

Article

The Impact Of The KartuPrakerja Program On Unemployment Using Geographically Weighted Panel Regression (GWPR) In Indonesia

Yonata Putri¹, Chairullah Amin², Rizal Rahman H. Teapon³

1,2,3 Universitas Khairun

*Correspondence: yonata.putri@bps.go.id

Abstract: Various efforts and programs are being implemented by the government to continue to reduce unemployment rates and the proportion of young people who are not working, not pursuing education, or training. The pre-employment card is a training cost assistance for the Indonesian people who want to acquire or enhance their skills. According to regulations, all individuals aged 18 and above who are not currently attending school/college can enroll in this program. Furthermore, the program also focuses on job seekers, workers who have been laid off, workers who need competency enhancement (including those who have been furloughed and micro & small business owners). From May 2020 to April 2023, this program has been conducted in 51 waves with a total of 14.9 million participants. As for 2023, the government has allocated a budget of Rp4.37 trillion with a target of 1 million recipients. This study aims to examine the impact of the pre-employment card program and other macroeconomic variables such as HDI, minimum wage, inflation, and economic growth using Geographically Weighted Regression (GWR) model. The resulting model shows a determination coefficient of 87.04%, with the factors most influencing the decrease in unemployment rates in Indonesia being HDI, job market size, and minimum wage. Additionally, the pre-employment card program is only effective in reducing unemployment rates in 7 provinces in Indonesia, namely Riau Island, Riau, Jambi, DKI Jakarta, Central Java, Yogyakarta, and East Nusa Tenggara.

Keywords: Unemployment, Kartu Prakerja, Macroeconomics, Spatial Panel Regression.

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1. Introduction

Demographic bonus can be likened to a coin with two sides, where both sides can either be advantageous or disadvantageous for a country. A demographic bonus is beneficial when a large productive population is accompanied by quality education and skills, as well as job opportunities that can accommodate the workforce to generate output for the nation. However, when a large productive population is not matched with adequate education and sufficient employment opportunities, it can lead to an increase in unemployment rates, ultimately impacting the level of criminality in a region. One instance of a poorly utilized demographic bonus phenomenon occurred in South Africa. According to an article by Mogomotsi on Apnews, the unemployment rate in South Africa has reached 33%, making it the highest in the world. This has resulted in riots, looting, and over 350 fatalities. (Magome, 2023)

Unemployment is one of the major enemies in the phenomenon of demographic bonus as high levels of unemployment can lead to a decrease in national income, an increase in poverty, a decrease in consumption, an increase in criminality, social conflicts, mental health issues, educational barriers, and erosion of cultural values. Unemployment is also addressed as one of the issues under the Sustainable Development Goals (SDGs)

Point 8 aimed at reducing the proportion of young people not working, not in education, or training. Indonesia Central Statistics Agency shows that in 2022, the unemployment rate in Indonesia was 5.86 percent. According to the National Medium-Term Development Plan (RPJMN) 2020-2024 document, the target for unemployment in Indonesia is 4 percent. (Kementerian Perencanaan Pembangunan Nasional/ Badan Perencanaan Pembangunan Nasional, 2017)

The government is implementing various efforts and programs to continue reducing the unemployment rate and the proportion of young people not working, not in education, or training. One of the challenges for the government in addressing socio-economic issues in Development is regional challenges. Indonesia is an archipelagic country that has unique characteristics and features in each of its islands. Each region in Indonesia has its own uniqueness and characteristics, which pose diversity but also challenges in addressing development issues like unemployment.

One of the government's efforts to enhance human resources in Indonesia is through the implementation of the Kartu Prakerja program, which began in 2020. The Kartu Prakerja program is an online training program, and its effectiveness in boosting employment opportunities relies on good internet penetration. (D. Prasetyo & Khodijah, 2020). Additionally, research by (Zaki & Pertiwi, 2023) that there is a significant positive impact between the provision of the "Kartu Prakerja" program and the level of labor absorption. Research from (Putri, 2022) said that "Kartu Prakerja" program is have been effective in enhancing social welfare amidst COVID-19 through effective criteria in terms of program targeting, program socialization, program monitoring, and program objectives.

