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Article

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DEVELOPMENT ECONOMICS | RESEARCH ARTICLE

Reemployment during the Covid-19 pandemic in Indonesia: What kinds of skill sets are needed?

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Abstract: The COVID-19 pandemic has disrupted the labor market leading to significant unemployment. This study explores the 2019, 2020, and 2021 National Labor Force Survey (Sakernas) to examine the labor market changes and the relationship between workers' skill sets, such as hard skills (vocational education), soft skills, and digital literacy and reemployment during the COVID-19 pandemic. Our descriptive statistics analysis confirms that the scarring effect exists as the share of the informal sector increases by around 4.5 percentage points during the COVID-19 pandemic. Moreover, our estimations using the Bivariate Probit Model show that social skills and digital literacy are important determinants for reemployment at the national level. In contrast, vocational education and problem-solving skills are statistically insignificant. Workers with social skills tend to have a higher probability of being reemployed, by 41% in 2020 and 27% in 2021, compared to workers without any. Our study also finds a heterogenous relationship between skill sets and reemployment. Social skill is significantly correlated with reemployment in an urban area, Java-Bali, and young workers in the 15–24 age group. In addition, vocational education is crucial for reemployment, especially among young workers during the economic recovery period in 2021. Our study suggests that the government should focus on preparing the correct and relevant skill sets for young workers aged 15–24 to respond to the significant demand changes in the post-pandemic labor market.

Subjects: Economics and Development; Population & Development; Economics

Keywords: Covid-19; reemployment; hard skill; soft skill; digital literacy; bivariate probit

1. Introduction

Since the COVID-19 pandemic was declared in early 2020, most governments worldwide implemented restrictions on economic activities and people mobility, resulting in significant disruptions to the labor market, leading to job losses and unemployment as many workers struggled to find new employment opportunities. The International Labour Organization (2020) reported that confinement measures impacted nearly 81% of the global workforce, and 38% remain at high risk of experiencing adverse employment outcomes such as unemployment and reduced working hours. Evidence from Germany, the UK, and the US also show that labor market shocks magnify disparities within the workforce, mainly among women and young workers with lower skills (Adams-Prassl et al., 2020). While recent studies have seen a return in rural to urban migrations, the COVID-19 pandemic in India saw a mass exodus of migrant workers from major urban centers to

their native villages (Misra, P & Gupta, J, 2021). As mobility restrictions have eased, recovery has begun. Still, historical experience warns for caution: the unemployment rate following the 1980 recession in the US remained high even almost a decade after the recession (Elsby et al., 2011).

Indonesia's own National Labor Force Survey (Sakernas) shows that the unemployment rate was 7.07% in August 2020 (2.56 million), increasing by 2.13 percentage points from 4.94% in February 2020. Around 24 million workers experienced a decline in working hours, while the share of those working in the informal sector increased from 56% (August 2019) to 60.5% (August 2020) (Statistics Indonesia, 2020, 2021). This unprecedented spike in unemployment was accompanied by an increase in the poverty rate, which saw 1.63 million people living in poverty and 5 million people losing their health protection as of March 2020 (Sparrow et al., 2020). Data from the Social Security Agency for Employment (BPJS Ketenagakerjaan-SSAE) also showed a 3% decrease in its Old-Age Program's membership numbers. 2021 saw gradual economic recovery as the Sakernas showed a decline in the national unemployment rate from 7.07% (August 2020) to 6.49% (August 2021), and a decrease in the share of those working in the informal sector by around one percentage point (which remains higher than pre-pandemic levels). These two conditions indicate reemployment and an early indication of a scarring effect in the labor market.

As reemployment is an essential factor in leveraging household welfare toward the nation's economic recovery, reemployment has become a central concern for governments worldwide, and numerous policy packages have been implemented to encourage reemployment. These policies have emphasized the need for workers to have a range of skill sets to meet the changing demands of the job market during the pandemic. The OECD (2021) and European Commission (2020) highlight that those workers who can adapt quickly to new situations, acquire new skills, and embrace remote work and digital tools are in high demand. They note that the fundamental skills necessary for reemployment during the pandemic include digital literacy, technical skills, soft skills, language skills, creative skills, and health and safety skills.

International consensus underlined that education (hard skills) positively and significantly impacts labor market outcomes during economic shocks. However, Deming (2017) argued that soft and social skills also contribute to the probability of employment and higher incomes, complementing existing hard skills. Furthermore, problem-solving skills are also argued as soft skills that should be possessed in the twenty-first-century workplace (OECD, 2013a, 2013b), alongside digital skills, which have become prominent as social distancing due to the pandemic, have ushered drastic changes in the work landscape. In the time of Covid-19, social distancing drives the contactless economy, and those businesses pursuing digital technology are most able to thrive and recover.

Therefore, there is an urgent need to explore the relationships between the role of skill sets and reemployment during the pandemic, especially in developing countries such as Indonesia, where evidence is less available for policy formulation. This evidence is urgently required to help workers navigate the current job market and prepare for the future. By identifying the skills in demand and the most effective training programs, policymakers and employers can help ensure that workers have the skills they need to succeed in the post-pandemic job market.

This study will then empirically test three hypotheses using Indonesia's National Labor Force Survey. First, workers with higher hard skills (vocational education) should be more likely to be reemployed than workers with lower hard skills. This study investigates whether workers with vocational education are more likely to reemployment. Second, workers with soft skills, including social and problem-solving skills, should be more likely to be reemployed than workers who do not have soft skills. Third, workers with digital skills should have a higher probability of being reemployed than workers who do not have digital skills.

The rest of this paper is structured as follows. Section 2 depicts the economic and labor market condition in Indonesia. Section 3 reviews the literature on Covid-19, reemployment, hard skills, soft

skills, and digital literacy. Section 4 explains our data and econometric method. Section 5 describes our analysis and discusses the result. Last, section 6 concludes the paper.

2. Labor market condition in Indonesia

Economic transformation can lead to changes in the types of jobs available in the labor market, as well as the skills in demand. For example, as economies transition from agricultural to manufacturing or service-based economies, the demand for workers with technical, digital, or soft skills may increase. This can lead to a shift in the training and education programs needed to prepare workers for these jobs.

Dartanto et al. (2018) confirm that Indonesia experienced an agriculture—service transition before the industrial sector matured. The labor market has also undergone a fundamental transition, with the growth of employment occurring in the services sector while agricultural employment is on a decline. Yet, although the country's economic structure has become more service-oriented (see Table 1), the labor market remains dominated by workers in agricultural sectors: although the services sector contributes the highest share of GDP, almost one-third of Indonesia's workforce is employed in agriculture.

Like many developing economies, informality is high in Indonesia: almost 63% of all workers in Indonesia belong to the informal sector (see Table 2). However, Suryahadi et al. (2018) noted that formal sector employment in Indonesia is on the rise, particularly in urban, industry, and services, supported by the employment of younger, more educated workers, primarily new entrants to the labor market. On the labor supply side, the size and quality of Indonesia's workforce are influenced by moderately fast growth in the working-age population, the "demographic bonus" which is expected to last until around 2030, urbanization that has been quite rapid, a relatively high female participation rates in the workforce, and low in average years of schooling (Manning & Pratomo, 2018). Hence, the transformation of the country's economic structure, the evolution of labor market conditions, and the ramifications of the COVID-19 pandemic are poised to shift the skills required for job demand and reemployment in Indonesia.

3. Literature review

3.1. Covid-19 and reemployment

The impact of the COVID-19 pandemic on the labor market has been severe and fast-paced. Due to social distancing and mobility restrictions, governments, private offices, and companies have partially or fully implemented work from home (WFH) policies. This has led some companies to reduce their activities, forcing many to close. The resulting unemployment has created scarring and habituation effects (Clark et al., 2001). The scarring effect in the labor market refers to the negative long-term impact that a person's early experiences of unemployment and/or underemployment in the job market can have on their future career prospects and earning potential. This includes difficulties in finding stable, well-paying jobs later in life. Unemployed workers may enter the informal sector or low-paid jobs after losing a career in the formal sector (Cruces et al., 2012). If an individual has been unemployed for some time, they become accustomed to the situation: a condition called "habituation". This habituation can lead to lower incentives to change one's labor force status, including the duration of their unemployment. Thus, the worker has difficulties returning to work, then, in the end, they should be released from the labor market (Cockx, 2000; OECD, 2002).

