J-naker
Jurnal Ketenagakerjaan

Jurnal Ketenagakerjaan
Volume 20 No. 3, 2025
Online ISSN: 2722-8770
Print ISSN: 1907-6096

The Impact of Kartu Prakerja Program Participation on the Decision to Become a Gig Worker and Gig Worker Earnings in Indonesia

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Abstract

The COVID-19 pandemic caused many individuals to lose their jobs and face economic uncertainty, prompting a shift toward more flexible work arrangements such as gig worker work—freelance jobs based on digital platforms without formal employment contracts. To address the employment impact, the government launched the Kartu Prakerja Program as an effort to enhance skills and support labor adaptation. This study aims to analyze the general characteristics of Kartu Prakerja recipients and examine its impact on individuals' decisions to become gig workers, as well as its effect on their earnings. The data used in this study come from the August 2024 National Labor Force Survey (Sakernas) by BPS-Statistics Indonesia, employing the Propensity Score Matching (PSM) method to reduce potential estimation bias and the Tobit model to account for censored earnings data. The findings reveal that the Kartu Prakerja Program increases the likelihood of individuals becoming gig workers but reduces their earnings. These results suggest that, although the program effectively facilitates transitions into the digital sector, further evaluation is necessary to ensure its benefits are distributed more evenly, particularly in supporting skill development and earnings growth among gig workers.

Keywords: gig worker, kartu prakerja program, propensity score matching, tobit.

DOI: 10.47198/jnaker.v20i3.539 Received: 20-08-2025 Revised: 17-12-2025 Accepted: 26-12-2025

1. Introduction

In recent years, the gig economy has gained significant attention in line with the rapid advancement of digital technologies and the emergence of online platforms that facilitate flexible, project-based (on-demand) work. Workers in this system-commonly referred to as gig workers-typically operate without formal contracts, depend on fluctuating market demand, and generally lack access to social protection and earnings security. As a result, gig workers are often classified as part of the informal sector (International Labour Organization, 2021).

The challenges faced by gig workers are not limited to economic vulnerability but also encompass low levels of skill and digital literacy, particularly in utilizing information technology to improve productivity. According to the Pathways Commission (2022), only around 50 percent of Indonesia's workforce possesses basic to intermediate digital skills, with less than 1 percent demonstrating advanced digital capabilities. Similarly, the World Bank (2021) reports that a large portion of Indonesian digital users—many of whom are new users post-pandemic—struggle with basic digital functions such as using computers, navigating online applications, and conducting effective online searches. Moreover, the digital divide in Indonesia remains substantial. The Asia Competitiveness Institute highlights that the gap in internet access between urban and rural areas was approximately 22.5 percentage points in 2021 (ACI Perspectives, 2023), reflecting persistent structural inequalities in digital infrastructure and literacy. These disparities are especially pronounced among informal and gig economy workers, who often lack the training and access needed to fully benefit from digital platforms.

This phenomenon was further exacerbated by the COVID-19 pandemic, which caused widespread job losses in the formal sector and forced many individuals into informal employment, including gig work. Data from BPS-Statistics Indonesia show that in 2020. The proportion of informal workers surged to 60.47 percent due to economic pressures and layoffs (BPS-Statistics Indonesia, 2020). As of 2024, the gap between the formal and informal sectors remains relatively stable, suggesting that this labor market shift is not merely temporary (BPS-Statistics Indonesia, 2024).

To address the challenges faced by gig workers, the Indonesian government launched the Kartu Prakerja Program as a policy response to the pandemic's impact. The program aims to support affected workers-among them gig workers-by providing access to skills training and financial incentives. Its flexible training structure allows gig workers to adjust their learning schedules around their main job responsibilities. Overall, the Kartu Prakerja Program is expected to enhance the competitiveness and self-sufficiency of gig workers in Indonesia, particularly in adapting to a rapidly changing labor market (Anggara & Auwalin, 2024).