Research by (Azmi & Rizqi, 2019) in Central Java Province shows spatial connections in cases of unemployment. There are regional groupings based on open unemployment levels in Central Java. That is why researchers feel the need to conduct a study on impact of the implementation of Kartu Prakerja on unemployment in Indonesia by involving regional aspects.

2. Materials and Methods

The use of the GWPR method in measuring the influence of the Kartu Prakerja program and other macroeconomic variables is still limited. Research by (A. Prasetyo & Rachmawati, 2022) states that the Kartu Prakerja program is an online training program, which optimally increases labor absorption only when supported by good internet penetration. (Zaki & Pertiwi, 2023) states that there is a significant positive effect between the provision of the Kartu Prakerja program and the level of workforce absorption.

The determination of indicators in this research is based on the aim to identify the determinant factors that influence unemployment in Indonesia. The dependent variable covers the unemployment rate of all provinces in Indonesia, while the independent variables include the percentage of participants in the Kartu Prakerja program, labor force participation rate, provincial minimum wage, human development index, economic growth, and inflation. The unit of analysis is all provinces in Indonesia. The description of the average values of variables for each unit of analysis is shown in Table 1.

Table 1
Data Information of Dependen Variable and Independen Variable

Regions	Average (2020 -2023)						
	Y	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆
	Unemployment Percent (%)	TPAK Percent (%)	PP Percent (%)	UMP (Rp)	IPM Percent (%)	Inflasi Percent (%)	PE Percent (%)
Aceh	6.27	64.23	4.62	3,227,547	72.59	3.31	2.60
North Sumatera	6.32	70.69	2.78	2,557,987	72.46	3.01	2.80
West Sumatera	6.41	69.23	4.28	2,555,774	73.01	3.35	2.59
Riau	4.84	64.62	3.69	2,976,839	73.30	3.32	2.70
Jambi	4.84	68.23	4.76	2,725,575	71.96	3.56	3.30

South Sumatera	4.81	69.79	3.26	3,184,045	70.69	3.12	3.45
Bengkulu	3.68	70.81	6.35	2,271,245	72.00	3.08	2.88
Lampung	4.53	70.19	3.10	2,484,444	70.30	3.29	2.33
Bangka Belitung Islands	4.90	67.21	7.20	3,305,853	72.06	3.50	2.79
Riau Islands	8.82	69.13	5.98	3,085,072	76.24	3.01	2.40
Special Region of Jakarta	8.29	63.68	6.26	4,559,047	81.50	2.40	2.84
West Java	9.01	66.08	2.83	1,862,215	72.85	3.10	2.81
Center of Java	5.78	70.72	2.11	1,828,025	72.55	2.95	2.73
Special Region of Yogyakarta	4.22	73.58	3.46	1,823,076	80.48	3.34	3.26
East Java	5.49	71.55	2.14	1,892,341	72.50	3.33	2.86
Banten	8.81	64.49	3.61	2,521,119	73.09	2.88	2.78
Bali	4.62	76.85	3.38	2,554,661	76.18	3.84	-0.40
West Nusa Tenggara	3.30	72.01	3.64	2,236,596	69.14	2.99	2.55
East Nusa Tenggara	3.68	75.21	2.45	1,999,749	65.76	2.84	1.70
West Kalimantan	5.45	69.66	3.66	2,460,582	68.40	3.06	3.08
Center of Kalimantan	4.37	67.88	4.87	2,977,455	71.53	3.33	3.09
South Kalimantan	4.69	69.61	4.95	2,952,837	71.63	3.41	2.84
East Kalimantan	6.18	65.62	4.74	3,044,663	77.19	2.94	2.36
North Kalimantan	4.47	68.84	7.48	3,067,512	71.54	2.81	3.26
North Sulawesi Utara	6.79	63.43	4.94	3,354,292	73.60	2.43	3.50
Center of Sulawesi	3.37	69.76	4.32	2,399,427	70.14	3.03	11.20
South Sulawesi	5.22	65.63	3.68	3,205,174	72.61	3.26	3.27
Southeast Sulawesi	3.75	69.85	5.01	2,609,758	72.03	3.48	3.48
Gorontalo	3.23	68.04	7.29	2,841,896	69.49	3.99	2.76
West Sulawesi	2.77	71.16	6.94	2,727,096	66.74	3.21	2.51
Maluku	6.92	65.07	5.39	2,660,516	70.09	3.10	3.24
North Maluku	4.54	65.79	4.87	2,820,503	69.23	3.07	17.56
West Papua	5.85	69.58	5.55	3,187,800	65.73	2.74	1.12
Papua	3.28	77.40	1.12	3,615,007	61.18	2.69	8.70

