there was a change in average earnings compared to February 2020, when COVID-19 pandemic outbreak was initially registered. If that-time income was lower than the income in February 2020, a respondent's status was identified as "decreased income". In terms of the "job loss", Sakernas survey asked (question 29.a) whether a respondent ever stopped working between August 2019 and August 2020, thereby imposing a filtering condition. Next, it inquired (question 29.b) whether a respondent lost his/her job during the COVID-19 period (March 2020-August 2020). Respondents who answered assertively to both questions are the ones who lost their job during the pandemic.

According to Table 1, median age of the respondents is 40 years old, and 35.6% are females. The sample includes roughly equal sizes of urban (49%) and rural (51%) residents. 48% of the subjects work informally, i.e. either as temps or as self-employed. Regarding the levels of education, overwhelming majority (51%) of the survey subjects have an incomplete high-school education, 31% have a high-school certificate, 4% — professional diploma, and 14% — high-education certificate. 34% of the respondents have internet access and 10% have opportunities to work from home. Finally, 82% of survey subjects are married, and 54% are household heads. The most notable Pearson correlation coefficients presented in Table 2 look as follows. First, males are likely to be household heads (r = 0.54). Second, older people have higher chances of being married (r = 0.5). Third, relatively educated respondents are likely to use internet (r = 0.54) and work from home (r = 0.44). On the other hand, low levels of education are associated with informal

Table 2
Pearson correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Urban (Rural)														
2. Gender	−0.04***													
3. Age	−0.01***	−0.01***												
4. Income	0.15***	0.12***	0.02***											
5. Using Internet	0.21***	−0.07***	−0.21***	0.29***										
6. Work from home	0.08***	−0.13***	−0.02***	0.20***	0.35***									
7. Education	0.17***	−0.13***	−0.18***	0.34***	0.54***	0.44***								
8. Household head	−0.05***	0.54***	0.42***	0.12***	−0.13***	−0.08***	−0.17***							
9. Income lost	0.04***	0.06***	0.07***	−0.14***	−0.14***	−0.12***	−0.22***	0.08***						
10. Married	−0.05***	−0.03***	0.52***	0.07***	−0.11***	0.00*	−0.10***	0.42***	0.05***					
11. Informal	−0.17***	0.03***	0.26***	−0.24***	−0.37***	−0.23***	−0.42***	0.14***	0.29***	0.15***				
12. Job lost	0.00	0.04***	−0.04***	−0.06***	−0.04***	−0.04***	−0.05***	0.01***	0.06***	−0.02***	0.04***			
13. GCMR	−0.17***	0.02***	−0.01***	−0.08***	−0.08***	−0.04***	−0.03***	0.01***	−0.04***	0.01***	0.05***	0.00*		
14. FDG	−0.36***	0.02***	−0.02***	−0.12***	−0.17***	−0.07***	−0.06***	0.02***	−0.08***	0.03***	0.09***	−0.01***	0.52***	
15. COVID per 1000	0.10***	0.00*	0.00	0.10***	0.07***	0.05***	0.05***	0.00	0.00*	−0.01***	−0.04***	−0.01***	−0.63***	−0.39***

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 3
Labor deprivations by type of employment.

	Overall (N = 307 329)	Regular (N = 159 241)	Self-employed (N = 104 212)	Temp (N = 43 876)
Income loss	122,925 (42%)	43,080 (28%)	61,299 (61%)	18,546 (47%)
Job loss	10,300 (3.5%)	4280 (2.8%)	3387 (3.4%)	2633 (6.4%)
Working hours' loss	85,829 (29%)	46,069 (30%)	29,267 (29%)	10,493 (26%)

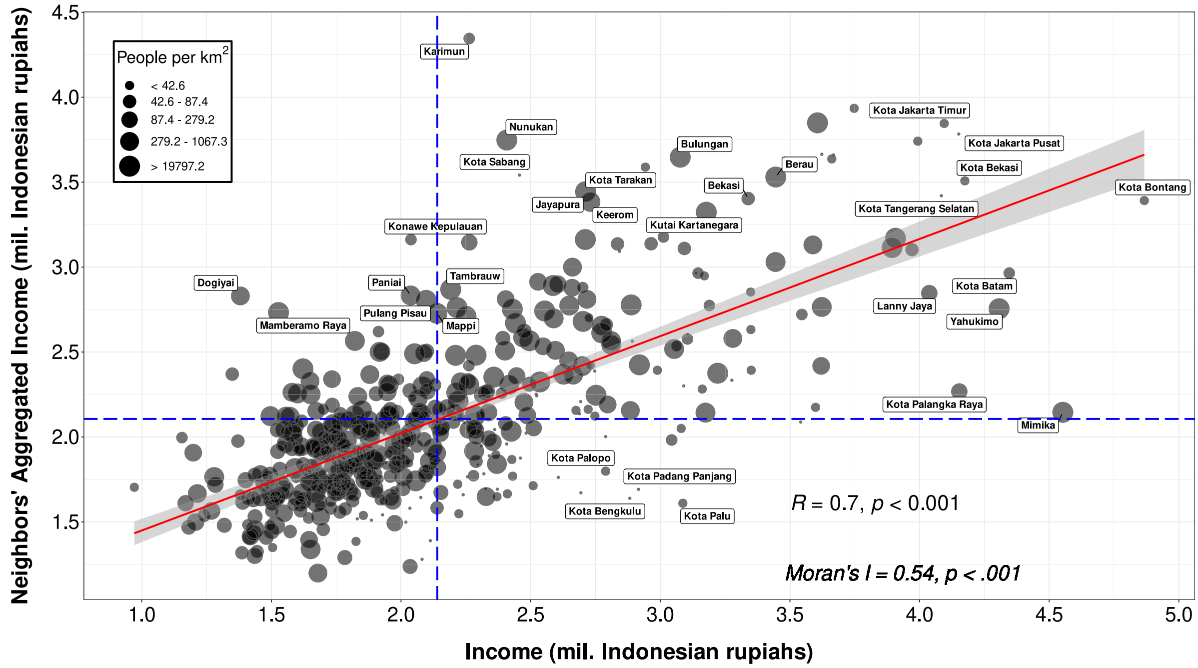

Fig. 1. Moran scatterplot of contiguous neighbors.