Previous studies have indicated that the Kartu Prakerja Program has the potential to improve participants' skills and job readiness. It offers access to training opportunities that help individuals transition from being unskilled to skilled and fosters a greater interest in self-development (Predianto & Khoirurrosyidin, 2020). The program has also proven effective in supporting those who lost their jobs by enhancing their employability and providing incentives to pursue new opportunities. However, these studies have yet to specifically examine the program's impact on the gig worker population. Therefore, this study aims to analyze the effect of participation in the Kartu Prakerja Program on the decision to become a gig worker and on the earnings of gig workers themselves. It also seeks to provide a general overview of the characteristics and determinants of program recipients, thereby contributing to the development of more inclusive labor policies in the digital economy era.

Furthermore, although the Kartu Prakerja Program has been continued under the new administration, its sustainability should be accompanied by a more comprehensive evaluation. Policy decisions should not merely focus on maintaining existing programs without carefully assessing their actual effectiveness, especially in light of the increasingly flexible and digitized structure of the labor market. Evaluation should extend beyond administrative metrics and recipient counts to include program outcomes for diverse target groups, including gig workers. Methodologically, previous studies have predominantly relied on ordinary least squares regression, which may suffer from potential endogeneity bias. This study offers a more robust approach by employing Propensity Score Matching (PSM) and the Tobit model to provide more accurate estimates of the program's impact on the decision to engage in gig work and on earnings.

2. Research method

2.1. Data Source

This study utilizes raw data from the August 2024 wave of the National Labor Force Survey *(*Sakernas*), c*onducted by BPS-Statistics Indonesia. To examine the impact of the Kartu Prakerja Program on (1) the decision to become a gig worker and (2) gig workers' earnings, the data processing was carried out in two stages corresponding to the two outcome variables. For the first outcome, the unit of analysis consists of 16,394 individuals who are self-employed, work in the service sector, and meet the eligibility criteria for the Kartu Prakerja Program. For the second outcome, only individuals classified as gig workers are included, resulting in a reduced sample of 11,331 individuals.

2.2. Variable Operationalization

2.2.1 Gig Workers

In this study, a gig worker is defined as a self-employed individual in the service sector who uses the internet as a primary tool in their main job (Natalia & Putranto, 2023; Permana et al., 2023). This operational definition reflects the core characteristics of the gig economy, in which labor services—rather than physical goods—are traded. According to BPS-Statistics Indonesia (2024), self-employment refers to individuals who run their own business and bear the associated economic risks independently, without hiring paid or unpaid workers. Based on the Indonesian Standard Industrial Classification (KBLI), gig workers are identified within the following service sectors: transportation and warehousing (code 8), information and communication (code 10), financial and insurance services (code 11), real estate (code 12), business services (code 13), education services (code 15), health services (code 16), and other services (code 17).

2.2.2 Kartu Prakerja Program

Based on Presidential Regulation Number 76 of 2020, the criteria for the Kartu Prakerja Program recipient are Indonesian citizens aged 18–64 who are not enrolled in formal education and are not employed as government officials, civil servants, military or police personnel, village heads or officials, or board members of state/regional-owned enterprises. Applicants register online via the official platform, completing identity verification, a motivation and aptitude test, and a wave-based selection process. Recent updates to the Kartu Prakerja Program indicate that, under the 2024 normal scheme, participants receive Rp 4.2 million in total benefits: Rp 3.5 million for a training voucher, a one-time post-training incentive of Rp 600,000, and up to two survey incentives of Rp 50,000 each. Participants can select online courses from a wide range of topics using training vouchers, complete interactive video modules, and obtain certificates upon passing both pre- and post-tests (Manajemen Pelaksana Program Kartu Prakerja, 2023; GovInsider, 2023).

2.3. Variables and Measurement

This study includes three types of variables: outcome variables, covariates, and the treatment variable. The full list of variables is presented in Table 1.