The impact of job loss varies according to income levels, job skills, education, and age. Belotti et al. (2021), reviewing the various COVID-19 and work-related aspects studies, found that the most affected were low-income, low-skill jobs, and temporary workers. Still, they are also able to get back to work quickly. Fewer older workers lose their jobs, but it is more difficult to find a new job (Belotti et al., 2021). In Indonesia, where there is no unemployment insurance, people who have lost their jobs are forced to be reemployed as soon as possible. However, the reemployment process during the pandemic is challenging. Therefore, this calls for a holistic exploration of skills

Table 1. Sectoral Gross Domestic Product (GDP) and Labor productivity

No	Sectoral/Industry	GDP (billion rupiah)			Productivity (GDP/Number of Labor)		
		2019	2020	2021	2019	2020	2021
1	Agriculture, Forestry & Fisheries	1,354,399.10	1,378,331.40	1,403,710.00	38,205,585	36,058,969	37,804,590
2	Mining	806,206.20	790,475.20	822,099.50	564,350,435	584,568,966	569,548,961
3	Manufacturing	2,276,667.80	2,209,920.30	2,284,821.70	118,589,326	126,405,044	122,219,167
4	Electricity and Gas	111,436.70	108,826.40	114,861.10	306,452,074	358,511,090	403,704,159
5	Water supply, sewerage, Waste management and Recycling	9,004.90	9,449.30	9,919.20	17,927,941	19,245,637	17,627,051
6	Construction	1,108,425.00	1,072,334.80	1,102,517.70	127,765,721	132,936,862	132,933,254
7	Trading	1,440,185.70	1,385,747.40	1,450,226.30	59,600,638	56,097,013	56,349,864
8	Transportation	463,125.90	393,437.90	406,187.60	81,877,686	70,358,021	74,616,719
9	Accommodation & Food-Beverages Services	333,304.60	299,122.40	310,754.70	38,927,330	35,010,488	33,850,021
10	Information & Comunication	589,536.10	652,062.90	696,460.40	639,971,624	698,683,986	697,716,988
11	Financial Services and insurance	443,093.10	457,482.90	464,638.60	249,589,278	293,648,483	290,798,064
12	Real Estate	316,901.10	324,259.40	333,282.90	784,591,217	823,693,750	936,306,275
13	Company/Business Services	206,936.20	195,671.10	197,106.70	106,498,570	108,902,494	97,719,267
14	Government Administration	365,538.80	365,439.30	364,233.40	73,877,967	79,965,781	75,115,468
15	Education Services	341,349.90	350,264.60	350,655.30	53,200,245	58,100,391	54,016,543
16	Health Services and Social Activities	127,487.90	142,228.40	157,104.70	64,299,854	70,918,394	71,498,065
17	Other services	205,011.40	196,608.70	200,772.90	32,212,758	30,674,251	34,772,620
Total		**10,498,610**	**10,331,662**	**10,669,353**	**81,539,267**	**80,430,719**	**81,414,041**

Source: Statistics Indonesia (2022)

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Table 2. Labor status (formal and informal) by sector

No	Sectoral/ Industry	Labor								
		2019			2020			2021		
		Formal	Informal	Total	Formal	Informal	Total	Formal	Informal	Total
1	Agriculture, Forestry & Fisheries	4,400,819	31,049,472	35,450,291	4,368,059	33,856,312	38,224,371	4,295,790	32,834,886	37,130,676
2	Mining	912,841	515,715	1,428,556	789,125	563,111	1,352,236	846,874	596,548	1,443,422
3	Manufacturing	12,473,585	6,724,330	19,197,915	10,698,254	6,784,595	17,482,849	11,667,186	7,027,277	18,694,463
4	Electricity and Gas	326,546	37,089	363,635	262,181	41,370	303,551	253,843	30,675	284,518
5	Water Supply, Sewerage, Waste Management and Recycling	248,216	254,067	502,283	237,259	253,725	490,984	253,168	309,558	562,726
6	Construction	4,451,736	4,223,713	8,675,449	3,438,172	4,628,325	8,066,497	3,366,161	4,927,608	8,293,769
7	Trading	8,276,988	15,886,943	24,163,931	7,387,081	17,315,614	24,702,695	7,909,540	17,826,570	25,736,110
8	Transportation	2,303,309	3,353,005	5,656,314	2,400,088	3,191,853	5,591,941	2,365,404	3,078,250	5,443,654
9	Accomodation & Food-Beverages Services	2,763,773	5,798,453	8,562,226	2,232,434	6,311,360	8,543,794	2,300,628	6,879,712	9,180,340
10	Information & Comunication	643,676	277,515	921,191	641,139	292,134	933,273	675,289	322,910	998,199
11	Financial Services and Insurance	1,726,042	49,247	1,775,289	1,502,637	55,290	1,557,927	1,535,031	62,774	1,597,805

(*Continued*)

Table 2. (*Continued*)

No	Sectoral/ Industry	Labor								
		2019			2020			2021		
		Formal	Informal	Total	Formal	Informal	Total	Formal	Informal	Total
12	Real Estate	312,612	91,294	403,906	238,356	155,309	393,665	204,062	151,893	355,955
13	Company/ Business Services	1,514,533	428,556	1,943,089	1,374,076	422,679	1,796,755	1,584,801	432,270	2,017,071
14	Government Administration	4,947,873	-	4,947,873	4,569,946	-	4,569,946	4,848,980	-	4,848,980
15	Education Services	6,206,669	209,653	6,416,322	5,720,359	308,251	6,028,610	6,193,224	298,404	6,491,628
16	Health Services and Social Activities	1,813,792	168,917	1,982,709	1,812,799	192,723	2,005,522	1,969,734	227,594	2,197,328
17	Other Services	3,481,297	2882,995	6,364,292	3,099,884	3,309,684	6,409,568	2,872,363	2,901,516	5,773,879
Total		**56,804,307**	**71,950,964**	**128,755,271**	**50,771,849**	**77,682,335**	**128,454,184**	**53,142,078**	**77,908,445**	**131,050,523**

Source: Statistics Indonesia, 2022

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among job seekers as structural changes in working conditions demand improving their skills (Wanberg et al., 2002). Once job seekers have the skills preferred by work environments, their employment probability will also increase (Voogt & Roblin, 2012).

3.2. Worker's skill sets

The pandemic has created a need for workers to have diverse skills, including hard skills, soft skills, complex problem-solving skills, and digital literacy, to be reemployed in the current job market. Heckman et al. (2006) showed that a higher level of hard skills has a positive relationship with productivity, while OECD (2020) showed that cognitive skills had become an essential skill in the current era of automation. Education, often characterized as a tool for assessing hard skills, remains critical. The positive impacts of higher education levels on labor market outcomes are well-documented and include a lower unemployment rate and a shorter length of unemployment (Grossman, 2005; Hanushek & Woessmann, 2008).

During the pandemic and its resulting recession, workers with lower education levels have generally experienced the brunt of the impact of the economic downturn. However, evidence shows that the demand for higher education has increased following the recession. This is echoed in history: during the recovery from the Great Recession, the requirement for bachelor's degrees and college degrees in the job demand reached almost 67%, and the need for those with a high-school degree or lower fell to only 1%. (Carnevale et al., 2016).

Despite solid evidence that the relationship between education and reemployment is positive and significant, this study posits that soft skills, defined as a cluster of capabilities that enable workers to work productively (Eyster et al., 2013), also play an essential role in the transition process of reemployment following the pandemic. In addition, this study posits that problem-solving skills, defined as a process of acquiring new knowledge and a set of acts to investigate the problem, identify the possible alternative solutions, and provide an action to be taken (Funke, 2010; Gonzalez et al., 2005; Greiff et al., 2013), have become crucial in affecting the dynamics of reemployment despite low-skill jobs not taking advantage from problem-solving skills (Athanasou, 2012)

Meanwhile, social skills have risen in importance in the workplace (Lonnides & Datcher-Loury, 2004). Social skills are described as the ability to conduct networking to gain job opportunities (Van Hoye et al., 2009; Wanberg et al., 2000). They have been shown to positively and significantly affect labor market success (Beaman, 2012; Hulshof et al., 2020; Van Hoye et al., 2009). Information gathered from social networks, and colleagues play an essential role in reemployment (Giles et al., 2006), although some studies have found a negative relationship between social skills and the job-finding rate (McArdle et al., 2007; Saks, 2006).

