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Article

Determining the Unemployment Rate in Indonesia during the COVID-19 Pandemic

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Abstract: Unemployment is one of Indonesia's main economic development problems during the COVID-19 pandemic. This study aims to determine the chances of a person becoming unemployed in Indonesia during the COVID-19 pandemic, which individual and household characteristics influence. The data were collected from National Labour Force Survey (SAKERNAS) in August 2020. The data were analysed using a logistic regression model. The result proved that there was a significant opportunity between individual characteristics, namely age, gender, household head status, marital status, education level, training, work experience, and household characteristics, namely the number of household members, against unemployment. While the location of the household is not significant because this research was only conducted in the city centre so that with the same characteristics of the city in each region, the labour force living in the city is less likely to become unemployed. The coefficient value showed that women are more likely to become unemployed. Thus, the government is expected to focus on providing facilities to increase the human capital of the young female workforce, such as creating job training programs and mastering information and technology, given the changes in the digital age.

Keywords: Unemployment, COVID-19 pandemic, Logit

1. Introduction

Unemployment is a major issue in economic development. The problems that afflict these developing countries will have an impact on the economy and cause social problems. Because high unemployment is the root cause of poverty and crime (Akhtar Gul et al., 2020; Ayhan & Bursa, 2019; Benjamin et al., 2019; Nordin & Almén, 2017), programs to reduce unemployment are still on the agenda of every country and even world organisations. As the eighth goal of the Sustainable Development Goals (SDGs), the United Nations aims to achieve permanent and productive work and decent work for all without exception by 2030 to support inclusive and sustainable economic growth, full and productive employment, and decent work for all (Un & Asakawa, 2015). The Pandemic of Covid-19, which occurred at the end of 2019, exacerbated global unemployment. The government has implemented several policies and measures to limit people's movement to reduce the number of infections and deaths (Mursalina et al., 2022).

Along with the pandemic, unemployed people increased by 33 million in 2020. It is estimated that by 2022 the global number of unemployed will reach 205 million people (International Labour Organization, 2020). This significant increase in the number of unemployed is caused by the economic recession and changes in people's behaviour related to the Covid-19 pandemic and government policies on social restrictions, both on a small and large scale. Most people think there is no point in looking for work during the lockdown or under social restrictions. As a result, many companies are not producing, reducing working hours and additional tasks to take care of the household and educate children during these restrictions. It has resulted in a substantial decline in the global workforce participation rate in 2020 of 81 million people.

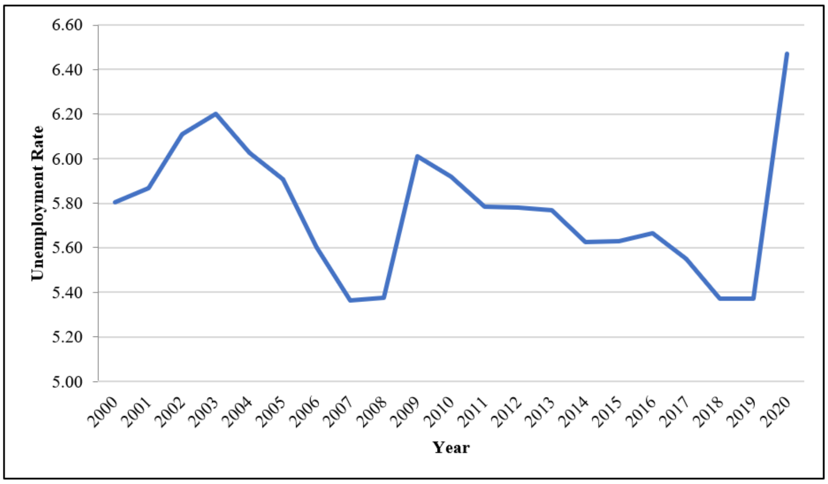

Figure 1. Global Unemployment Rate 2000-2020.

Source: World Bank (2021)

Figure 1 shows the highest record global unemployment rate for the last 21 years occurred in 2020, with an unemployment rate of 6.47 percent, an increase of 1.1 percent from the previous year. If viewed in more detail, the upward trend in the global unemployment rate had occurred twice before, although the percentage was still below the unemployment rate in 2020. The first peak of the increase in the unemployment rate occurred in 2003 at 6.2 percent. The increase in unemployment and underemployment during the first half of 2003 was caused by slow growth in the economic situation of the industrialised world, the impact of SARS (Severe Acute Respiratory Syndrome) on employment in Asia and the impact of armed conflict, the latter largely on travel and tourism employment (International Labour Office, 2004). The second increase occurred in 2009, with a global unemployment rate of 6.01 percent. This increase was due to the global recession that occurred in 2008-2009 (Verick & Islam, 2010).