employment ($r = -0.43$). Finally, COVID-related indices on a provincial level are closely linked, whereby higher infection rates per capita correspond to lower Google ($r = -0.63$) and Facebook ($r = -0.59$) mobility rates.[5]

Our dependent variables — "income loss" and "job loss" — possess the following characteristics. During the initial stage of the pandemic from February to August 2020, around 42% of the respondents have experienced income loss, 30% — working hours' loss, and 4% — job loss. On a more detailed level, Table 3 presents the following information. Income loss has been most pronounced among the self-employed (61%), followed by temporary (47%) and regular (28%) employees. Job loss has been most widespread among temps (6.4%), followed by self-employed (3.4%) and regulars (2.8%).

The total number of regions included in our logistic regression is 34. We argue that incorporating fixed regional effects is important due to the following reasons. First, apart from the introduction of the mobility restrictions in the late March 2020, most

[5] This FDG value is aggregated on a provincial level, while the value of $r = -0.39$ from Table 2 corresponds to a *sub-provincial* level. As expected, provincial GCMR and FDG are highly correlated ($r = 0.77$).

Table 4
The estimated coefficients and marginal effects of logit regressions for the income loss (The dependent variable of income loss takes unity when a respondent suffers income loss, otherwise 0).

	Model 1		Model 2	
	Coefficient	ME	Coefficient	ME
Gender *(base group = Female)*	0.252***	0.058***	0.256***	0.061***
	(0.009)	(0.002)	(0.011)	(0.003)
Education (base group = less than high school)				
High school	−0.141***	−0.038***	−0.128***	−0.038***
	(0.010)	(0.002)	(0.010)	(0.002)
Diploma I/II/III	−0.639***	−0.148***	−0.573***	−0.142***
	(0.025)	(0.005)	(0.026)	(0.005)
Bachelor/Diploma IV	−0.920***	−0.211***	−0.804***	−0.198***
	(0.015)	(0.003)	(0.017)	(0.003)
Employment (base group = Regular)				
Self-employed	1.106***	0.254***	1.082***	0.248***
	(0.013)	(0.003)	(0.013)	(0.003)
Temporary	0.572***	0.149***	0.541***	0.144***
	(0.016)	(0.004)	(0.016)	(0.004)
Urban area *(base group = Rural area)*	0.217***	0.074***	0.257***	0.084***
	(0.012)	(0.003)	(0.012)	(0.003)
Employment × residency (base group = "Regular × Urban")				
Self-employed × Urban	0.453***	–	0.453***	–
	(0.018)		(0.018)	
Temporary × Urban	−0.047	–	−0.057*	–
	(0.025)		(0.025)	
Age			−0.010***	−0.002***
			(0.001)	(0.001)
Internet usage			−0.039***	0.005
			(0.011)	(0.003)
Work from home			−0.037*	−0.006
			(0.017)	(0.004)
Household head			0.114***	0.023***
			(0.012)	(0.003)
Married			0.167***	0.039***
			(0.014)	(0.003)
Income			−0.138***	−0.032***
			(0.004)	(0.001)
Intercept	−0.845***		1.281***	
	(0.039)		(0.066)	
Regional effects	NO		YES	
AIC	356 723.959	3 602 18.686	354 514.367	358 209.238
Log likelihood	−178 318.980	−180 099.343	−177 208.184	−179 088.619
Num. obs.	291 919	291 919	291 919	291 919

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

of the municipalities have clear geographic boundaries that determine local idiosyncratic features.[6] Second, Indonesia is known for its cultural heterogeneity, with about 1300 ethnic groups populating the country. To a certain degree, regional boundaries replicate this complex variety. Third, controlling for provincial effects is important in the context of heterogenous responses to the COVID-19 pandemic. At the same time, the inclusion of region-specific dummies does not by itself reflect local infection rates. To mitigate this problem, below we employ the propensity score matching (PSM) based on the sub-provincial Facebook mobility levels serving as COVID-19 proxy. Fourth, as presented by Fig. 1, the levels of income across sub-provinces show strong spatial autocorrelation. Significant ($p < 0.001$) Moran's I statistic of 0.54 prompts us to reject the null hypothesis of spatial randomness in our data set. In other words, in case of sub-provinces with high (low) income levels, their neighboring sub-provinces are also likely to share high (low) income levels. This is presumably true for other socioeconomic indicators as well. If left unaccounted, such contiguity would violate the underlying assumption about the independence of observations.

We run logit regression by taking "income loss" and "job loss" as dependent variables, and working status, education, telework infrastructure as well as basic socio-demographic factors as independent variables. Due to the fact that the range of our dependent variables lies within the interval between 0 and 1, logit regression is considered to be appropriate. Logit regressions assume a logit form of the following distribution function:

$$\text{Prob}(y_{\text{i}} = 1) = \frac{\exp(X_{\text{i}}\beta)}{1 + \exp(X_{\text{i}}\beta)} \tag{1}$$

[6] Being the largest archipelago in the world, Indonesia consists of 5 major islands and around 30 minor islandic groups.

Table 5
The estimated coefficients and marginal effects of logit regressions for the job loss (The dependent variable of job loss takes unity when a respondent suffers income loss, otherwise 0).