Source: (BPS RI, 2023)

Data in the form of provincial panels in Indonesia for the period 2020 – 2023 is obtained through documentation on websites provided by the Central Statistics Agency and the Indonesian Data Center.

Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) model, first introduced by Fotheringham in 1967, is an extension of the classic ordinary linear regression (OLR) model. GWR is a regression model developed to analyze data with continuous response variables, taking into account spatial or locational aspects.

The approach used in GWR is a point approach. Each parameter value is estimated at each observation location point, so each observation location point has different parameter values. Regression estimation in Geographically Weighted Regression (GWR) is done

using the Weighted Least Square (WLS) method, which is the least squares method with different weighting at each observation location point. The weighting is in the form of a diagonal matrix where the diagonal elements are a weighting function of the observation location point.

Spatial Weighting

Formation of spatial weighting matrix or weighting matrix in the GWPR method involves creating a weighting matrix for each region i at coordinates (u_i, v_i) with other observation areas without any explicitly stated relationship, represented by $W(u_i, v_i)$. (Fotheringham et al, 2002)

In determining the magnitude of the weight for each region, the selection of appropriate weights according to their conditions can be made. This research will use kernel functions to estimate the parameters of the GWPR model. The kernel weight functions consist of the Gaussian kernel function, the bisquare kernel function, and the tricube kernel function. The Gaussian kernel function by (Fotheringham et al, 2002) is defined as

$$w_{ij} = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}}{b} \right)^2 \right]$$

This function will provide weighting that decreases gradually following a normal curve between regions i and j as the distance between regions i and j increases.

Determining the bandwidth value for a specific weighting function is important in GWR analysis. Bandwidth plays a role as a smoothing parameter, where the larger the bandwidth value, the smoother the resulting parameters will be. A bandwidth value that is too large will result in almost identical parameter values in each local model generated, while a value that is too small will lead to excessive variation in the parameters of the local model formed. (Fotheringham et al, 2002)

To obtain the optimal bandwidth value, one way that can be used is to select the bandwidth value that minimizes the cross-validation (CV) function.

CV is a technique to select the optimal bandwidth value that minimizes the following value :

$$CV = \sum_{i=1}^n [(y_i - \widehat{y}_{i \neq i})^2]$$

$\widehat{y}_{i \neq i}$ is an estimate of y_i where the i -th observation value is removed from the GWR model estimation. The calculation of CV can only be performed when the number of observation areas is equal to the number of local regression models that can be formed.

3. Results

The examining the impact of the Kartu Prakerja program policy and macroeconomic variables on unemployment, spatial panel regression analysis is used. The first step taken by the researcher is to conduct regression on panel data followed by testing classic assumptions. When conducting classic assumption tests, the data available has met the classic assumption tests including multicollinearity. The test for multicollinearity is done using the VIF test, where if the VIF value is less than 10, it can be interpreted that there is no multicollinearity among all independent variables.

After the classic test, the best regression model to be used is selected. The selection of the best regression model is done to ensure appropriate estimates. This selection is done in two stages, first by comparing the common effect model (CEM) with the fixed effect model (FEM) and second by comparing the fixed effect model (FEM) with the random effect model (REM). In the first stage, the Chow test is used to compare CEM with FEM. Whereas in the second stage, to compare FEM with REM, the Hausman test is used. From the chow test results, the probability value of the Cross-section Chi-square is (p-value = 0.0000), meaning that H_0 (common effect model) is significantly rejected, showing individual heterogeneity in the model. This is indicated by a p-value of (p-value

= 0.000) < 0.05. If individual heterogeneity is found in the model, FEM will provide better results compared to CEM.