Tabel 1. Variable Description

Variable	Name	Description
Outcome variable (Y)		
Y_1	Decision to become a gig worker	0 = non-gig worker, 1 = gig worker
Y_2	Gig workers' earnings	earnings per hour (in IDR/hour)
Covariates variable (X)		
X_1	Gender	0 = female, 1 = male
X_2	Age	Age of the individual (in years)
X_3	Years of schooling	Length of formal education (in years)
X_4	Marital status	0 = single/divorced, 1 = married
X_5	Area classification	0 = rural, 1 = urban
X_6	Migration status	0 = non-migrant, 1 = migrant
X_7	Work experience	0 = no experience, 1 = has experience
Treatment variable (Z)	Participation in Kartu Prakerja Program	0 = no participate, 1 = participate

Source: Natalia & Putranto, 2023; Permana et al., 2023

2.4. Analysis Method

This study employs the PSM method. In this method, the first step involves estimating each individual's propensity score using logistic regression (Greene, 2012):

$$ln\left(\frac{P(Z_i=1)}{P(Z_i=0)}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + \varepsilon_i \quad (1)$$

where $P(Z_i = 1)$ is the probability of participating in the Kartu Prakerja Program, ε_i is the error term, and β_i are the parameters to be estimated. To assess the relationship between the covariates and treatment participation, both simultaneous and partial hypothesis tests are conducted. The simultaneous test evaluates the null hypothesis H_0:β_1=β_2=⋯=β_7=0 against the alternative that at least one $\beta_j \neq 0$. while the partial test examines the influence of each covariate individually with H_0:β_j=0 versus H_1:$\beta_j \neq 0$. The logistic regression results are interpreted using the Average Partial Effect (APE), which is computed by averaging the individual Partial Effects (PE_i) (Greene, 2012). For dummy covariates (e.g., gender X_1), the individual partial effect is calculated as the difference in the predicted probability of treatment between categories (Equation 2). For continuous covariates (e.g., age X_2), partial effects can be calculated using Equation 3.

$$PE_{1i} = P(Z_i = 1|X_2, X_3, X_4, X_5, X_6, X_7; X_1 = 1) - P(Z_i = 1|X_2, X_3, X_4, X_5, X_6, X_7; X_1 = 0) \quad (2)$$

$$PE_{2i} = \frac{exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i})}{[1 + exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i})]^2} .\beta_2 \quad (3)$$

$$APE_1 = \frac{\sum_{i=1}^{N} PE_{1i}}{N} \quad (4)$$

$$APE_2 = \frac{\sum_{i=1}^{N} PE_{2i}}{N} \quad (5)$$

The second step of the PSM method is the selection of a matching algorithm. Several matching approaches are commonly used, including nearest neighbor matching, caliper/radius matching, and kernel matching (Khandker et al., 2009). Then, the third step involves checking the common support assumption, which requires that the distribution of propensity scores overlaps between the treatment and control groups (Heckman et al., 1997). Individuals whose propensity scores fall outside the region of common support may be excluded from further analysis to ensure comparability (Ravallion, 2005). The fourth step is to evaluate the quality of matching. This step aims to assess whether the covariates are balanced between the treatment and control groups after matching. While graphical checks can illustrate the extent of overlap in propensity scores, statistical tests are needed to confirm that the two groups are indeed comparable. Caliendo and Kopeinig (2005) recommend three main diagnostics:

1) The standardized bias test, which measures the difference in the mean of covariates between the two groups after matching.
2) The *t*-test, which assesses the statistical significance of mean differences for each covariate.
3) The pseudo-R^2 statistic, which indicates how well the covariates explain treatment assignment. A lower pseudo-R^2 after matching suggests improved balance.

The fifth step is to estimate the Average Treatment Effect on the Treated (ATT), which represents the average difference in potential outcomes between treated individuals and their counterfactual outcomes had they not received treatment:

$$ATT = E[Y_i(1) - Y_i(0)|Z_i = 1] = \frac{1}{N_T} \sum_{i:Z_i=1} Y_i - \sum_{j:Z_j=0} \omega(i,j) Y_i \quad (6)$$

After matching is completed to ensure covariate balance between treated and control groups, the impact of the program on the decision to become a gig worker is analyzed using a logit model. While the impact of the program on gig workers' earnings is analyzed using a Tobit model.