	Model 1		Model 2	
	Coefficient	ME	Coefficient	ME
Gender *(base group = Female)*	0.330***	0.006***	0.250***	0.004***
	(0.029)	(0.001)	(0.037)	(0.001)
Education (base group = less than high school)				
High school	−0.019	−0.001	−0.043	−0.001**
	(0.030)	(0.001)	(0.032)	(0.001)
Diploma I/II/III	−0.559***	−0.009***	−0.487***	−0.008***
	(0.098)	(0.001)	(0.100)	(0.001)
Bachelor/Diploma IV	−0.800***	−0.012***	−0.586***	−0.010***
	(0.060)	(0.001)	(0.066)	(0.001)
Employment (base group = Regular)				
Self-employed	0.112*	0.001	0.080	0.001
	(0.044)	(0.001)	(0.045)	(0.001)
Temporary	0.458***	0.012***	0.435***	0.011***
	(0.047)	(0.001)	(0.048)	(0.001)
Urban area *(base group = Rural area)*	−0.143***	−0.001	−0.090*	0.000
	(0.042)	(0.001)	(0.042)	(0.001)
Employment × residency (base group = "Regular × Urban")				
Self-employed × Urban	0.341***	–	0.337***	–
	(0.059)		(0.059)	
Temporary × Urban	0.369***	–	0.375***	–
	(0.068)		(0.068)	
Age			−0.024***	−0.001***
			(0.001)	(0.001)
Internet usage			−0.149***	−0.001*
			(0.035)	(0.001)
Work from home			−0.178**	−0.003**
			(0.066)	(0.001)
Household head			0.251***	0.004***
			(0.039)	(0.001)
Married			0.189***	0.003***
			(0.044)	(0.001)
Income			−0.152***	−0.003***
			(0.005)	(0.000)
Intercept	−3.696***		−0.810***	
	(0.108)		(0.136)	
Regional effects	NO		YES	
AIC	58 897.301	59 366.858	57 849.194	58 290.979
Log likelihood	−29 405.650	−29 673.429	−28 875.597	−29 129.490
Num. obs.	291 919	291 919	291 919	291 919

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

where y_i is a binary dependent variable, X_i is a vector of independent variables, and β is a vector of unknown parameters. With this distributional assumption, the maximum likelihood methods estimate the unknown parameters of β, enabling the identification of the marginal probability of one person to experience income loss or job loss when the independent variable increases by one unit (holding other independent variables fixed). Tables 4 and 5 contain the results of the logistic regressions with fixed effects aggregated on a provincial level. Since the response variables are on a log-odds scale, we derive their predicted values based on the marginal effect (ME) of independent variables.

People facing precarious employment conditions are also the ones who experienced idiosyncratic risks stemming from the initial COVID-19 outbreak. Among them, "self-employed" appear to be particularly vulnerable. Their chances of losing income are 25% higher than those of the regularly-employed. As seen from Table 4, marginal effect (ME) of income loss for the self-employed remain robust both with and without including the control variables. The situation is further exacerbated for the self-employed who reside in urban areas. They have higher probabilities of losing both income and job as compared to rural self-employed. Another group that sustained a large damage due to the COVID-19 pandemic are the "temporarily employed". Although they are 11% less likely to lose income than self-employed, their associated probabilities of income loss and job loss are, respectively, 14% and 1% higher than for regulars. Importantly, the ME for this group are consistently robust both in the context of income loss and job loss, as Tables 4 and 5 demonstrate.

On top of employment patterns, heterogeneity in job- and income-loss odds has a demographic dimension. First, males are 6% more likely to experience income loss and 0.4% more likely to experience job loss than females. This result is consistently robust in both contexts. Second, the presence of dependents and the martial bonds also appear to increase the income- as well as the job-loss

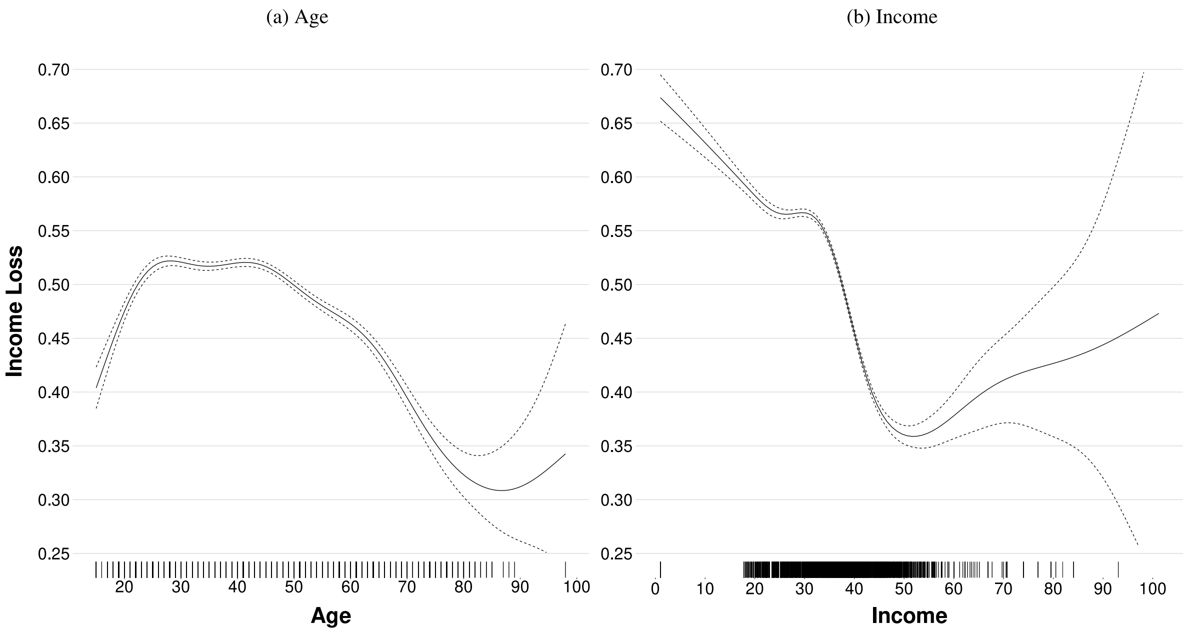

Fig. 2. Income loss probability — GAM.