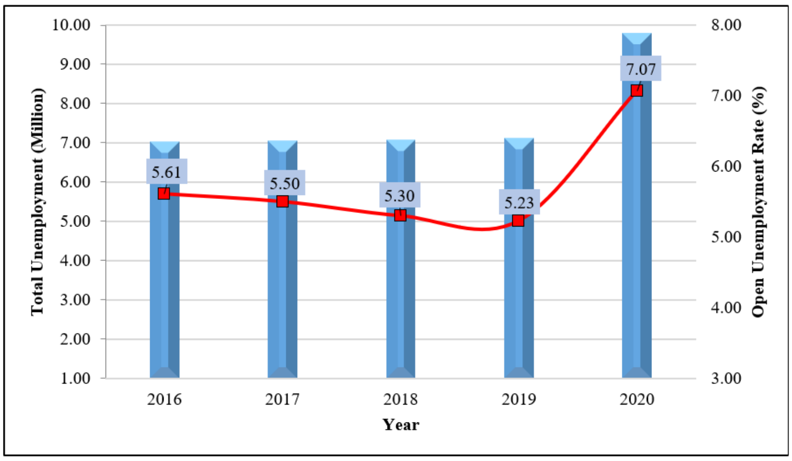

Figure 2. Number and Rate of Open Unemployment in Indonesia in 2016-2020.

Source: Statistics Indonesia (2021)

The Covid-19 virus was discovered in Indonesia on March 2, 2020, and its impact on the rise in the number of unemployed people was felt immediately that year (Alam et al., 2021; Amien, 2020). Statistics Indonesia (2021b) reported that the unemployment rate in Indonesia declined from 2016 to 2019, with a rate of 5.23 percent in 2019. However, the unemployment rate increased 1.84 percentage points to 7.07 percent in 2020, with 9.77 million people out of work. The increase in unemployment in Indonesia is due to the contraction of economic growth by 2.19 percent in the fourth quarter of 2020 (Indayani & Hartono, 2020; Verico, 2021) and the decline in the manufacturing sector, the collapse of businesses for Micro, Small, and Medium Enterprises (MSMEs) (Alam et al., 2021). The Covid-19 pandemic has harmed various economic sectors, and tourism is the most affected in Indonesia. As a result of policies carried out by various countries, including Indonesia, such as lockdown, social distancing, and its kind, economic activity has slowed, tourist arrivals have decreased drastically, and investment has decreased due to the uncertainty caused by the pandemic (Mursalina et al., 2022). Various locked-down activities have caused economic sectors to decline, so worker reductions are often carried out, resulting in movement.