The Tobit model is appropriate because the dependent variable-hourly earnings-is continuous but censored, as some individuals report zero earnings at the time of the survey (Wooldridge, 2010). This model is specified as follows:

$$Y_i = \begin{cases} Y_i^* & jika\ Y_i^* > 0 \\ 0. & jika\ Y_i^* \leq 0 \end{cases} \quad (7)$$

where $i = 1,2, \dots, N$ and Y_i^* is the latent variable defined by:

$$Y_i^* = X_i{}^T \beta + \mu_i \quad (8)$$

Here, Y_i is the observed outcome (hourly earnings), ${X_i}^T$ is a vector of covariates, β is a parameter vector, and μ_i is the error term, which is assumed to follow a normal censored distribution.

The final step is to conduct a sensitivity analysis to assess whether the estimated treatment effects are robust to potential hidden biases, particularly for the binary outcome variable representing the decision to become a gig worker.

3. Results and Discussion

3.1. Impact Analysis Using PSM: Equation for the Decision to Become a Gig Worker

To understand the impact of the Kartu Prakerja Program on the decision to become a gig worker and on gig workers' earnings in Indonesia, this study analyzes the characteristics of individuals who participated in the program. Out of 16,394 eligible individuals in the sample, only 702 individuals, or approximately 4.28 percent, were recorded as participants of the Kartu Prakerja Program. The descriptive analysis includes key covariates, as summarized in Table 2. Regarding gender, male participants dominate the program (75.78%,) while women account for only 24.22%. This aligns with Miller (2018), who documented how patriarchal norms in Southeast Asian households often lead to men's greater participation in public upskilling programs. Participants are on average younger (37.35 years) compared to non-participants (42.71 years), consistent with demographic trends reported in Indonesia's Rencana Pembangunan Jangka Menengah Nasional (RPJMN) 2020–2024, which indicate that adults aged 20–39 are the primary beneficiaries of government-sponsored vocational training (Bappenas, 2020). In terms of education, participants have an average of 11.71 years of schooling—higher than the 9.71 years among non-participants. Pratiwi and Wibowo (2022) suggest that high-school graduates are most likely to meet program eligibility and administrative requirements. Married individuals show higher program participation than single or divorced respondents, possibly reflecting the family responsibilities that Abdullah et al. (2021) identify as key motivators for seeking skills training. Urban residents participate at greater rates than rural ones—echoing findings by the Bappenas (2014) evaluation of Program Nasional Pemberdayaan Masyarakat (PNPM) Mandiri, which emphasizes better infrastructure and access in cities. Participation is also higher among non-migrants than migrants; Nugraha and Santoso (2020) explain this as a result of simpler administrative processes for local residents compared to internal migrants. Finally, those with prior work experience are more likely to enroll in the program—supported by Febriani and Lestari (2021), who show that labor market experience increases readiness for further upskilling, and Kurniawan and Sari (2020), who found that prior training history enhances both awareness and eligibility for programs like Kartu Prakerja.

Table 2. Descriptive Statistics of Individual Characteristics by Participation in Kartu Prakerja Program (Outcome: Decisions to Become a Gig Worker)

Covariates Variable (X)	Category	Participation in Kartu Prakerja Program	
		No Participate	Participate
Gender (X_1)	0: female	3,620 (23.07%)	170 (24.22%)
	1: male	12,072 (76.93%)	532 (75.78%)
Average age (X_2)		42.71 years	37.35 years
Average years of schooling (X_3)		9.71 years	11.71 years
Marital status (X_4)	0: single/divorced	4,054 (25.83%)	159 (22.65%)
	1: married	11,638 (74.17%)	543 (77.35%)
Area classification (X_5)	0: rural	4,605 (29.35%)	171 (24.36%)
	1: urban	11,087 (70.65%)	531 (75.64%)
Migration status (X_6)	0: non-migrant	15,188 (96.79%)	655 (93.30%)
	1: migrant	504 (3.21%)	47 (6.70%)
Work experience (X_7)	0: no experience	6,235 (39.73%)	193 (27.49%)
	1: has experience	9,457 (60.27%)	509 (72.51%)