magnitudes. Household heads have 2% and 0.4% higher chances of losing, respectively, income and job, than respondents with other family roles. Likewise, married respondents experience 4% and 0.3% higher probabilities of losing, respectively, income and job, than unmarried. Third, younger respondents find themselves in a precarious position both as income earners and as mere participants of the labor market. Yet, ME corresponding to age as a predictor of income loss and job loss appear significant but small. In this regard, generalized additive model (GAM) relationships provide a clearer and a more nuanced perspective.

According to Fig. 3(a), job loss probability almost linearly decreases with an additional year for the demographic group between 30 and 70 years old. On the other hand, the interpretation of the age as an income-loss predictor is not straight-forward, as seen from Fig. 2(a). First, respondents between 15 and 30 years of age do not acquire higher salary or a mere job security as they get older. Quite on contrary, an additional year within this cohort corresponds to the drastic increase in precariousness. This is most likely due to the fact that young respondents find it problematic to find stable employment, particularly during crises, when they appear as easy targets for corporate "optimization" strategies. Second, age does not make a difference in terms of altering the income-loss odds for the demographic group between 30 and 50 years old. Third, additional year significantly alleviates the income-loss probability for the "50-75 year-old" cohort. This is likely to be for the reason that recent decades have been marked by intensified migration from rural to urban areas resulting in informal employment growth for cities' inhabitants (Rothenberg et al., 2016). Being the vanguard of this internal migration, Indonesian youth has therefore experienced relatively more serious consequences of the COVID-19 crisis as compared to elderly people.

Apart from employment and demographics, following socioeconomic factors are instrumental for alleviating the devastating impacts of the COVID-19 pandemic. First, respondents with higher educational levels are certainly less prone to losing income or job due to the crisis. Whereas the owners of a high-school certificate are 4% less likely to lose income than those who did not graduate from a high school, the respective numbers increase to 14% for those having a professional diploma, and to 20% — for those with a higher education. These results appear consistently robust, as Table 4 demonstrates. Likewise, higher educational levels are associated with lower job-loss probability as Table 5 shows. Here, the results also appear consistently robust for all levels of education vis-à-vis the base group. Second, those having an internet access are 0.3% less likely to lose their job than those without it. This is due to the fact that proper telework environment is essential for the sectors that opted to abandon a conventional office format. Third, a one-percent-higher income prior to the COVID-19 outbreak is associated with 3% and 0.3% less likelihood of suffering, respectively, income loss and job loss. In this regard, a stronger evidence is provided by GAM. According to Figs. 2(b) and 3(b), with salary increasing from the lowest observed level to the 45th percentile, income- and job-loss probabilities drop from 67% and 88% to 38% and 32% respectively.

Next, we discuss the regional patterns of income loss and job loss. Chronological mobility developments on a provincial level are displayed in Fig. 4. It can be inferred from this graph that densely populated regions, such as Bali, Jakarta and Yogyakarta, are the ones that experienced the most substantial drops in activities as a result of lockdown measures caused by the COVID-19 outbreak. Notably, these are also the municipal units with relatively high levels of predicted income loss and job loss as Figs. 5 and 6 show. Other provinces occupying top ranks of the job-loss probability index such as West Nusa Tenggara, Central Java and West Java are

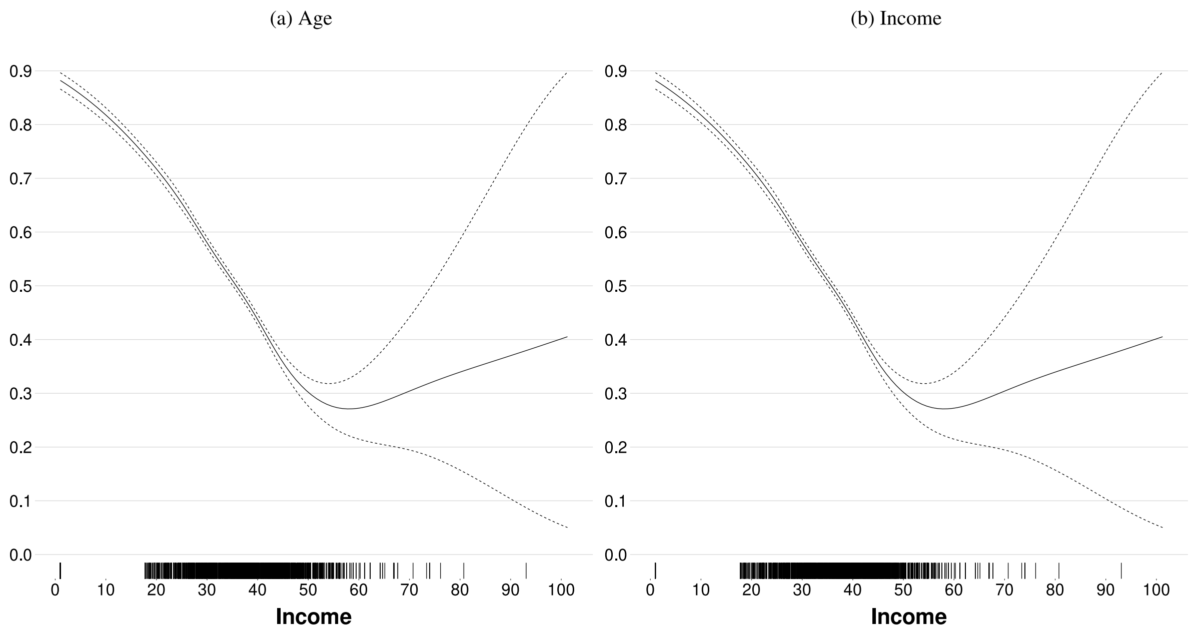

Fig. 3. Job loss probability — GAM.