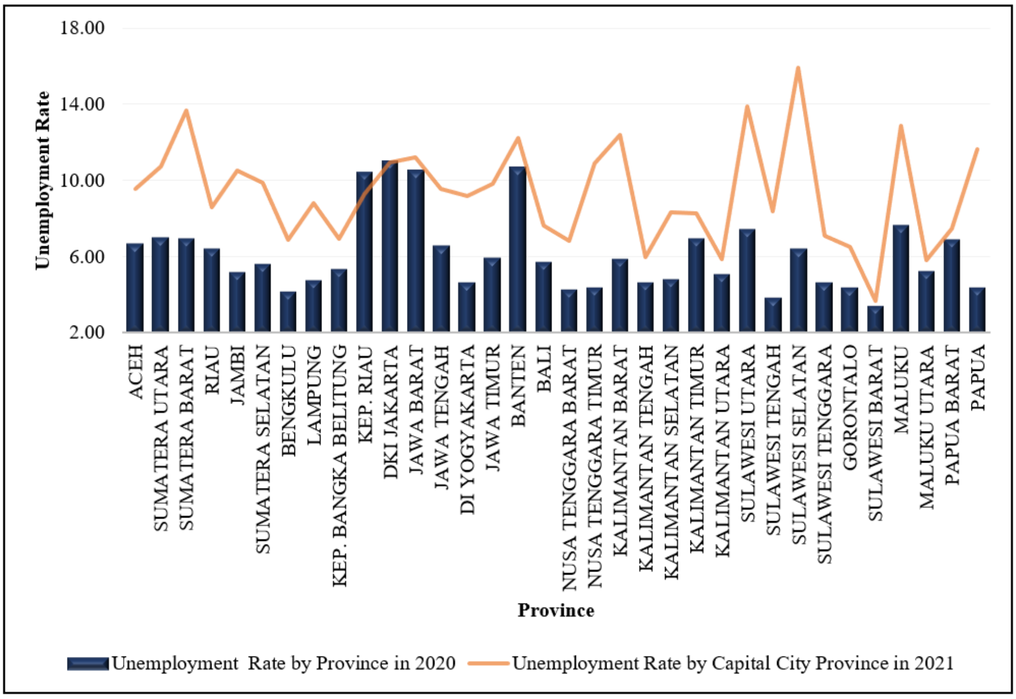

Figure 3. Open Unemployment Rate by Province and Provincial Capital in Indonesia in 2020

Source: Statistics Indonesia (2021)

If we look more closely, the open unemployment rate during the pandemic in each province varies greatly. It is due to differences in the severity of the pandemic that impact economic activity and differences in policies regarding large-scale social restrictions (PSSB). As seen in Figure 3, In 2020, the open unemployment rate in Indonesia was 7.07 percent, while the provincial open unemployment rate ranged from 3.32 percent to 10.95 percent. DKI Jakarta Province has the highest open unemployment rate and the highest increase in the unemployment rate in Indonesia, with an increase of 4.41 percent compared to the open unemployment rate in 2019, which had a value of 6.54 percent. West Sulawesi Province has the lowest unemployment rate, with an unemployment rate of 3.32 percent. It shows that industrial provinces and growth centres impact the increased number of unemployed during the pandemic.

Brooks et al. (2021) reported that the employment rate in urban areas had the most impact during this pandemic. People cannot work and cannot find work because COVID-19 cases are mostly found in densely populated urban areas with high community mobility. Figure 3 shows the unemployment rate in the capital cities of each province in Indonesia, which incidentally is an urban area, has an unemployment rate far above the provincial unemployment rate. Thus, the capital of each province is very interesting to be used as a research area for determining unemployment in Indonesia during the COVID-19 pandemic.

Besides DKI Jakarta Province, five other provinces are above the value of Indonesia's open unemployment rate, namely Banten Province and West Java, Kep. Riau, Maluku, and North Sulawesi. It shows that industrial and growth centres provinces have the most impact on the increase in unemployment during the pandemic. In addition, when viewed by age level, the unemployment rate during the pandemic is much higher than the unemployment rate for all ages, with a value of 20.46 percent. It indicates that the employment rate for young people who have just entered the labour market is much more vulnerable to unemployment than those who have just entered at other age levels.

On the one hand, Indonesia is during a demographic boom, with the proportion of the productive-age population expected to reach 70.72 percent in 2020 (Pramana et al., 2022). On the other hand, if properly managed, the demographic bonus will benefit economic growth, particularly in Indonesia's employment sector, by creating a skilled workforce as human capital to increase labour productivity. Productivity is defined as the value of output produced by one unit of labour or capital (Adriani & Yustini, 2021; Samosir & Rajagukguk, 2017), as demonstrated in China, where economic growth increased by 3.2 percent as a result of the demographic bonus, as well as in South Korea, Singapore, and Thailand (Maryati, 2015). But on the other hand, with the current pandemic conditions, the demographic bonus will backfire on the Indonesian economy if not handled carefully. The increase in the number of unemployed due to restrictions on economic activities as a result of the pandemic, coupled with an increase in the productive age population which is not followed by the creation of employment opportunities, will cause new problems such as increased unemployment, poverty, and social inequality (Nurfitriani & Hartarto, 2018).

The importance of solving the unemployment problem in Indonesia during this pandemic has made many people research it, as reported by Indayani and Hartono (2020) and Rizky et al. (2020), which stated that during the pandemic, the unemployment rate in Indonesia increased dramatically. If viewed broadly, the unemployment rate in developing countries was three times higher. It took twice as long to overcome the impact of the Coronavirus when compared to developed countries in the coming years (Lai et al., 2021). However, it is rare to see the causes of unemployment during the pandemic. The possibility of someone being unemployed during this pandemic is influenced by many things, one of which is individual characteristics (Berhe, 2021). As research conducted by Baah-Boateng (2015) on the causes of unemployment in Ghana. The estimation results state that education, age, marital status, gender, individual characteristics, and household location (household characteristics) cause the increase or decrease in unemployment in the country.