After obtaining the best model in the Chow test phase, the next step is to compare the Fixed Effects Model (FEM) and random effect model using the Hausman test. The Hausman test results show that the probability value of Cross-section random is (p-value = 0.0000) > 0.05, thus rejecting the null hypothesis (H0). This means that the appropriate model for panel data analysis in this study is the FEM. Additionally, an R2 value of 0.6272 or 62.72% indicates that the independent variables used sufficiently describe the model. Next, it is necessary to conduct classical assumption tests, namely the normality test and multicollinearity test. The normality test results show that the Kolmogorov-Smirnov test probability value is (p-value = 0.04405) > 0.05, thus accepting the null hypothesis (H0). This signifies that the residual data in the regression model follows a normal distribution.

Residual testing continued with autocorrelation testing using the Breusch-Godfrey test, yielding a significance value of 0.06919, indicating no autocorrelation among the independent variables in the regression model. Additionally, residual testing using the Breusch-Pagan test resulted in a significance value of 0.4593, meaning there is no heteroscedasticity present.

Geographically Weighted Panel Regression (GWPR) analysis is essentially the same as GWR cross-sectional analysis. GWPR analysis assumes that the temporal sequence of observations at a geographic location is a realization of a smooth spatiotemporal process. This process follows a distribution where nearby observations are more related than distant ones. The objective of GWPR analysis is to collectively combine locations and observations. The estimation of GWPR model parameters uses the Weighted Least Squares (WLS) approach similar to the GWR model.

In conducting GWPR modeling, the initial step is to measure the Euclidean distance between provinces. Geographic coordinate data, including latitude and longitude, are used for this purpose. The geographic coordinate data utilized in this study are the centroids of each province obtained using R software. Once the Euclidean distances are calculated, the next step is to select the most appropriate spatial weighting function to obtain the spatial weighting matrix for use in GWPR modeling.

The selection of weights can be done by comparing the values of the Akaike Information Criterion (AIC) to find the smallest one. The AIC values of each kernel function weight are useful in defining the kernel function needed during GWPR modeling. (Fallis, 2013)

Table 2
AIC and Error Comparison for Each Type of Weighting

Wheighting	RSS	R ²	R ² Adj	AIC
Adaptive Bisquare	10.019	0.976	0.927	110.917
Adaptive Gaussian	96.325	0.777	0.708	363.720
Adaptive Exp	82.452	0.809	0.728	346.139
Fixed Bisquare	22.407	0.948	0.870	211.598
Fixed Gaussian	7.0822	0.983	0.926	75.647
Fixed Exp	0.333	0.999	0.913	-303.936

Table 2 above shows that the Fixed Kernel Exponential weighting function has the lowest error and AIC values with the highest R2 and R2 adj values. Hence, the selected weighting function is Fixed Kernel Exponential. The Fixed Exponential weighting function has the minimum CV value, specifically Fixed bandwidth: 0.6296803 with a bandwidth value of 68.49432.

Therefore, the spatial weighting matrix can be determined using the Fixed Exponential weighting function. This spatial weighting matrix will be used to conduct GWPR modeling to estimate the parameter values of the model. The estimated parameter values in GWPR modeling will vary for each province but remain constant for each year.

Using six independent variables will result in 204 parameters (β_k) (u_{i,v_i}) and 34 models with maximum and minimum values presented in Table 4.

Since 34 model equations have been formed with different significant independent variables, for ease of discussion, the provinces will be grouped based on the similarity of significant independent variables in Table 4.

Table 4.
Grouped Based On The Similarity Of Significant Independent Variables.

No	Independent Variable	Province	Count
1	Labor Force Participation Rate	North Sumatra, Riau, South Sumatra, Bengkulu, Lampung, DKI Jakarta, West Java, Central Java, East Java, Banten, Bali, West Nusa Tenggara, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi	18
2	Kartu Prakerja	Riau, Jambi, Riau Islands, DKI Jakarta, Central Java, DIY Yogyakarta, East Nusa Tenggara	7
3	Minimum Wage	Riau, Jambi, South Sumatra, Bengkulu, Bangka Belitung Islands, Riau Islands, DKI Jakarta, West Java, Central Java, Yogyakarta, Banten, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, Maluku, West Papua, Papua.	18
4	HDI	Aceh, North Sumatra, West Sumatra, Riau, Jambi, Lampung, Bangka Belitung Islands, Riau Islands, Jakarta Special Capital Region, West Java, Central Java, Banten, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, Gorontalo, Maluku, West Papua.	27
5	Inflation	Jakarta, North Sulawesi, Gorontalo	3
6	Economic Growth	West Sumatra, Riau, Jambi, Bengkulu, Lampung, Riau Islands, DKI Jakarta, West Java, Yogyakarta, Banten, West Nusa Tenggara, East Nusa Tenggara, Maluku, North Maluku, West Papua, Papua.	17