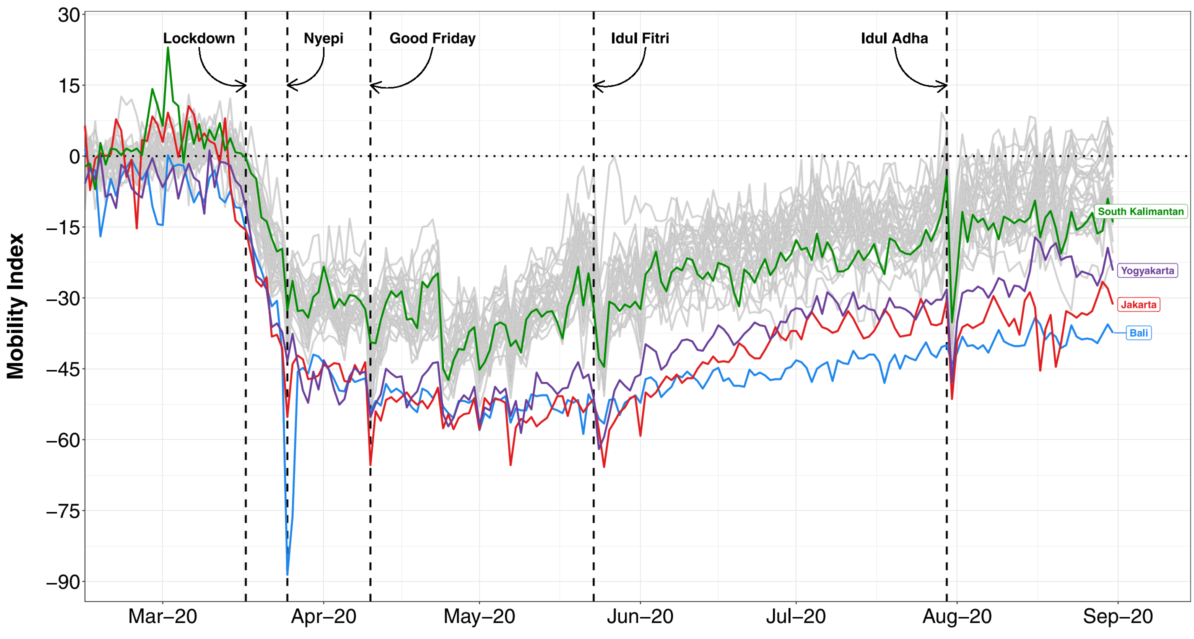

Fig. 4. Indonesia's regional trends according to Google Community Mobility Report.

also the ones having 8th, 5th and 2nd largest population densities respectively. This confirms our argument about the higher risks of job loss for the more urbanized regions. Similar patterns can be observed regarding the predicted income loss, as Fig. 7 shows.

While our dependent variables reflect socioeconomic changes registered after the pandemic outbreak, we implement additional robustness checks for elucidating whether COVID-19 has been the *cause* of employment-related deprivations. We run the propensity score matching (PSM) with the help of "MatchIt" R-package (Ho et al., 2011) to estimate the average marginal effect (ME) of the "COVID-19" treatment on income- and job-loss probabilities accounting for confounding by the covariates used in the initial logit regression as independent variables. The treatment dummy takes unity for respondents residing in the provinces that, as of 31 June 2020, experienced more than 14% drop in Facebook mobility as measured by FDG, otherwise zero. The FDG values' distribution including the chosen threshold are shown on the Fig. S4 from the Appendix.

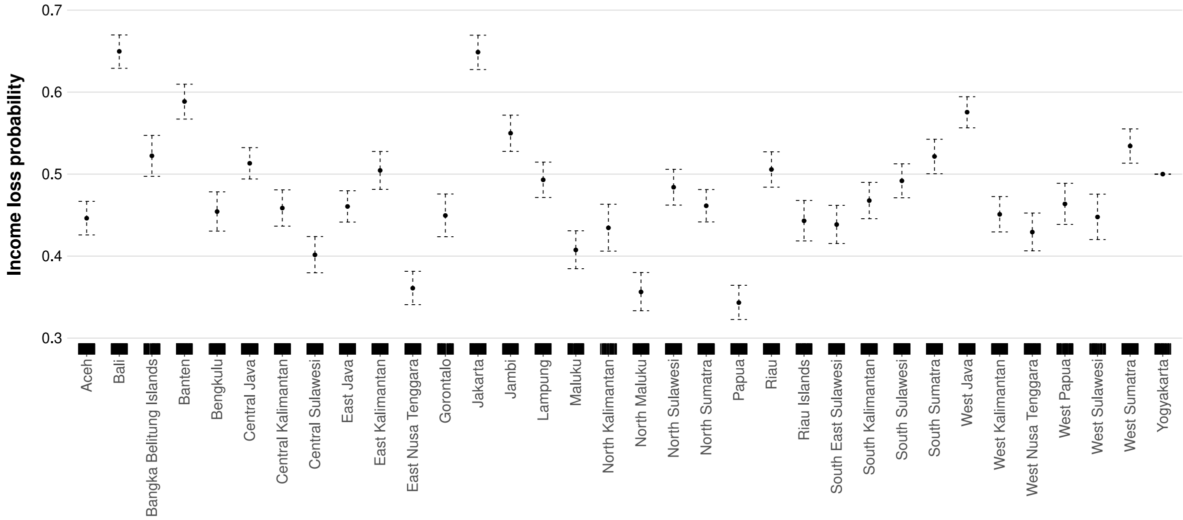

Fig. 5. Regional patterns of income loss.