Similarly, Isazadeh et al. (2021) investigated unemployment in Iran. It turns out that what affects the number of unemployed is marital status, household location, work experience, and education. This study is interesting to explore because everyone is inseparable from individual and household characteristics to determine whether to become unemployed or not, especially during this pandemic, so it can be a reference for solving unemployment problems in Indonesia. Therefore, the goal to be achieved in this study is to determine the probability of a person being unemployed in Indonesia during the covid-19 pandemic, which is influenced by individual characteristics (age, gender, status of head of household, marital status, education level, training, work experience) and household (number of household members, and household location).

The household size (number of members) significantly affects unemployment (Hoang & Knabe, 2021). Households with a larger number of members require a higher cost to meet their needs. This condition will encourage other household members to work, so the larger the household size will reduce the number of unemployed. The location of households in urban or rural areas affects unemployment.(Baah-Boateng, 2015) found that the unemployment rate in urban areas is much higher than in rural areas. The phenomenon of high urban unemployment rates is partly explained by the regular migration of the population, particularly the young, from rural areas to urban centres in search of better economic opportunities, which can be difficult to come by at times. The lack of appeal of rural living due to a lack of amenities such as electricity and water, as well as the low income associated with rural economic activity dominated by agriculture, drives many rural youths to urban areas, resulting in a labour surplus in urban areas. Because the island of Java is currently the focus of Indonesia's economic growth, proxies from urban areas are on the island.

2. Materials and Methods

2.1. Materials

The purpose of this study is to determine the level of unemployment in Indonesia during the COVID-19 pandemic. The variables used in this study include unemployment (the dependent variable), individual characteristics (age, gender, head of the household status, marital status, education, training, and work experience), and household characteristics (age, gender, head of the household status, marital status, education, training, and work experience) (number of household members). as independent variables (households and household location). The data used in this study is primary data from Sakernas August 2020 survey results obtained from the Central Statistics Agency. This study examines labour force data from 34 provinces and 38 regencies/cities, the capitals of each province, as well as all cities in DKI Jakarta. The research sample used was 65,535 people aged 15 years and over.

2.2. Methods

The logit model can estimate the probability of a binary response based on a set of predictor variables (Dawood et al., 2019 and Mahfuzah et al., 2020). The dependent variable in the logit model has two possible (binary) values, namely the value "1" if it meets certain criteria given or the value "0" if other than that. Some of the advantages of this logit model are that the linear relationship between the dependent and independent variables is not required, the dependent variable does not have to be normally distributed, and it does not have to avoid heteroscedasticity. Previous researchers have widely used the logit model to determine the determinants of unemployment, such as Baah-Boateng (2015), Aden (2017) and Polonyankina (2018). The logit model can be written as the following equation:

$$Ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \tag{1}$$

Pi is a Bernoulli random variable defined as the probability that the ST variable is 1 with the condition Z and can be written as follows

$$P_i = E\left(ST = \frac{1}{Z_i}\right) = \frac{1}{1+e^{-Z_i}} \tag{2}$$

Individual characteristics that will be seen for their influence on unemployment are Age (UMR), Gender (JK), Head of Household Status (KRT), Marital Status (KWN), and Education Level (PEND), Training (PEL), and Work Experience (KER). The household characteristics include the number of household members (JAK), and the location of the household (LOK). Thus, the model in this study can be written as follows:

$$\begin{aligned} PGG = \beta_0 + \beta_1 UMR + \beta_2 JK + \beta_3 KRT + \beta_4 KWN + \beta_5 PEND + \beta_6 PEL + \beta_7 KER + \\ \beta_8 JAK + \beta_9 LOK + \varepsilon \end{aligned} \tag{3}$$

With PGG was unemployment, β_0 is intercept, β_1 *to* β_9 are the estimated regression coefficient, *and* ε was an *error term*. Methods include the stages and formulas used in data analysis arranged sequentially step by step.