One final skill to consider as global trends accelerated by the pandemic continue to transform the workplace is digital literacy. Digital technology has become a necessity of the workplace (Coibion et al., 2020; Van Laar et al., 2017, Shkalenko & Fadeeva, 2020), disadvantaging most of those with the least education (Dingel & Neiman, 2020; Espinoza & Reznikova, 2020; Sostero et al., 2020). Their greater difficulties in utilizing technologies threaten to worsen inequalities in the labor market, especially as recent trends have pushed businesses of all sizes to be increasingly dependent on digital technologies. However, as digital technologies help companies to survive, Lane and Conlon (2016) have concluded that digital technologies can benefit even low-educated workers so long as they are effectively managed.

4. Data and methodology

4.1. Data dan measurement

We employ the Sakernas to explore the relationship between skill sets, including hard skills, problem-solving skills, social skills, digital skills, and reemployment during the COVID-19 pandemic in Indonesia. The Sakernas records employment characteristics, unemployment, and underemployment, and

documents the working-age population regardless of their labor force participation status. Moreover, the Sakernas also records comprehensive demographic, gender, age, education, residence, digital literacy, and soft skills data. The Sakernas is regularly conducted twice yearly, in February which is only possible for analysis at the provincial level and in August which allows an analysis at the district level. As this study aims to investigate the labor force condition following the COVID-19 pandemic, we mainly utilize the more granular data available in August 2019, August 2020, and August 2021 Sakernas, which allows us to compare labor market conditions before, during, and during the recovery from the COVID-19 pandemic.

Figure 1, 2 , and 3 shows the sample chart of 2019, 2020, and 2021 Sakernas. The 2019 Sakernas collected data from 782.8 thousand respondents representing 197.9 million people in Indonesia's working-age population. Around 34.3 thousand respondents experienced job losses; however, approximately 48% have been reemployed. The number of respondents in the 2020 and 2021 Sakernas does not vary much from the 2019 Sakernas, with only the main difference being that the share of workers experiencing job losses in 2020 was lower (16%) and even lower in 2021 (15.4%).

Although the Sakernas may not be the most appropriate dataset to answer the relationship between skill sets and reemployment during the COVID-19 pandemic, the Sakernas is the most comprehensive, nationwide, and accessible secondary data on the labor force in Indonesia. Therefore, given the limitations of the Sakernas, we conduct only a baseline assessment on how skill sets influence reemployment in Indonesia during the pandemic. The main challenge of using the Sakernas is to classify the existing sample because not all respondents were asked the same questions. Questions related to social and problem-solving skills are only asked respondents still looking for a job. Therefore, respondents to these questions can be both those unemployed and those currently having a job but still searching for another job.

We measure hard skills based on formal education and highlight formal vocational education to focus on respondents who are prepared to work immediately. We create an indicator variable taking the value 1 for those who graduated from either vocational schools *(SMK-Sekolah Menengah Kejuruan)* or diploma programs (graduated from polytechnics) and the value 0 for those who graduated from other institutions. We control for this as evidence finds that people with vocational education tend to find employment sooner after school than those with a general education qualification (Forster et al., 2016).

Digital literacy is also constructed as a binary variable and is measured based on internet utilization in the workplace. Hence, we use the "use of the internet" variable as a proxy to extract a digital literacy variable. The value 1 represents those who use the internet for work, and the value 0 is assigned to respondents who do not use the internet for work. The Sakernas only asks working respondents this question. Therefore, we apply the "use of the internet of the head of household for unemployed respondents" as a proxy for the digital literacy variable for respondents who are not working. We also take a similar approach to construct the problem-solving skill binary variable using proxy questions in the Sakernas (questions can be seen in appendix 1). To capture reemployment in our sample, we similarly use binary data, with the value 1 for workers who previously lost a job but are currently employed and 0 for workers who previously lost a job but are still unemployed.

This study further uses other indicators and data: (i) GDP data from Statistics Indonesia, (ii) cases of positive COVID-19 cases up to August 2020 from the Kawal Covid dataset, (iii) poverty level data from the National Socio-Economic Survey (Susenas), and (iv) data on the number of BTS, the number of cellular operators, elevation levels, soil ruggedness, rainfall, and cooperation participation in each city and district from the Village Potential survey (PODES). To complement our quantitative analysis, we interviewed a small sample of those who lost their jobs due to the pandemic. Interviews were conducted in Pemalang and Tegal, two areas contributing to labor in Jakarta.

4.2. Methodology of bivariate probit model

This study quantitatively estimates skill sets' effect on reemployment during the COVID-19 pandemic. We suspect that the relationship between skill sets and reemployment may suffer from endogeneity and reverse causality as reemployed workers tend to have higher skill sets, and simultaneously those with higher skill sets tend to be reemployed. In addition, sample selection bias may be present as all respondents were not asked the same questions, and we use only a subsample with complete information about skill sets. This will result in erroneous conclusions when we use these non-random-selected samples to estimate behavior relationships (Heckman, 1974). Heckman (1979) suggests a two-stage estimation method to correct for endogeneity bias which can be a sample selection bias.

As our outcome variable is binary, we use Probit models to estimate our relationships of interest. The IV Probit and Bivariate Probit models are the two main approaches used to estimate the probability of reemployment. The Bivariate Probit is a technique that is commonly used when two related binary outcome variables are jointly determined (Wooldridge, 2010 p. 477). For example, education and employment may be endogenous, meaning that unobserved factors may affect both education and employment outcomes. In sample selection bias, the bivariate probit can correct for selection bias if the selection process is based on one of the binary variables being analyzed (Wooldridge, 2010, p. 477). The method allows for the joint estimation of the selection process and the outcome of interest, leading to more accurate estimates of the relationship between the variables of interest (Holm & Jaeger, 2011). Meanwhile, the IV Probit is appropriate when the binary outcome variable is potentially endogenous due to omitted variables. In this case, the explanatory variable of interest is correlated with the error term in the model, which requires using an instrumental variable that is correlated with the endogenous explanatory variable but is not directly related to the outcome variable (Wooldridge, 2010, p.472). Moreover, the IV probit assumes that the endogenous covariates are continuous variables.

Grappling with sample selection bias, binary endogenous covariates, two related and jointly determined binary outcome variables, and not strictly focused on causal inference, this study applies the Bivariate Probit to estimate the relationship between skill sets and reemployment in Indonesia. The general Bivariate Probit model is as follows:

$$Y_i = \beta_1 X_i + \delta B_i + \mu 1_i$$

$$B_i = \beta_2 X_i + \alpha Z_i + \mu 2_i \;\; E[\mu 1] = E[\mu 2] = 0$$

$$Var[\mu 1] = Var[\mu 2] = \sigma$$

$$Cov[\mu 1, \mu 2] = \rho$$

where Y is the dependent variable of reemployment; B is skill sets; X is a vector of exploratory variables; Z is a vector of exogenous covariate/instrumental variables. ρ is the correlation between B (the endogenous variable) and Y (the dependent variable). The Wald test (significance of ρ) can be applied to test the endogeneity of Y and B: if $\rho \neq 0$,then the relationship is endogenous. Meanwhile, we apply the first stage F-statistic (Sandersons-Windmeijer, Stock-Yogo, and Wald) to test the correlation between the instrument and our endogenous independent statistics (Stock & Yogo, 2005 pp. 80–108; Windmeijer, 2005). A strong fit must exist between an endogenous regressor and the instrument variable. Weak instruments are a threat due to their asymptotic biases, increasing with the instrument's weakness (Bascle, 2008).