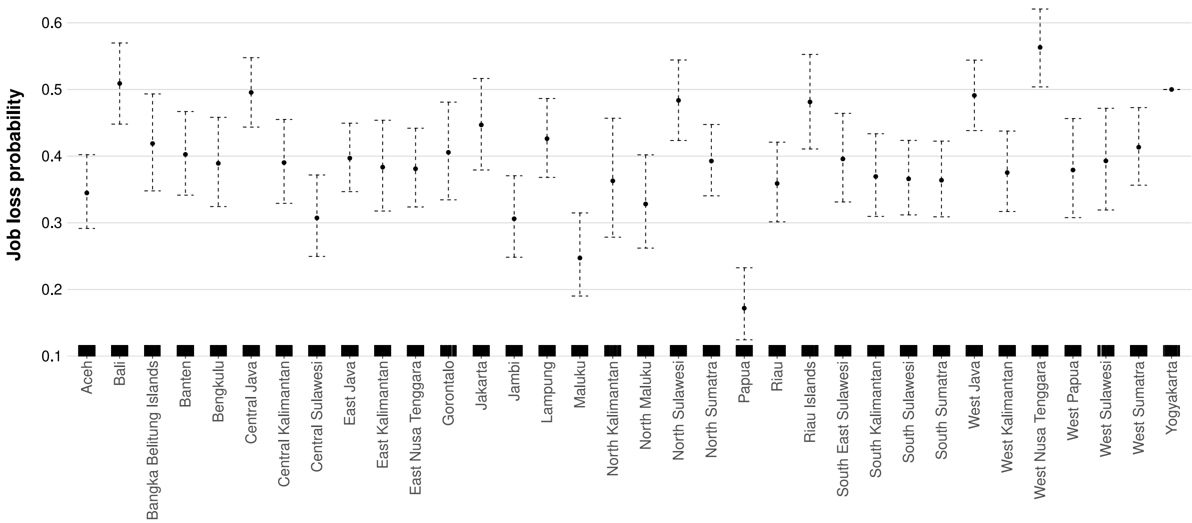

Fig. 6. Regional patterns of job loss.

We estimate the Average treatment effect (ATE) and the Average treatment effect on treated (ATT) using the matching methods that employ the following types of distance measurements: (1) nearest neighbor, (2) scaled Euclidean, (3) Mahalanobis and (4) robust rank-based Mahalanobis. All four types of matching are conduced without replacement. According to Fig. 8, the standardized mean differences for the covariates of the matched sample are below 0.1, indicating that the only difference between the control and the treatment group stems from the COVID-19-related threshold. This key requirement would be violated, had we included provincial dummies, similarly to logit regressions. Since our treatment dummy (FDG) already captures regional idiosyncratic features, this would result in perfect collinearity. Using the g-computation algorithm (Snowden et al., 2011), we fit logit regression models with income- and job-loss probabilities as the outcomes, “COVID-19” as treatment, and covariates interacted with treatment as predictors, presenting the results in Table 6. The estimated ATE and ATT on the response variables are positive and significant at the 1% level for all matching methods, indicating that the “COVID-19” effect increases the income- and job-loss probability.

Whereas our initial logit regressions include regional dummies, they only indirectly explicate COVID-19-related policies based on provincial socio-demographic features. In this respect, PSM enables us to build upon the obtained findings by including sub-provincial COVID-19 proxy to compare low-infection-rate regions with their high-infection counterparts. The evidence of significantly higher income- and job-loss probabilities within the latter group points at the causal relationship existing between

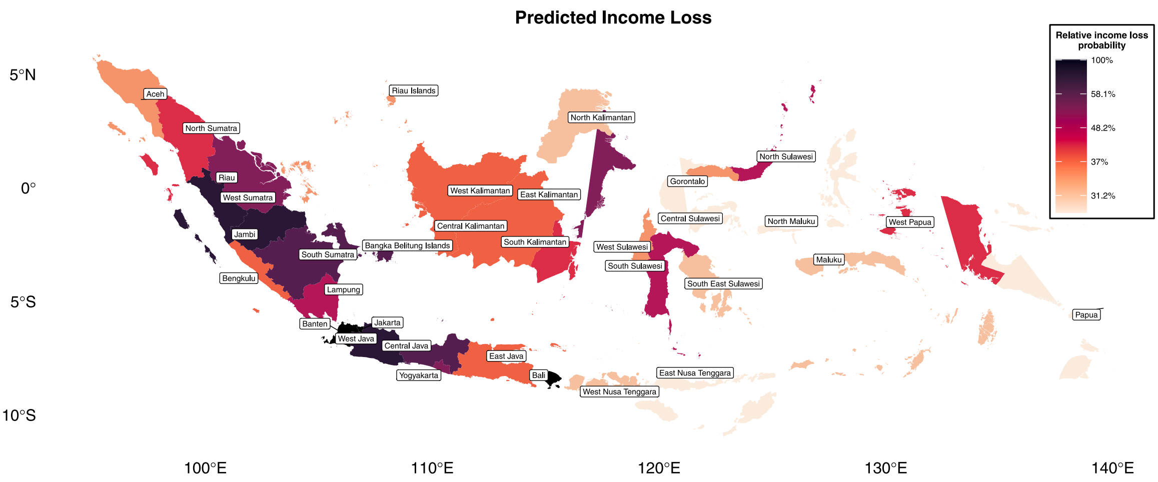

Fig. 7. Predicted income loss by Indonesian provinces.