3. Results and Discussion

3.1. Model Significance Test (Likelihood Ratio Test)

The significance test in this study can be seen based on Table 1 from the August 2020 run data from The National Employment Survey. The feasibility of this model using the Likelihood Ratio Test with the hypothesis used was H_0: $\beta_1 = \beta_2 = \ldots = \beta_k = 0$ (there is no independent variable that affects the dependent variable) *exists* $\neq 0$ for $j = 1, 2, \ldots, k$ (there is at least one independent variable that affects the dependent variable).

Table 1. Result of Omnibus Tests of Coefficients Model

	Chi-square	df	Sig.
Step	9732,911	9	0.000
Block	9732,911	9	0.000
Model	9732,911	9	0.000

Table 1 explains that the significance level of the model is 0.000 <0.05, which means that with a 95 percent confidence level, at least one independent variable affects the dependent variable. Thus, the tested model deserves further analysis. The results of this study are in line with the research of Zakki & Sayyida, (2016), which states that the significant value for the model was 0.050 < (in this case = 15% or 0.15), then rejected Ho so that it could be concluded that the logit model in this study pretty good.

Table 2. The Result of the Unemployment Classification Status

Observed		Predicted		
		Unemployment		Percentage Correct
		Work	Not Work	
Unemployment	Work	26.612	10.493	71.7
	Not Work	12.241	16.189	56.9
Overall Percentage				65.3

Table 2 explains that the overall percentage in the Classification Table is 65.3. The model can accurately predict child labour based on independent variables by 65.3 percent. The results of research conducted by Agustiana (2020) showed that a slope of 0.0012 means that the open unemployment rate increases by 0.0014 for every one-year increase. And the coefficient b is positive, meaning that the open unemployment rate and the increase in years have a positive effect. In line with Jalil & Kasnelly (2019), which shows that the Covid-19 pandemic influences increasing unemployment rates, it is predicted that it will continue to increase if this pandemic is not immediately passed or resolved.

3.2. Partial Test (Wald Test)

Partial testing is needed to see the independent variables significantly affecting the dependent variable. The influential independent variable is based on the Wald statistic, which is indicated by the significance value of the Wald statistic, which is less than the maximum error tolerance of 0.1.

Table 3. Result of Logistic Regression Model Effect of Individual and Household Characteristics on Unemployment

Variable	B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
UMR	0.991	0.027	1365,327	1	0.000	2.693	2.555	2.838
JK	-0.808	0.020	1594,059	1	0.000	0.446	0.429	0.464
KRT	-0.552	0.023	559,482	1	0.000	0.576	0.550	0.603
KWN	-0.337	0.021	260,101	1	0.000	0.714	0.685	0.744
PEND	-0.286	0.018	243,849	1	0.000	0.752	0.725	0.779
PEL	-0.292	0.024	147,329	1	0.000	0.746	0.712	0.783
KER	-0.230	0.018	159,245	1	0.000	0.795	1.214	1.304
JAK	-0.017	0.005	9,560	1	0.002	0.984	0.973	0.994
LOK	0.002	0.018	0,019	1	0.889	1.002	0.968	1.038
Constant	0.448	0.033	187,554	1	0.000	1.565		

a. variable (s) entered in step 1: UMR, JK, KRT, KWN, PEND, PEL, KER, JAK, LOK.

Table 3 displays the level of statistical significance for the variables of age (UMR), gender (JK), head of household status (KRT), marital status (KWN), education (PEND), training (PEL), and work experience (KER) is less than 0.01. It provides strong evidence not to reject H1, which means that these variables significantly affect unemployment with a confidence level of 99 percent. The variable number of household members (JAK) has a statistical significance of 0.02. There is evidence that this variable also significantly affects unemployment with a confidence level of 95 percent, only the household location variable (LOK) has no significant effect on unemployment with a wald statistic of 0.889. This insignificant relationship can be explained because the sample areas taken are all provincial capitals as well as the most developed and densely populated areas in each province, so the location variables in Java Island and Outside Java Island have almost the same characteristics. The results of this regression output can be written as an applied model with Equations 4 and 5.

$$PGG = 0.448 + 0.991UMR - 0.808JK - 0.552KRT - 0.337KWN - 0.286PEND - 0.292PEL - 0.230KER - 0.017JAK + 0.002LOK \tag{4}$$