From Table 4, we can see that the variable HDI has the most significant impact on the unemployment rate in 27 provinces in Indonesia, while the variables Labor Force Participation Rate and UMP are significant in 18 provinces in Indonesia. As for the variable percentage of pre-employment cards itself, it is only significant in 7 provinces in Indonesia, namely Riau, Jambi, Riau Islands, DKI Jakarta, Central Java, Yogyakarta, and East Nusa Tenggara.

When viewed from the regional distribution, in the Eastern part of Indonesia, the variables that have a significant impact are economic growth and wages. In the Western part of Indonesia, factors that greatly affect the unemployment rate are TPAK and IPM. Meanwhile, in the Western part of Indonesia, more significant factors influencing unemployment include TPAK, IPM, UMP, and economic growth. This could be a consideration for the government to focus more on addressing unemployment based on the variables that impact unemployment in each respective region.

Table 5
Range of estimated coefficients for GWPR model

Variabel	Minimum	Maximum
Intersep	-66.9888783	48.4860486
Labor Force	-0.63	0.243
Kartu Prakerja	-0.27	0.41
Minimum Wage	-0.000005446	0.000002276
HDI	-0.714	1.152
Inflation	-0.344	0.520
Economic Growth	-0.42	0.057

Source : Output Software R GWPR analyze

From Table 5, it can be seen that the intercept coefficient and all independent variables have maximum values with positive coefficients and minimum values with negative coefficients. Negative coefficients indicate that the variable has a negative impact on the unemployment rate, while positive coefficients indicate a positive influence.

4. Discussion

TPAK, which represents the profile and size of the workforce potential in a region, can increase the unemployment rate in that area if the TPAK increases but is not accompanied by the availability of job opportunities in that region. This finding aligns with research on the unemployment rate in Central Java from 2009-2014 by Kasanah and others, which states that an increase in the population will result in a growth in the labor force, so with the available job positions not able to fully absorb the labor force, ultimately leading to an increase in the unemployment rate. (Kasanah et al., 2018)

On the other hand, improving TPAK can help reduce unemployment rates if the increase in workforce is accompanied by the availability of job opportunities so that the workforce is adequately absorbed. This is in line with Adam Smith's theory that an increase in population as a workforce can have a positive impact on marginal production because additional labor can also produce more output. (Smith, 1776)

The province that has a positive coefficient for the parameter β of the variable participants in the Kartu Prakerja program from the GWR model is Riau Islands Province, which is 0.386. This means that, assuming all other variables remain constant, an increase of 1 level in the participants of the Kartu Prakerja program will increase unemployment by 0.386.

This can happen if job seekers who have completed training cannot find suitable jobs that match the skills acquired through their training in their area. Some studies also suggest that in the short term, job training may increase unemployment rates due to the time it takes to find a job that aligns with the job seekers' abilities. However, in the long run, job training will have a positive impact on job stability and worker well-being.

On the other hand, the spatial regression model of GWPR results in Central Java Province shows that the coefficient of the independent variable, participants of the kartu prakerja program, is -0.18. An increase of 1 level in participants of the kartu prakerja program will decrease the unemployment rate by 0.18 percent with the assumption that other variables remain unchanged. This indicates that the kartu prakerja program has successfully achieved its goal as one of the solutions to reduce the unemployment rate. This aligns with research stating that the government's provision of the worker card program has benefits for recipients to participate in job training, equipping them with sufficient skills to enter the workforce. Furthermore, research by Indah in Aceh in 2022 also concluded that the Kartu Prakerja Program was able to reduce the unemployment rate in Aceh from 160,562 individuals in 2021 to 150,176 in 2022. (Indah, 2022)