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Table 3. Description of variables

Dependent Variable		Data Type
Reemployment	Value 1 for a respondent who does reemployment process, 0 otherwise	Binary
Variables of Interest		
Digital Literacy	Value 1 for respondents who use the internet, 0 otherwise	Binary
Problem-solving	Value 1 for a respondent who has a problem-solving skill, 0 otherwise	Binary
Social Skill	Value 1 for a respondent who has social, 0 otherwise	Binary
Vocational Education	Value 1 for a respondent who has vocational education and Diploma Degree, 0 otherwise	Binary
Control Variable		
Gender	Value 1 for male and 2 for female	Binary
Age	Current respondent age	Continuous
Unemployment rate	Unemployment rate based on province	Continuous
Poverty rate	Poverty rate based on province	Continuous
Covid case	Number of covid cases up to august 2020 based on province	Continuous
GRDP	Ln from GRDP based on district/city	Continuous
Instrumental Variables		
Mutual cooperation	% mutual cooperation in the district/city	Continuous
Rainfall	% rainfall in the district/city	Continuous
Ruggedness	% ruggedness in the district/city	Continuous
BTS (Base Transceiver Station)	number of BTS in the district/city	Continuous
Operator	Number of operators in the district/city	Continuous
Elevation	Elevation level in the district/city	Continuous

Source: Authors

Following Heckman (1979), we run a two-stage estimation method to correct for endogeneity bias, which can be a form of sample selection bias. Our Bivariate Probit equation is as follows:

First Equation

$$Skill_i^k = \beta_0 + \beta_l \sum_{l=1}^{L} Z_i^l + \beta_m \sum_{m=1}^{M} IndChar_i^m + \beta_n \sum_{n=1}^{M} RegChar_i^n + \varepsilon_i$$

Second Equation

$$Reemploy_i = \delta_0 + \delta_l \widehat{Skill_i^k} + \delta_m \sum_{m=1}^{M} IndChar_i^m + \delta_n \sum_{n=1}^{M} RegChar_i^n + \mu_i$$

where *Skill* refers to several skill sets, including vocational education as a proxy for hard skills, problem-solving skills, social skills and digital literacy skills; *IndChar* is individual characteristics including age and gender; *RegChar* is regional characteristics including unemployment rate, poverty rate, COVID-19 cases, and Gross Regional Domestic Product (GRDP); *Z* is instrumental variables including cooperation, rainfall, ruggedness, BTS, operator, and elevation[1]; *i* refers to the working individual; ε and μ are error terms. Table 3 describes each variable, and Appendix 1 describes how skill sets and reemployment are extracted from the Sakenas dataset.

5. Results and discussion

5.1. Descriptive analysis

5.1.1. Reemployment

During the COVID-19 pandemic, many companies struggled to keep their businesses afloat. Some companies left the industry, and others were forced to lay off their employees. The unemployment rate increased by 1.79 percentage points from 5.28% in 2019 to 7.07% in 2020. Figures 1, 2 , and 3 compare reemployment in 2019, 2020, and 2021, showing the growing trend of reemployment. Despite the struggling business climate, three possibilities can explain the growing reemployment during the COVID-19 pandemic. First, an increased number of people laid off and temporarily out of work during Covid-19, in turn, increased job seekers who will continuously seek jobs to be reemployed. Second, unemployment is a luxury for low-income groups without social protection, especially those without unemployment insurance. Third, as the business sector readjusts, they require employees either by recruiting new employees or reemploying old ones.

Table 4 shows that in 2019, reemployed workers were almost evenly split across the formal and informal sectors, 54% and 46%, respectively. In 2020, around 65% of reemployed workers were in the informal sector, indicating a scarring effect on the labor market. A lack of employment opportunities in the formal sector drove workers to seek informal employment through self-employment. This is in line with the results of our qualitative interviews. Generally, those who have lost their jobs have turned to selling in the market or opening food stalls with a much-reduced income from their previous job. The increasing number of sellers in the local market, alongside the reduced purchasing power of consumers, has exacerbated the already reduced income of local traders. However, interviewees note that some well-established companies have

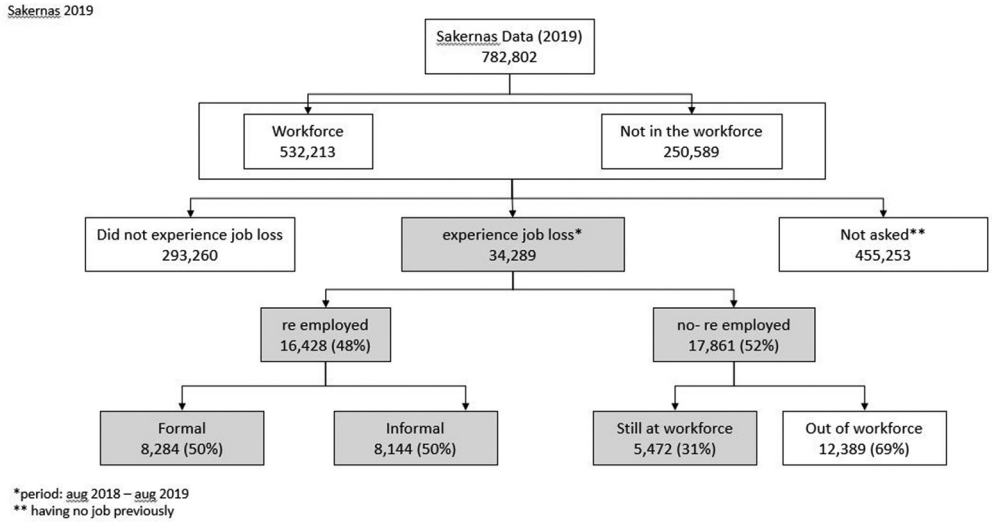


Figure 1. 2019 sakernas sample.

Source: Statistics Indonesia (2022)

Figure 2. 2020 sakernas sample.

Source: Statistics Indonesia (2022)

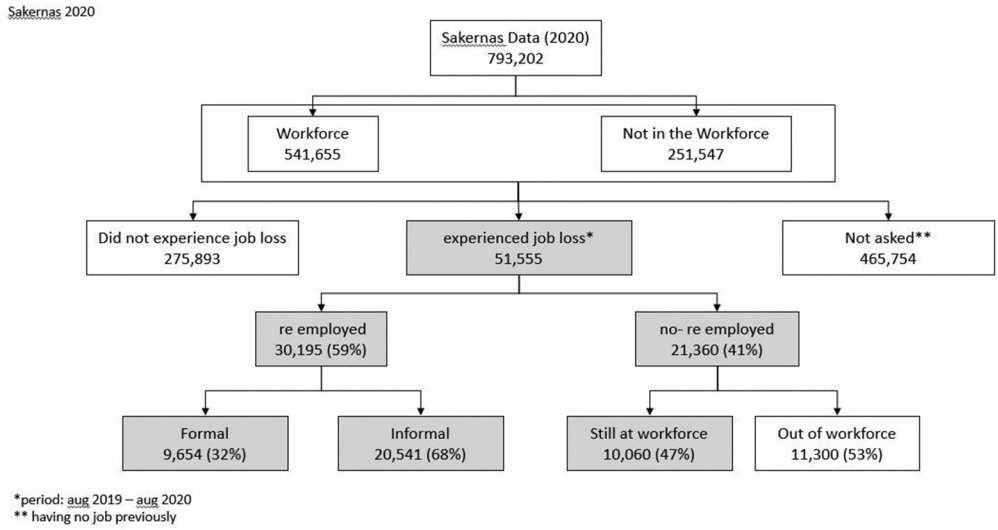
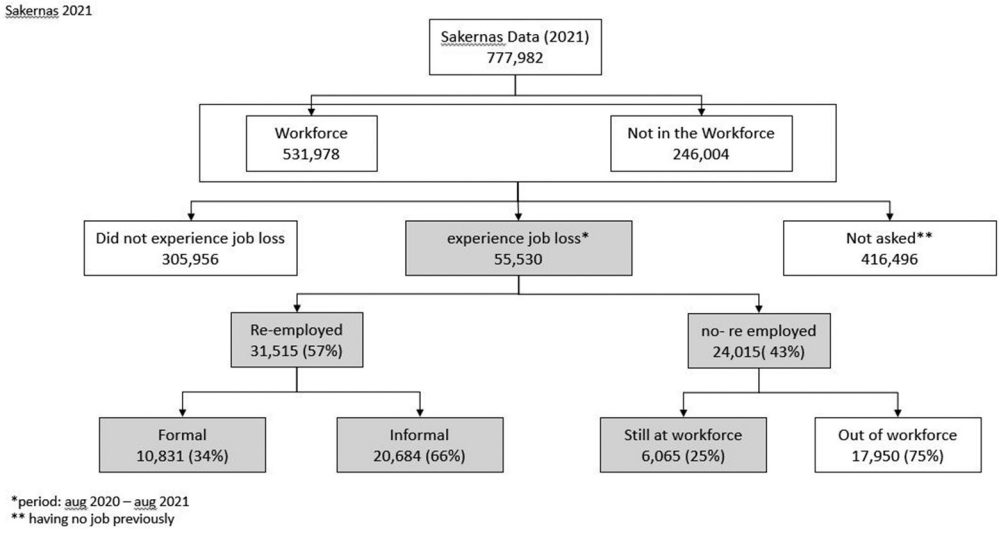


Figure 3. Sakernas Sample 2021.