The intercept of Equations 4 and 5 showed that the proportion of the unemployed labour force was greater than those who were not. A person is more likely unemployed if other variables do not influence it. For example, a young woman around 15 – 24 years old, not the head of the family, has marital status and has higher education, has never attended training and has never worked before, has a family of five, and lives on the island of Java.

$$PGG = 0.448 + 0.991(1) - 0.808(0) - 0.552(0) - 0.337(1) - 0.286(1) - 0.292(0) - 0.230(0) - 0.017(5) + 0.002(1) = 0.733 \tag{5}$$

$$P = \frac{e^{PGG}}{1+e^{PGG}} = \frac{e^{0.733}}{1+e^{0.733}} = 0.675 \tag{6}$$

It means that a young man and woman aged 15 – 24 years, not the head of the family, marital status, and has higher education, has never attended training and has never worked before, having a family of five and living on the island of Java will have a 67.5 percent chance of being unemployed, ceteris paribus. In line with research by Zakki & Sayyida (2016), the results of the logistical analysis showed that the four welfare factors analysed, namely the type of business (side business, joint venture, or main), capital (small, medium, or large capital), land ownership (land owned by someone else). Others rent or own ownership and income (small, medium, or large income). Only land ownership is a factor that has a significant effect on welfare.

3.3. Tendency Ratio (Odds Ratio)

The magnitude of the influence of each variable on the chances of children becoming child laborers can be seen through the value of the odds ratio in the Exp(B) column and the sign in the column (B) in the row that corresponds to the following variables:

3.3.1. Individual Characteristics Variables

Age

The age coefficient is positive, which is 0.991, which means that the young workforce aged 15-24 years is more likely to become unemployed. An odds ratio of 2.693 indicates that the opportunity for the workforce aged 15-24 years to become unemployed is 2.693 times greater than that of those aged over 24 years. The results of this study are in line with the research of Eichhorst & Rinne (2015), Caliendo & Schmidl (2016) and Grashuis (2021). A significant decrease in the demand for labour during the pandemic due to many companies going out of business and stopping production activities has caused young people who have just entered the labour market and have no previous experience to be a last resort compared to the older age group (Salauddin et al., 2022). On the other hand, young workers are the first choice at the time of termination of employment (PHK). Wong et al. (2020) noted that the largest layoffs occurred in the young age group 15-24 years, with 34.5 percent. It is associated with a low cost of compensation compared to the older age group with much longer tenure (Luppi et al., 2021).

Gender

The gender variable describes a person's tendency to become unemployed in terms of gender. The gender coefficient is negative, with a value of -0.808, indicating that the female workforce is more likely to be unemployed. The odds ratio value is 0.446, which is less than 1, so the chance that the female workforce becomes unemployed is P = 1/0.446 = 12,242 times that of the male workforce. The large opportunity for women to become unemployed is due to women who are not skilled workers (Queneau & Sen, 2012), difficulty finding work in the formal sector, and job discrimination that can only be done by men (Rusdianti, 2019). The existence of a school-from-home (SFH) policy to anticipate the spread of COVID-19 increases the workload of women in the domestic sector related to child care. It prevents women from working and becoming unemployed (Apriani et al., 2020). These results agree with the findings of Gezici & Ozay (2020) and corroborate the research of Ulfa et al. (2020) and Salam et al. (2021), which states that gender is an important factor in explaining unemployment in Indonesia.

Head of Household Status

The head of the household is the most responsible person in the household. The labour force with the status of the head of the household has a lower risk of becoming unemployed. It can be seen from the negative coefficient, which is -0.552. The value of the odds ratio is 0.576, which means that the labour force which is not the head of the household is more likely to become unemployed by P = 1/0.552 = 1.812 times than the labour force with the status of the head of the household. This study's results align with Olurinola & Fadayomi (2013) and Corbacho et al. (2007) where status other than the head of the household is more vulnerable to being unemployed. The status of the head of the household correlates with unemployment. The head of the household is less likely to be unemployed in urban and rural areas. It is because the head of the household has many responsibilities; thus, when he is unemployed, he seeks work intensively, unlike other household members (Kirika, 2014).

Marital status

The marital status variable has a negative coefficient of -0.337, indicating that the labour force with a status other than married has a higher risk of becoming unemployed. The odds ratio value is 0.714, explaining the risk of the labour force with a status other than married to becoming unemployed is 1/0.714 = 1.401 times that of the labour force with married status.