The training/course for the Kartu Prakerja program is conducted through digital platforms. Partner digital platforms include Tokopedia, Bukalapak, Skill Academy, Pintaria, and others. The facilities obtained by the community members who passed the pre-work card selection include training costs of 1 million, incentive costs of 600 thousand rupees per month paid for 4 months, and survey intensive costs of Rp. 500,000. From May 2020 to April 2023, this program has been implemented for 51 waves with a total of 14.9 million recipients. For the year 2023, the government has allocated a budget of Rp4.37 trillion with a target of 1 million individual recipients.(Muhamad Ibrahim, 2023)

This Kartu Prakerja program is expected by the government to address the issue of unemployment caused by Pigou in 1968, which is the mismatch between the skills possessed by workers and the qualifications needed by companies or employers.(Pigou, 1968) Job training is an intervention that can reduce the duration of unemployment for individuals. Job-oriented skill training will have long-term positive effects. Although skill training may initially extend the period of unemployment, in the long run, job training will impact job opportunities and ensure stable income that can last for years to come.(Osikominu, 2021)

The Kartu Prakerja program only affects unemployment in 7 provinces in Indonesia and does not have an impact on the other 27 provinces. This is in line with research that indicates the Kartu Prakerja program is less effective due to the online registration process, leading some individuals to use the services of agents because of their lack of understanding of technology. Furthermore, participating in the Kartu Prakerja program does not guarantee immediate employment.(Yana, 2021)

Consistent with this, other research from (Geraldo & Pingkan, 2024)also states that the Kartu Prakerja Program is ineffective in reducing the duration of job search for job seekers. The average duration of job search between job seekers who have participated in the Kartu Prakerja program and those who are not graduates of the program does not differ significantly.

Another study on the Kartu Prakerja Program from (Tritanti, et al 2021) conducted in East Jakarta shows that one of the obstacles affecting the effectiveness of this program is the need for sufficient and stable internet quota and signal. When these are not available, participants are unable to fully engage in the training program.

From the wage perspective, the province of Riau with a regression coefficient of UMP variable -1.07×10^{-6} implies that for every increase of Rp. 1,000,000 (one million rupiah) in UMP, unemployment rate will decrease by 1.07%, assuming other variables remain constant. UMP can reduce unemployment rate according to Keynes' view that wage increases lead to higher consumption due to enhanced income, resulting in an increased demand for labor to boost production processes.

This result is also in line with the research conducted by (Setyawan, 2021)but contradicts the research by (Baihawafi & Sebayang, 2023) In the study it is stated that wages have a positive impact on the unemployment rate. Increasing wages will increase the unemployment rate in accordance with the wage rigidity theory. Wage rigidity refers to a situation where the wage level of workers is higher than the equilibrium level in the labor market, which can lead to higher unemployment rates. Inflexible wages can make it difficult for companies to adjust wages to existing economic conditions, thus affecting their ability to employ a large number of workers.(Ricardo & Iron, 1834)

In some provinces in Indonesia, the increase in UMP also affects the rise in unemployment. From the GWPR regression modeling in DKI Jakarta Province, the regression coefficient is 2.09×10^{-6} , meaning that every increase in UMP of Rp.1,000,000,- will increase unemployment by 2.09%. Wage increases will also cause companies to raise the criteria for worker quality, making it difficult for job seekers who do not meet the required criteria to find employment and become unemployed.

In terms of human quality, one of the regions with a negative coefficient is the East Nusa Tenggara Province, which is at -0.241. A 1-level increase in HDI in this province will decrease the unemployment rate by 0.241 percent.

Several empirical studies such as research by (Sebayang, 2023)(Lailan Syafrina, 2023), and (Charen, 2022) show consistent results that there is a negative relationship between the Human Development Index (HDI) and the unemployment rate. This means that the higher the HDI in a region, the tendency is for the unemployment rate to be lower. This is because the improvement in human resource quality can drive economic growth and job creation.