Source: Statistics Indonesia (2022)



begun operating again and are re-hiring, opening up hope for more reemployment opportunities in the formal sector.

Yet, the 2021 Sakernas shows that the condition of reemployment in the informal sector did not change a year into the pandemic. Workers who are reemployed in the informal sector remained at 59.5% in 2021. The formal sector is still recovering and struggling to return to its previous level of operations. However, with assistance programs from the government, such as "Kartu pra-Kerja," unemployed workers can improve their skills to work independently. Working through self-employment or in the informal sector can help provide livelihoods, but it offers little, if any, in terms of a social safety net. The deteriorating prospect for the labor market can be called the "scarring effect," which also applies to workers in the informal sector. The impact of the scarring effect is the propensity for higher unemployment and lower earnings (Pritadrajati et al., 2021).

Table 4. Heterogeneous characteristics of reemployment

	Reemployed									No Reemployed		
	Total			Formal			Informal					
Characteristics	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**
Gender	**4,892,316**	**8,664,646**	**9,212,851**	**2,659,153**	**3,005,649**	**3,485,664**	**2,233,163**	**5,658,997**	**5,727,187**	**5,283,780**	**6,761,845**	**7,279,960**
Male	70.8%	72.2%	70.6%	68.3%	71.7%	69.6%	73.9%	72.5%	71.2%	42.9%	51.4%	45.4%
Female	29.2%	27.8%	29.4%	31.7%	28.3%	30.4%	26.1%	27.5%	28.8%	57.1%	48.6%	54.6%
Rural-Urban	**4,892,316**	**8,664,646**	**9,212,851**	**2,659,153**	**3,005,649**	**3,485,664**	**2,233,163**	**5,658,997**	**5,727,187**	**5,283,780**	**6,761,845**	**7,279,960**
Urban	62.5%	56.8%	55.4%	72.4%	68.9%	68.4%	50.6%	50.4%	47.4%	61.7%	67.4%	62.6%
Rural	37.5%	43.2%	44.6%	27.6%	31.1%	31.6%	49.4%	49.6%	52.6%	38.3%	32.6%	37.4%
Regional	**4,892,316**	**8,664,646**	**9,212,851**	**2,659,153**	**3,005,649**	**3485,664**	**2,233,163**	**5,658,997**	**5,727,187**	**5,283,780**	**6,761,845**	**7,279,960**
Sumatera	18.7%	18.5%	18.0%	19.4%	20.0%	19.2%	18.0%	17.7%	17.3%	18.6%	17.2%	17.7%
Jawa Bali	62.9%	63.9%	62.6%	64.0%	64.3%	64.8%	61.6%	63.6%	61.3%	63.6%	67.5%	64.4%
Kalimantan	7.0%	5.6%	5.2%	7.9%	6.2%	6.4%	6.0%	5.4%	4.6%	5.8%	5.0%	5.5%
Sulawesi	5.9%	5.5%	6.3%	5.1%	5.4%	5.7%	6.9%	5.6%	6.6%	6.9%	5.7%	6.7%
Others	5.4%	6.5%	7.9%	3.6%	4.1%	4.0%	7.6%	7.8%	10.2%	5.2%	4.6%	5.7%
Education	**4,892,316**	**8,664,646**	**9,212,851**	**2,659,153**	**3,005,649**	**3,485,664**	**2,233,163**	**5,658,997**	**5,727,187**	**5,283,780**	**6,761,845**	**7,279,960**
No Formal Education	9.1%	9.4%	11.5%	5.8%	5.2%	5.1%	13.1%	11.6%	15.3%	14.2%	8.9%	13.8%
Primary School	19.2%	25.2%	24.8%	13.5%	17.5%	16.4%	25.9%	29.3%	30.0%	19.0%	19.6%	21.8%
Junior High School	20.0%	20.7%	18.7%	18.4%	19.5%	16.9%	21.9%	21.3%	19.7%	19.3%	18.7%	17.9%
Senior High School	19.6%	19.4%	19.0%	21.9%	22.5%	22.4%	16.8%	17.8%	16.9%	20.7%	22.4%	20.6%
Vocational School	21.2%	17.2%	17.1%	25.5%	22.8%	24.7%	16.0%	14.2%	12.5%	17.2%	20.0%	17.4%

(*Continued*)

Table 4. (*Continued*)

	Reemployed									No Reemployed		
	Total			Formal			Informal					
Characteristics	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**
Diploma	2.8%	2.2%	2.6%	3.6%	2.9%	3.8%	1.8%	1.8%	1.9%	2.8%	3.0%	2.6%
>= Bachelor	8.1%	5.9%	6.3%	11.2%	9.6%	10.7%	4.5%	4.0%	3.7%	6.7%	7.4%	5.8%
Age	**4,892,316**	**8,664,646**	**9,212,851**	**2,659,153**	**3,005,649**	**3,485,664**	**2,233,163**	**5,658,997**	**5,727,187**	**5,283,780**	**6,761,845**	**7,279,960**
15-24	28.2%	18.6%	18.9%	35.3%	25.9%	29.2%	19.8%	14.8%	12.6%	31.8%	28.5%	24.5%
25-40	47.1%	43.6%	42.7%	47.8%	47.9%	47.6%	46.3%	41.3%	39.6%	34.3%	36.9%	32.6%
>40	24.6%	37.8%	38.4%	16.8%	26.1%	23.2%	33.9%	44.0%	47.7%	33.9%	34.7%	42.9%

Source: Authors' estimation based on Sakernas 2019, 2020 and 2021

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Surprisingly, the number of workers not reemployed who are "still in the workforce" category in 2020 (54%) is higher than those in 2019 (37%). This is likely due to the early pandemic stage, where people still hope that the pandemic will pass soon and hold out for job opportunities. Indeed, in 2021, 70% of those who have not been reemployed shifted out of the workforce. This reflects the striking habituation effects a year into the pandemic. Indonesia's economy has not fully recovered: scarce job opportunities have pushed the unemployed out of the workforce.

5.1.2. Heterogeneous characteristics of reemployment

Table 4 describes reemployment by gender, rural-urban, regional, education, and age. Before the pandemic, in 2019, youth workers (15–24 years) dominated almost 30% of the reemployed workers, but during the pandemic years of 2020 and 2021, youth workers had the lowest reemployment rate, 18.6%, and 18.9%, respectively. Employers need workers who have more experience in hard times. In 2020 and 2021, workers aged 25–40 years had the highest reemployment rate at roughly 42%. Thus, the limited experience of youth workers has become a barrier to having decent work with good incomes. Disruptions in education and training further compound the issue as those who recently graduated during the pandemic experienced learning loss.

Vocational education has played a role in the reemployment process: it is the education category with the highest proportion of workers reemployed in 2019. Yet, this has changed during the pandemic: the highest proportion of reemployed workers is entitled to only those with a primary school background, 25.2% in 2019 and 24.8% in 2020. During the pandemic, having a vocational education background did not significantly affect reemployment outcomes, and people with lower education were more easily reemployed. In this situation, workers are forced to work in the more flexible sector, or informal sector or are self-employed, so vocational education is no longer valued as highly.

The pandemic has also affected the proportion of people who stopped working and are reemployed based on their geographic location. In 2019, the urban-rural proportion of reemployed workers was 62.5% and 37.5%. Following the pandemic, the proportion of those reemployed in urban areas remains higher than those in rural areas, 56.8% in 2019 and 55.4% in 2021. Indeed, the impact of the pandemic is more pronounced in rural areas. This is aligned with Mueller's (2020) results that rural areas are dominated mainly by a single industry, such as agriculture, making them more vulnerable and disproportionately impacted by the pandemic. The low rate of reemployment in rural areas may also be either directly due to a decrease in the purchasing power of the local community or indirectly due to the decline in demand from other regions, including urban areas. However, the rural-urban proportion trend has seen the share of rural reemployment rise from 43.2% in 2020 to 44.6% in 2021. This reflects a negative aspect of rural employment: employment in rural areas is generally more flexible, causing migration back into villages to seek informal reemployment.