Education

The education variable has a negative coefficient of -0.286, indicating that the workforce with the lowest education level at the junior high school level is more at risk of becoming unemployed. The odds ratio value is 0.752, explaining that the risk of the workforce with low education becoming unemployed is 1/0.752 = 1.330 times that of the workforce with a high school education/equivalent and above. (Capps et al., 2020),(Bell & Blanchflower, 2020), and (Holmes et al., 2020) noted that the low-educated group was the group most vulnerable to being fired during a pandemic in England and the United States. The low level of education means that most of these groups can only work in the informal sector, such as construction, manufacturing, and transportation, and cannot work from home. So that when the implementation of the Lockdown and Large-Scale Social Restrictions policy, the worker becomes the first choice to be fired. The results of this study confirm the findings of (Aden, 2017) that the probability of becoming unemployed is smaller if the level of education is higher. Individuals who do not have certificates, diplomas, or degrees have the highest probability of being unemployed.

Training

The training variable has a negative coefficient of -0.292, indicating that the workforce which has never attended training has a higher risk of becoming unemployed. The odds ratio value is 0.746, explaining that the risk of the workforce who has never attended training becoming unemployed is 1/0.746 = 1.340 times that of the workforce who have attended the training. This finding is in line with the results of research by Daminov et al., (2021) that providing experience abroad through training can reduce the number of unemployed, especially youth unemployment, and also the results of research by Oswald-Egg & Renold, (2021) that work experience from education and vocational training makes it easier for college graduates smoothly enter the job market so that unemployment can be reduced. One of the policies that can be applied to reduce unemployment during the pandemic is job training, as described by Tcherneva, (2022) and Fernández-Marín et al., (2022). This training provides new experience and skills to adapt abilities to pandemic conditions, upgrade technology knowledge, and create products or businesses that continue to run during social restrictions, making it easier for them to re-enter the job market.

Work experience

The coefficient of work experience is negative, which is -0.230, which means that the workforce without work experience is more likely to become unemployed. An odds ratio of 1.258 indicates that the opportunity for the workforce without work experience to become unemployed is 1.258 times greater than the workforce without work experience. The results of this study corroborate the results of research by DEREJE, (2018) and Eshetu et al., (2022) that, saying work experience negatively affects unemployment at a significant level of 1 percent. (Isazadeh et al., 2021) examined the duration of unemployment in Iran. The results showed that people with previous work experience were much more likely to be hired than people without previous work experience. Women with work experience have three times the chance of getting out of unemployment compared to women without experience.

3.3.2. Variables of Household Characteristics

Number of Household Members

The sign on the variable coefficient of the number of household members is negative, namely -0.017, and the odds ratio is 0.984. By reducing the number of household members, the labour force will increase to 1/0.984 = 1.016 times. This finding is in line with the research of (Hoang & Knabe, 2021), which found that the house size (number of members) significantly influences the effect.

Household Location

It provides significant evidence that the labour force in Java is more likely to be unemployed, although the effect is not significant. An odds ratio value of 1.002 explains that someone who lives in Java is at risk of becoming unemployed by 1.002 times more than the workforce who lives outside Java. This study's results align with (Baah-Boateng, 2015), who states that the unemployment rate in urban areas is much higher than in rural areas. Before the pandemic, population migration to Java Island always occurred and caused a very high population spike. In addition, the Large-Scale Social Restrictions (PSBB) and the Enforcement of Restrictions on Community Activities (PPKM) have been carried out several times as a policy to reduce the spread of COVID-19 on Java Island, which has weakened economic activity and increased unemployment on the island, compared to other areas.

4. Conclusions

This study aims to determine the likelihood of a person being unemployed in Indonesia during the COVID-19 pandemic. Unemployment is influenced by individual characteristics (age, gender, head of household status, marital status, education level, training, and work experience) and household characteristics (number of household members and household location). With logistic regression, this study observes data from 65,535 workforces aged 15 years and over in the August 2020 Sakernas. The results of this study provide strong evidence that there is a significant effect between individual characteristics (age, gender, head of the household status, marital status, education level, training, work experience), and household characteristics (number of household members), except household location variable on a person's probability of becoming unemployed. The young workforce (15 – 24 years) is in line with the increase in a person's chances of becoming unemployed. While men, heads of families, married, have higher education, have attended training, have work experience, and the number of household members is in line with the decrease in a person's chance of becoming unemployed.

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