Table 6
The ATE and the ATT statistical results.

	Income loss		Job loss	
	ATE	ATT	ATE	ATT
(1) Nearest neighbor	0.07***	0.071***	0.006***	0.006***
	(0.004)	(0.004)	(0.001)	(0.001)
(2) Euclidean scaled	0.068***	0.069***	0.006***	0.006***
	(0.004)	(0.004)	(0.001)	(0.001)
(3) Mahalanobis	0.068***	0.069***	0.006***	0.006***
	(0.004)	(0.004)	(0.001)	(0.001)
(4) Mahalanobis robust	0.069***	0.07***	0.005***	0.006***
	(0.004)	(0.004)	(0.001)	(0.001)

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

the degree of infection spread on one hand and the socioeconomic deprivations on the other. While it can be argued that our choice of the "COVID-19 threshold" is arbitrary, it is in fact very close to the mean Facebook-mobility value of 13%, as shown in Table 1.[7] In addition, we confirm that the same qualitative propensity score matching (PSM) results are obtained by employing different threshold levels within a certain range for dividing the samples between control and treatment groups. Notwithstanding some possible limitations in the methodology, it is our belief that the PSM results provide legitimate causal inference of COVID-19 on income loss and job loss.

4. Discussion

This paper illustrates the heterogenous effects of the COVID-19 pandemic on the employment conditions among the citizens of developing states on the example of Indonesia. The long-term prevalence of informal sector within the local labor market has reinforced pronounced socioeconomic imbalances. Because of operating without a proper institutional backup, *self-employed* appear to be particularly vulnerable against exogenous adversities, such as the COVID-19 pandemic. This is especially evidenced in income loss, which is 25% more likely to be experienced by self-employed than by regular workers. In this context, urban self-employed find themselves in the most precarious situation. As compared to those rural self-employed who have some degree of self-sustainability, the income of city inhabitants is more dependent upon demand fluctuations.[8]

Another group facing insecure employment conditions are *temporary* workers. Possessing relatively high risks of losing an income, they are even further endangered in terms of losing a job. While self-employed and officially registered workers mostly experience negative adjustments of income, temporary workers are more likely to be dismissed. Due to their inferior socioeconomic status in organizations, non-regulars turn out to be the easiest targets for corporate layoffs during economic recessions. The precarity of temporary workers manifests itself in low wages and minimal social protection. In line with the previous studies, such as the

[7] Since the calculation of FDG is contingent upon the Internet access, the officially recorded average drops in Facebook mobility are likely to be lower than the actual figures in case of the rural regions.

[8] While the same is likely to be the case across most of developing countries, Qian and Fan (2020) demonstrate that, in case of China, it is rural residency that is associated with higher probability of partial income loss.

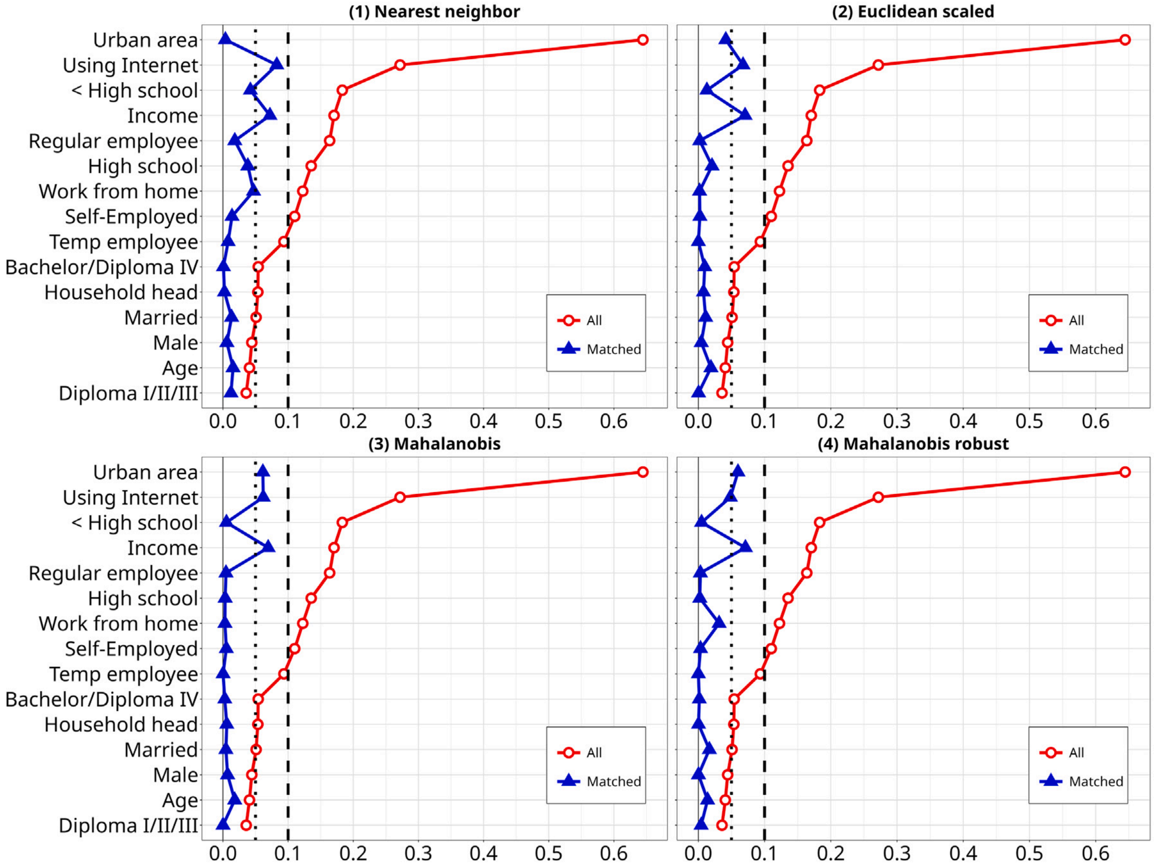

Fig. 8. Covariate balance — absolute standardized mean differences.

one by Dang et al. (2020) and Qian and Fan (2020), we find that lower income prior to the COVID-19 pandemic is associated with a higher probability of both income loss and job loss. On top of that, due to the small amounts of savings, poorer cohorts are particularly sensitive to job- and income-related disruptions. This accumulated strain is markedly palpable in the developing countries, such as Indonesia, where a sole breadwinner often provides for a whole family. As a result, collateral damage is being experienced by entire households.