5.1.3. Reemployment by skills

As explained in the literature review section, digital technology has become necessary in the workplace. However, Table 5 shows that, among the total who are reemployed, the share of those without digital literacy skills is higher than those with digital literacy skills. This is reasonable as higher reemployment occurs in the informal sector, which tends to be more traditional and thus does not require digital skills (La Porta & Shleifer, 2014).

Regarding problem-solving and social skills, our respondents already have a job but are still looking for another job. The table shows that, in the reemployment process, the share of people with problem-solving skills is lower than those who don't have those skills. The same reasoning as digital literacy is applied here; more reemployment occurs in the informal sector, which tends to absorb low-skill workers who do not require problem-solving skill qualifications.

Different findings are found in social skills. People who have social skills and are still looking for another job take up a higher share of those reemployed than people who do not have those skills. Even before the pandemic in 2020, social skills were already needed in the reemployment process.

Table 5. Reemployment by Skill

Characteristics	Reemployed									No Reemployed		
	Total			Formal			Informal			2019	2020	2021
	2019	2020	2021	2019	2020	2021	2019	2020	2021			
Digital Literacy	4,892,316	8,664,646	*	2,659,153	3,005,649	*	2,233,163	5,658,997	*	5,283,780	6,761,845	*
Have Digital Literacy	41.7%	40.1%	*	50.4%	52.0%	*	31.3%	33.8%	*	26.9%	30.5%	*
Does not have	58.3%	59.9%	*	49.6%	48.0%	*	68.7%	66.2%	*	73.1%	69.5%	*
Vocational Education	4,892,316	8,664,646	9,212,851	2,659,153	3,005,649	3,485,664	2,233,163	5,658,997	5,727,187	5,283,780	6,761,845	7,279,960
Vocational Education	24.0%	19.4%	19.7%	29.2%	25.7%	28.5%	17.8%	16.0%	14.4%	17.2%	23.0%	20.1%
No Vocational Education	76.0%	80.6%	80.3%	70.8%	74.3%	71.5%	82.2%	84.0%	85.6%	82.8%	77.0%	79.9%
Problem Solving	640,667	1,564,562	893,277	229,949	376,943	222,492	410,718	1,187,619	670,785	1,933,354	3,644,459	2,,219,541
Has Problem solving skill	43.2%	35.6%	36.6%	45.1%	44.7%	46.7%	42.1%	32.8%	33.3%	49.6%	44.3%	37.7%
Does not have	56.8%	64.4%	63.4%	54.9%	55.3%	53.3%	57.9%	67.2%	66.7%	50.4%	55.7%	62.3%
Social Skill	640,667	1,564,562	893,277	229,949	376,943	222,492	410,718	1,187,619	670,785	1,933,354	3,644,459	2,219,541
Has Sosial skill	87.2%	92.4%	91.6%	83.1%	90.8%	89.0%	89.5%	92.9%	92.5%	82.4%	77.2%	73.2%
Does not have	12.8%	7.6%	8.4%	16.9%	9.2%	11.0%	10.5%	7.1%	7.5%	17.6%	22.8%	26.8%

*due to the change of questions about internet utilization, the 2021 data is not comparable.

Source: Authors' estimation based on Sakernas 2019 –2021

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These skills have become more critical during the pandemic: the share of people among the reemployed with social skills rose from 87,2% in 2019 to 92,4% in 2020 and 91,6% in 2021. Networking is essential; people prefer to hire someone they know or have good references. According to a LinkedIn global survey, almost 80% of professionals consider professional networking important to career success. Career networking involves personal, familial, or professional contact to assist with a job search. This is consistent with the increase in the number of reemployed people with social skills in both the formal and informal sectors.

5.2. Estimation results of the bivariate probit model

Table 6 shows the marginal effect of the different skills on reemployment. In 2019, hard skills, proxied by vocational education, positively correlated with reemployment outcomes, but not in 2020 and 2021. While previous research show education is an important predictor during the recession (Isengard, 2003), this study provides the opposite result. This potentially hints that vocational education does not impact the Indonesian labor force during crisis periods as the highest reemployment occurs in the informal sector, which tends to employ less educated workers (Ginting et al., 2018). In 2020, the effect of vocational education turned negative in rural areas: having vocational education reduces the chances of reemployment. This is likely due to reemployment being dominated by the informal sector and by those with low levels of education.

Another possible explanation is the competencies of graduates of vocational education, which focus on occupations (OECD/ADB, 2020). The OECD stated that the Indonesian National Work Competency Standards (INWCS) and the Indonesian National Qualification Framework (INQF) are the standards that should be fulfilled to ensure harmonization between vocational education and each employment outcome. However, during the pandemic, the demand for competencies flexibility is high as people must work only based on limited job availability. Furthermore, nearly 30% of graduates with vocational education backgrounds are absorbed in manufacturing industries (Khurniawan & Erda, 2019). The growth of the manufacturing sector turned negative in the third quarter of 2020, resulting in many vocational education graduates becoming unemployed (Miftahudin, 2021). However, in 2021, vocational education again had a positive and significant correlation with reemployment outcomes, specifically for those in the 15–24 age group. Having vocational education background increased reemployed chances in the second pandemic year by 8.9%, with a 99% confidence level. This suggests that the Indonesian economy's manufacturing sector has gradually recovered.

Furthermore, this study suggests that digital literacy has significant and positive associations with reemployment outcomes in 2020. This implies that having digital literacy increases the probability of worker reemployment during the pandemic, but with a lower in 2020 (2.2%) than in 2019 (8%). It is plausible as almost all non-essential industries must be closed during the pandemic, so having digital literacy might not positively influence the reemployment outcome. This finding is consistent with prior expectations., and Zarska (2020)'s findings

However, this effect varies by age: digital literacy is significantly and positively associated with reemployment among youth workers (those aged 15–24). This indicates that youth workers are more aware of the demand for IT in employment. Following the COVID-19 pandemic, business closures dampened the need for IT expertise, but as recovery continues, the demand for workers in the IT sector continues to increase even as the shortage of IT professionals continues. This higher demand for IT thus increases the need for digital literacy (Vukmirović et al., 2021).

This study also provides an exciting finding that digital literacy in 2020 significantly predicts the reemployment outcome in rural areas. In addition to various government policies related to digital literacy in rural areas, the higher number of workers in the informal sector might explain a shift of workers from the formal sector in the urban area to the informal sector in the rural area. Workers from urban areas who tend to be more digitally literate bring their skills to the rural area. Field observations show several innovations in rural areas carried out by workers who previously worked

Table 6. Summary of estimation results

Classification	Vocational Education						Digital Literacy			
	2019		2020		2021		2019		2020	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
All	0.033***	0.007	0.01	0.011	-0.012*	0.007	0.080***	0.006	0.022**	0.009
Rural-Urban										
Urban	0.003	0.023	-0.009	0.021	-0.009	0.016	0.127***	0.015	0.025	0.023
Rural	-0.012	0.015	-0.025***	0.001	-0.004	0.012	0.051***	0.007	0.061***	0.014
Regional										
Sumatera	0.017	0.026	0.015	0.047	-0.015	0.013	0.052***	0.015	0.02	0.022
Jawa-Bali	0.030**	0.014	-0.011	0.016	-0.013	0.011	0.110***	0.011	-0.062*	0.014
Kalimantan	0.028**	0.013	0.026*	0.015	-0.02	0.012	0.075***	0.265	0.074**	0.030
Sulawesi	-0.046	0.020	-0.023	0.022	0.002	0.024	-0.023	0.230	-0.001	0.023
Others	-0.031***	0.005	-0.011	0.022	-0.019***	0.002	0.041**	0.185	0.009	0.029
Age										
15-24	0.075***	0.021	0.029	0.036	0.089***	0.022	0.131***	0.005	0.073***	0.019
25-40	0.033**	0.016	0.006	0.019	-0.014	0.012	0.800***	0.013	0.024	0.015
>40	0.016***	0.002	-0.005	0.013	-0.019***	0.001	0.035***	0.101	0.002	0.013

(*Continued*)

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Table 6. (*Continued*)