Other studies, such as research by (Lailatul Qamariyah et al., 2022) have found that an increase in the Human Development Index (HDI) has the opposite effect, namely, it positively impacts or increases the number of unemployed individuals in a region. This can occur because individuals with higher education levels tend to be more selective when it comes to job opportunities. They would rather wait and search for a job that aligns with their education and skills, instead of working in the informal sector. This could lead to an increase in unemployment among educated and qualified individuals if not accompanied by the availability of job opportunities that match the qualifications of job seekers. (Daniela-emanuela et al., 2023)

Inflation has a significant negative impact on unemployment in several provinces in Indonesia. In North Sulawesi, an increase in inflation reduces unemployment cases with a coefficient of -0.344. This means that for every one percent increase in inflation, the unemployment rate will decrease by 0.344 percent, assuming *ceteris paribus* or in other words, all other variables are considered constant.

This result is consistent with A.W Philips' theory explaining how the unemployment rate is related to inflation, assuming that inflation indicates an increase in aggregate demand (Mankiw, 2003) According to the demand theory, prices will rise if demand increases. To meet this demand, producers increase their production capacity by hiring more labor, which is the only input that increases output. As a result, unemployment decreases as the demand for labor increases with inflation. Additionally, this research findings are consistent with those of (Ummatin, 2020) and (Fahmi, 2022) which show that inflation has a significant impact on the unemployment rate.

Several other studies have found different results, namely that inflation has a positive impact on unemployment in a certain region. Research by (Astrid & Soekapdjo, 2020) shows that inflation affects the increase in prices of goods and the decrease in purchasing power of the population. In the long term, as the purchasing power of the population continues to decline, the demand for goods will also decrease, leading to companies adjusting their production and workforce numbers, ultimately resulting in an increase in the unemployment rate.

In line with the research, the inflation variable in the spatial regression equation in the DKI Jakarta Province has a coefficient of 0.52, which can be interpreted as every 1 level increase in inflation will increase unemployment in the DKI Jakarta region by 0.52% under the assumption of *ceteris paribus*.

Economic growth and unemployment are closely related because working population contribute to the production of goods and services, while the unemployed do not contribute. One of the reasons for high economic growth is the strengthening of consumer consumption. Large consumption is certainly an indication of high purchasing power of the population. With high purchasing power, they can spend large amounts of money. As a result, various economic sectors can thrive and grow. With high demand, supply from various sectors will be stimulated and new job opportunities will be created.

Aligned with that and the research by (Lailan Syafrina, 2023) and (Auliya & Agusalam, 2022) this study found that the variable of percentage of economic growth has a negative and significant impact in some regions on unemployment. In North Maluku Province, a regression coefficient of -0.082 was obtained. This means that, for every one

percent increase in economic growth, the number of unemployed individuals will decrease by 0.082 percent in North Maluku, assuming ceteris paribus or in other words, all other variables are held constant.

5. Conclusion

Kartu prakerja is a training cost assistance for Indonesian people who want to acquire or enhance their skills. According to the regulations, anyone aged 18 years and above who is not currently in school/college can enroll in this program. Furthermore, the program also focuses on job seekers, workers laid off, workers in need of competency improvement (including those who are temporarily laid off and micro & small business owners). According to Presidential Regulation No. 76 of 2020, the objectives of the Kartu Prakerja Program include developing workforce competencies, increasing workforce productivity and resilience; and promoting entrepreneurship. (Kementerian Sekretariat Negara Republik Indonesia, 2020)

The model analysis results show that the government-initiated Program Kartu Prakerja effectively influences the unemployment rate in 7 provinces in Indonesia, namely Riau, Jambi, Riau Islands, DKI Jakarta, Central Java, DIY Yogyakarta, and East Nusa Tenggara. Many factors contribute to the lack of success of the Kartu Prakerja in influencing unemployment cases in Indonesia, both in terms of training systems, human quality, job field distribution, and also infrastructure such as the necessary signal in online training.

The government needs to evaluate the online implementation of the Kartu Prakerja program, which offers the same type of training for all regions in Indonesia. It is advisable for the government to map out the specific skill needs of each region in Indonesia so that this program can effectively reduce unemployment rates nationwide. The government can also establish partnerships with companies in need of workforce, allowing program participants to undergo training aligned with the companies' requirements and directly enter the workforce upon completing the training. Furthermore, face-to-face training should be considered to minimize potential fraud among program participants.

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