This leads us to the discussion of the gender-related deprivations. The higher likelihood of males as compared to females to lose both their income and job is associated with the following factors. First (i), labor force participation rate for Indonesian males is 82.41% whereas for females — only 53.13% (BPS, 2021). As seen from Fig. S1 of the Appendix, males make up 75% workers in the agricultural sector which employs 30% of the total workforce. In addition, several manufacturing industries, such as construction, electricity & gas, mining and transportation are almost entirely male-composed. Thus, overall, employee-inflicted damages tend to be apparent for men due to their extensive integration in the labor market. Second (ii), according to the analyzed data and in line with the previous studies, such as the one by Cuevas et al. (2009), men earn more than women on average (2 328 866 vs. 1 764 686 Indonesian rupiahs respectively) as well as across most of the sectors, which results in a high income-loss magnitude for them. Third (iii), as seen from Table S1 of the Appendix, men are more likely to be employed as part-time workers than women (17% vs. 9% respectively), thus facing high chances of being dismissed.

These gendered employment patterns present a striking contrast with such developed countries from the EAP region as Japan, where more than 65% of the part-time employees are females.[9] Although both Indonesian and Japanese non-regular workers have experienced larger income losses than regular workers (Kikuchi et al., 2021), following differences exist between these countries. The transformed socioeconomic situation during the late-1990s prompted Japanese females to join the labor market, which was one of the main factors behind the surge in non-regular employment (Gordon, 2017). Differently from the highly-industrialized Japanese economy, the largest part of the Indonesian workforce is employed in the agricultural sector. Furthermore, as mentioned above, despite the growing pace of industrialization, socioeconomic structure of many Indonesian households is still centered around

[9] Importantly, part-time employment as well as other forms non-regular work in Japan belong to formal economy, as opposed to Indonesia, where temporary employment is classified as "informal", according to 2020 Sakernas Survey.

a male-breadwinner. Under these circumstances, numerous working-age females are not rushed to enter the regulated labor market, frequently finding themselves either as housewives[10] or as self-employed (see Table S1 of the Appendix). Figs. S1 and S2 of the Appendix demonstrate that self-employed females constitute large parts of such industries as accommodation & food, processing and retail.

Encompassing substantial parts of the working population, male-dominated industries (e.g., construction and agriculture) have the highest proportions of informally-employed. Figs. S1 and S2 of the Appendix demonstrate that almost entirely male-composed construction sector has by far the highest proportion (51%) of temporary employees. As for the agricultural sector, non-regular workers constitute 29%, while 49% of the workforce are self-employed. In a nutshell, income loss mostly associated with self-employment, and job-loss associated with part-time employment have been especially detrimental for males. As for females, their wide participation in informal economy has also been associated with substantial income losses.

The current paper highlights several factors that can strengthen the resilience against the crises, such as COVID-19. First (i), in line with (Qian & Fan, 2020), our study shows that securing an educational degree drastically decreases the probability of income loss. Fig. S3 of the Appendix demonstrates the contingency of employment quality upon educational level, whereby the share of informal employment decreases with the attainment of a higher degree. Second (ii), we confirm the slight yet a significantly positive relationship existing between the internet access as well as home-based telework environment on one hand, and income stability plus job security on the other. It demonstrates the importance of an online infrastructure during pandemic for developing economies. Lastly (iii), we find that relatively higher mobility during the lockdown period – an attribute of less densely populated and less urbanized regions – is associated with lower likelihood of income loss and job loss. Under conditions of an overwhelmingly large informal sector, people with higher mobility and higher self-sufficiency (characterizing rural residents) are better protected from external shocks.

5. Conclusion

Operating with the 2020 Indonesia's National Labor Survey (Sakernas), we analyze income- and job-related deprivations accruing against the impact of the COVID-19 pandemic. We find that both income loss and job loss are conspicuous among males, younger, poorer and less educated people. On top of that, labor precariousness matters, whereby self-employed have the highest risk of losing income, while part-time workers face the highest probability of losing their jobs. Urban residents and those having dependents experience these socioeconomic adversities of the pandemic to an even higher extent. Constituting the world's largest archipelago, Indonesian regions display idiosyncratic responses to the ongoing crisis. Among others, most affected areas are also the ones with the sharpest declines in mobility trends. Based on this consideration, we conduct the propensity score matching (PSM), identifying that the COVID-19 spread leads to higher income- and job-loss probabilities. Our findings attest to the fact that exogenous shocks such the one caused by the COVID-19 are disproportionately severe in regard to socioeconomically vulnerable layers of the society. This strain is further exacerbated for the inhabitants of such community-oriented societies as Indonesian, where losses experienced by breadwinners often extend to entire households. We believe that incorporating these conclusions can help policymakers mitigate potential consequences of future economic crises.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.asieco.2023.101631.

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[10] Although this cohort is not included into our statistical analysis, according to the 2020 Sakernas Survey, "family/unpaid" labor-force category is the largest among women, encompassing 15.6% of female respondents.

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