Classification	Problem Solving						Social Skill					
	2019		2020		2021		2019		2020		2021	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
All	-0.122***	0.041	-0.082**	0.039	-0.030	0.038	-0.155	0.163	0.412***	0.085	0.268***	0.086
Rural-Urban												
Urban	-0.190**	0.046	-0.041	0.053	0.015	0.047	-0.393***	0.077	0.598***	0.012	0.258***	0.084
Rural	-0.125***	0.031	-0.115***	0.011	-0.071	0.048	0.112	0.338	0.520***	0.110	0.325*	0.177
Regional												
Sumatera	-0.067	0.071	-0.048	0.066	-0.098***	0.030	-0.02	0.248	0.380**	0.151	0.285	0.270
Jawa-Bali	-0.207***	0.039	0.018	0.041	-0.034	0.053	-0.076	0.535	0.206	0.151	0.284**	0.142
Kalimantan	-0.088	0.092	-0.011	0.122	0.034	0.100	-0.43***	0.083	-0.012	0.336	0.323	0.201
Sulawesi	0.0738***	0.018	-0.025	0.115	0.058	0.039	0.083	1.025	-0.314***	0.076	0.012	0.219
Others	0.035	0.073	0.022	0.087	0.049	0.105	-0.458	2.966	0.208	0.287	0.572***	0.264
Age												
15-24	-0.086	0.079	-0.042	0.057	0.013	0.063	-0.287	0.175	0.230	0.151	0.340***	0.130
25-40	-0.126***	0.045	-0.121***	0.011	-0.054	0.054	-0.217	0.210	0.636***	0.032	0.204	0.213
>40	-0.019	0.077	-0.071	0.061	-0.034	0.040	0.536***	0.054	0.356	0.298	0.215*	0.127

Statistical significance: * at 10 percent, * at 5 percent, and *** at 1 percent level

Outcome variable is reemployment worker. Bivariate probit regression-based estimate the marginal effect of variables. Control variables applied in the biprobit model are gender, age, unemployment rate, poverty rate, GRDP, and covid case. Digital skill in 2021 is not estimated due to changes in the questionnaire in Sakernas 2021.

Source: Authors' estimation based on Sakernas 2019, 2020 and 2021

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in the city in marketing their businesses. Among these innovations is creating a WhatsApp group between sellers to buy each other's products or offer their products online. We also found an offer to become a member of the online marketplace. Several food stall owners and sellers were contacted to market their products via the marketplace. This is supported by previous studies on internet utilization in rural areas, which find that personal networks for internet use are significantly associated with adopting the internet in rural areas (Boase, 2010).

In terms of social and problem-solving skills, this study investigates both people who do not have jobs and already have a job, but are still struggling to find another job. This study reveals that workers with social skills have a higher probability of being reemployed during the pandemic than workers without social skills. In 2019, social skills did not affect reemployment outcomes, but in 2020 and 2021, social skills are valued as essential in determining reemployment outcomes. This finding resonates with previous studies which argue the importance of social skills during the job search process (Pierson, 2009). Moreover, Montgomery (1991) indicates in his study that 50% of new job seekers have access to work based on their social networking. This implies that social skills might be considered necessary in their role in increasing reemployment.

Sub-analysis based on rural-urban and age categories also shows that social skills increase the chance of being reemployed in rural and urban areas. Social skills will increase the opportunity of being reemployed by almost 60% in urban areas and 52% in rural areas. Regarding age group, social skills are only significant in increasing reemployed chances for workers in the 25–40 age group in 2020 (by 64%). However, in 2021, social skills were no longer significant for those aged 25–40 but became significant and positive (34%) for those aged 15–24. This is likely due to those in the 25–40 age group category being considered more experienced and more productive, and thus are more required during the first wave of the pandemic. However, in the second year of the pandemic, employers may start to look for those among the younger group of 15–24.

However, contrary to our hypothesis, problem-solving skills have a negative and significant relationship with reemployment outcomes in 2019 and 2020 and no effect in 2021. This implies that workers with high problem-solving skills are unlikely of being reemployed during the pandemic. This is likely due to informal sector workers dominating Indonesia's labor force, with their numbers rising further during the pandemic. This is in line with Singh, M (1998) results which find that workers in the informal sector have a shortage of problem-solving skills.

We conduct several robustness tests to check whether our Bivariate Probit estimations are appropriate to quantitatively measure the relationship between skill sets and reemployment in Indonesia. Appendix 2 and 3 show the results of OLS estimations for our models. The magnitude of OLS estimations is consistent with those of our Bivariate Probit estimations, except for vocational education and problem-solving in 2020. To confirm the validity of instrumental variables used in the Bivariate Probit, we test the weakness of instrumental variables using the Sandersons-Windmeijer, Stock Yogo, and Wald F tests. Keane & Neal (2022) notes that an F statistic over 10 is generally required to argue that instruments are sufficiently strong. Except for the Stock-Yogo F test, all tests show that our instrumental variables are adequately strong except for those of social skills (Appendix 4). In addition, we also offer the first regression using the ivprobit syntax in Stata (Appendix 5). As our primary purpose is not estimating a causal inference of skill sets' effect on reemployment, the application of the Bivariate Probit model to resolve issues of endogeneity and sample selection biases is an appropriate approach for estimating the relationship between skill sets and reemployment in Indonesia before, during, and during the recovery process in Indonesia.

6. Concluding remarks

The decrease in economic growth due to COVID-19 has resulted in a surge in unemployed workers. Reemployment becomes strategic to be investigated as previous studies have shown a positive association between reemployment and economic recovery during crises. Understanding the importance of predictors for reemployment during the pandemic is expected to mitigate long-term unemployment that historically persists following economic crises.

Our findings show that both the scarring and habituation effects were observed during the COVID-19 pandemic: more workers shifted their occupation from the formal to the informal sector, and many workers quit the workforce because of the pandemic. The reemployment process occurred mainly in the informal sector, in urban areas, among those with an elementary school background, in the 25–40 age group, and in the Java-Bali region. This potentially hints that workers with those backgrounds do not have many alternatives for livelihoods and have chosen to work even in jobs with lower occupational earnings.

The estimations of the Bivariate Probit model confirm that social skills and digital literacy are consistent determinants for reemployment during the pandemic. However, having digital literacy is valued less for reemployment during the pandemic compared to normal economic times. During the pandemic, workers with social skills tend to have a higher probability of being reemployed, 41% in 2020 and 27% in 2021 higher compared to workers without any social skills, but social skills were not a significant predictor for reemployment in 2019. Hence, having a network of friends and relatives, as a proxy of social skills, was extremely important for being reemployed during the pandemic, but not during normal periods. In addition, this study finds no evidence that vocational education and problem-solving are significant predictor for reemployment during the pandemic. High unemployment and an absence of unemployment insurance force unemployed workers to find any type of job for survival, so vocational education and problem-solving skills will be valued less for reemployment.

Our estimations also show heterogeneous relationships between skill sets and reemployment during the COVID-19 pandemic. For example, social skill is significantly correlated with reemployment in urban areas, the Java-Bali, and among young workers aged 15–24 in 2021; however, this pattern varies from 2020 to 2019. Surprisingly, digital skills are significantly and positively correlated with reemployment in a rural area, Kalimantan, and the age group of 15–24 years old. Moreover, during the economic recovery in 2021, vocational education was crucial for reemployment, especially among young workers.

Our study thus suggests that the government should equip young workers aged 15–24 years old with the correct and relevant skill sets for after the COVID-19 pandemic. As the economy recovers, skill sets will also evolve. Improving digital literacy, social skills, and vocational education should accelerate the reemployment of youth workers. Moreover, as social skills significantly predict the reemployment process, it should be critical in the optimization of job seeker ecosystems which enables information exchange between workers who are in the job search process.

Finally, this study, using the Sakernas 2019, 2020 and 2021 should be interpreted as an initial study and a rapid comparative assessment of the relationship between skill sets and reemployment before, during, and during recovery from the COVID-19 pandemic. The limitations of this study suggest several areas for improvement, including 1) a more extended study period, 2) a longitudinal study of workers, 3) causal inference methodologies for exact estimation of the relationship between skill sets and reemployment, and 4) a specific data set to avoid sample selection bias.

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Note
1. This study applies different exogenous variables or instrumental variables for predicting skill sets. The number of BTS and operators, and elevation are the instrumental variables for digital literacy skills (Isfahani et al., 2021). Problem-solving skills and social skills are instrumented by rainfall, soil ruggedness, and cooperation in the area. Geographical factors can affect human characteristics as well as their problem-solving approaches and how they interact each other. Hard skills, proxied by vocational education, is instrumented by rainfall, soil ruggedness, and cooperation in the area (Shah & Steinber, 2017).

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Appendix
Appendix 1. Deriving Variables from Sakernas 2020

Variable of Interest	**Questions Parameter**	**Data Source**	**Expected Hypothesis**
Reemployment	Current working status	Sakernas 2020 questions number 9a, 29a & 29b	Dependent Variable
	Have you ever stopped working in the period of August 2019- August 2020? When was it?		
Digital Literacy	Do you use the internet for this job?	Sakernas 2020 questions number 17a	+ (positive)
Cognitive Capability	What is the highest education you have completed?	Sakernas 2020 questions number 6a & 6b	+ (positive)
Problem-solving	Did you register on the job market?	Sakernas 2020 questions number 24a,24b, 24c, & 24e	+ (positive)
	Do you advertise yourself in print/electronic/ internet media?		
	Are you raising capital/ finding locations/ managing business licenses?		
	Did you contact the company/update and send your CV/biodata/ business profile?		
Social-skill	Have you contacted family/friends to find work or set up a business?	Sakernas questions number 24d	+ (positive)

Appendix 2. Linear Regression (Ordinary Least Square) Year 2020

	Vocational Educ	Vocational Educ	Digital Literacy	Digital Literacy	Prob solving	Prob solving	Sosial	Sosial
Variables	**No control**	**control**	**No control**	**control**	**No control**	**control**	**No control**	**control**
Vocational Education	−0.0524***	−0.0334***						
	(0.0058)	(0.0058)						
Digital Literacy			0.0633***	0.0962***				
			(0.0047)	(0.0046)				
Problem Solving					0.101***	0.0705***		
					(0.0056)	(0.0058)		
Social Skill							0.315***	0.302***
							(0.0042)	(0.0046)
Age		−0.0002		0.0003**		−0.0020***		3.94e-05
		(0.0002)		(0.0002)		(0.0002)		(0.0001)
Gender		0.229***		0.230***		0.166***		0.0744***
		(0.0044)		(0.0044)		(0.0045)		(0.0044)
unemploy_rate		−0.0237***		−0.0250***		−0.0098***		−0.0131***
		(0.0009)		(0.0009)		(0.0009)		(0.0009)
poverty_rate		0.0012***		0.0019***		0.0005		0.0008**
		(0.0004)		(0.0003)		(0.0003)		(0.0003)
GRDP 2020		0.0003		−0.0020		0.0048**		0.0004

(*Continued*)

(Continued)

	Vocational Educ	Vocational Educ	Digital Literacy	Digital Literacy	Prob solving	Prob solving	Sosial	Sosial
Variables	**No control**	**control**	**No control**	**control**	**No control**	**control**	**No control**	**control**
		(0.0023)		(0.0023)		(0.0024)		(0.0023)
Covid Case		0.0006		−0.0011		−0.0012		−0.0005
		(0.0016)		(0.0016)		(0.0017)		(0.0016)
Constant	0.559***	0.552***	0.530***	0.583***	0.147***	0.0651	0.0224***	0.0621
	(0.0024)	(0.0652)	(0.0027)	(0.065)	(0.0026)	(0.0681)	(0.0029)	(0.0632)
Observations	51,555	51,250	51,555	51,250	26,175	26,027	26,175	26,027
R-squared	0.002	0.071	0.004	0.078	0.012	0.070	0.176	0.196

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Appendix 3. Linear Regression (Ordinary Least Square) Year 2019

	Vocational Education		Digital Literacy		Problem Solving		Social Skill	
Variables	**No control**	**control**	**No control**	**control**	**No control**	**control**	**No control**	**control**
Vocational Education	0.0530***	0.0132*						
	(0.0070)	(0.0069)						
Digital Literacy			0.124***	0.128***				
			(0.0059)	(0.0057)				
Problem Solving					0.152***	0.104***		
					(0.0057)	(0.00597)		
Social Skill							0.256***	0.230***
							(0.00419)	(0.00479)
Age		−0.0042***		−0.0039***		−0.00193***		−0.000512***
		(0.0002)		(0.0002)		(0.000132)		(0.000128)
Gender		0.298***		0.300***		0.131***		0.0662***
		(0.0052)		(0.0051)		(0.00419)		(0.00425)
unemploy_rate		−0.00918***		−0.0106***		−0.00601***		−0.00724***
		(0.0011)		(0.0011)		(0.000846)		(0.000805)
poverty_rate		−0.0004		0.0004		−0.000986***		−0.000917***
		(0.0004)		(0.0004)		(0.000299)		(0.000285)
GRDP 2019		0.0004		−0.0027		−0.00283		−0.00310
	(0.0030)	(0.0774)	(0.0032)	(0.0768)	(0.0023)	(0.0616)	(0.00239)	(0.0588)

(*Continued*)

(Continued)

	Vocational Education		Digital Literacy		Problem Solving		Social Skill	
Variables	**No control**	**control**	**No control**	**control**	**No control**	**control**	**No control**	**control**
Constant	0.460***	0.509***	0.433***	0.556***	0.0764***	0.234***	0.0185***	0.169***
		(0.0026)		(0.0026)		(0.00207)		(0.00198)
Observations	34,289	34,059	34,289	34,059	19,937	19,817	19,937	19,817
R-squared	0.002	0.104	0.013	0.117	0.035	0.089	0.157	0.172

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 4. Weakness Instrument Test

Test Category	Vocational Education	Digital Literacy	Problem Solving	Social Skill
F test- sandersons -windmeijer	30.73	223.51	11.4	6.27
F test- stock yogo	9.08	9.08	9.08	9.08
F test- Wald	30.73	223.51	11.4	6.27
Number of observations	51,250	51,250	14,790	14,790

Source: Authors' estimation based on Sakernas 2020

Appendix 5. Test IV First Regression

Variables	Vocational Education	Digital Literacy	Problem Solving	Social
Rainfall	−2.31e-05***		−2.63e-05***	1.92e-05***
	(3.43e-06)		(4.35e-06)	(4.73e-06)
Mutual cooperation	0.0004		0.0023	−0.0008
	(0.0012)		(0.0015)	(0.0016)
Rugedness	−5.53e-05***		−2.99e-05*	−5.15e-05***
	(9.74e-06)		(1.63e-05)	(1.83e-05)
BTS		0.0302***		
		(0.00217)		
Operator		0.0382***		
		(0.00238)		
Elevation		9.83e-06		
		(7.76e-06)		
Age	−0.0061***	−0.0026***	−0.0062***	−0.0083***
	(0.00012)	(0.00014)	(0.00016)	(0.00019)
Gender	0.0103***	−0.0159***	0.0843***	0.323***
	(0.0033)	(0.0041)	(0.0048)	(0.0056)
Unemployment Rate	0.0068***	0.0027***	0.0121***	0.0123***
	(0.00071)	(0.0009)	(0.0010)	(0.0012)
Poverty Rate	−0.0025***	−0.0035***	−0.0017***	−0.0012***
	(0.00023)	(0.0003)	(0.00036)	(0.0004)
GRDP 2020	0.0108***	−0.0011	0.0243***	0.0225***
	(0.0018)	(0.0024)	(0.0027)	(0.0031)
Covid case	0.0116***	0.0058***	0.0039**	−0.0003
	(0.0013)	(0.0017)	(0.0019)	(0.0022)
Constant	−0.0216	0.267***	−0.617***	−0.109

(*Continued*)

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Variables	Vocational Education	Digital Literacy	Problem Solving	Social
	(0.131)	(0.0662)	(0.167)	(0.183)
Observations	51,250	51,250	26,027	26,027

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Statistical significance: * at 10 percent, * at 5 percent, and *** at 1 percent level

Note #1: Outcome variables are vocational education, digital literacy, problem-solving and social.

Note #2: Rainfall has a significant negative impact on vocational education and problem-solving. As mentioned earlier, higher rainfall can cause school dropout rates, especially in rural areas. Thus, higher rainfall could also decrease the participation in vocational education and the intensity of social networking. Ruggedness has a significant negative impact on vocational education, problem-solving and social. Geographical ruggedness makes it expensive to build infrastructures; thus, it is hard to build education facilities. People are also less to socialize with each other in the area with increased ruggedness. Operators and BTS have significant positive effects on Digital Literacy. The more operators and BTS in a room, the easier it will use the internet.