Source: Processed from Sakernas, August 2024

Table 3 highlights that among Kartu Prakerja participants, 83.48 percent were gig workers, indicating that the program has successfully reached its intended target group of informal and flexible laborers. These results are in line with Horton et al. (2016), who showed that workers in digital work systems tend to be more interested in participating in online training to improve their competitiveness. This high proportion suggests a strong alignment between the program's training focus and the upskilling needs of individuals engaged in gig work, which is typically characterized by limited job security and a lack of formal career development. Participation may be seen by gig workers as a strategic step to enhance their skills and improve employment prospects. However, the fact that 68.47 percent of gig workers did not join the program points to persistent barriers—such as limited access to information, bureaucratic hurdles, or a mismatch between training content and the practical demands of gig work (Woodcock et al., 2019)-underscoring the need for more inclusive outreach and better-targeted program design.

Table 3. The Number of Individuals by Kartu Prakerja Program Participation and Gig Worker Status

Participation in Kartu Prakerja Program	Outcome Variable	
	Non-Gig Worker	Gig Worker
No participate	4,947 (31.53%)	10,745 (68.47%)
Participate	116 (16.52%)	586 (83.48%)
Total	5,063	11,331

Source: Processed from Sakernas, August 2024

3.1.1 Determinants of Kartu Prakerja Program Participation in Indonesia

As explained in the methodology section, a logistic regression model was employed to estimate propensity scores and also to identify determinants of program participation. Table 4 presents the APE from the logit model used to estimate participation in the Kartu Prakerja program. The results show that although females are 0.46 percentage points more likely to participate than males, the effect is not statistically significant. Age has a significant negative effect, with each additional year decreasing the probability of participation by 0.19 percentage points. Each year of additional schooling increases the likelihood of joining the program by 0.51 percentage points. Marital status is also a significant factor, with married individuals being 1.94 percentage points more likely to participate. Urban residents have a 0.87 percentage point higher probability of participation than those in rural areas, which is statistically significant at the 5% level. Migration status does not have a significant effect on participation. Individuals with prior work experience are 2.51 percentage points more likely to participate in the program. These findings are consistent with Suryadarma and Suryahadi (2020), who emphasized the importance of human capital factors such as education, geographic context, and experience in shaping participation in skills development programs in Indonesia.

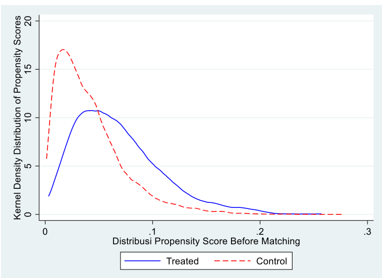
Table 4. APE Estimates from the Logit Model in the Kartu Prakerja Program Participation Equation

Covariate Variable	Observed Category	APE	Standard Error	*p*-value
Gender (X_1)	1: male	-0.0009	0.0037	0.182
Age (X_2)		-0.0019	0.0002	0.000***
Years of schooling (X_3)		0.0051	0.0005	0.000***
Marital status (X_4)	1: married	0.0194	0.0033	0.000***
Area classification (X_5)	1: urban	0.0087	0.0034	0.011**
Migration status (X_6)	1: migrant	0.0314	0.0077	0.101
Work experience (X_7)	1: has work experience	0.0251	0.0031	0.000***

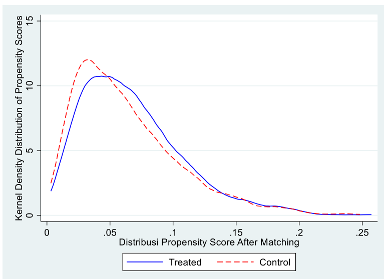
Source: Processed from Sakernas, August 2024
Note: ** Significant at 5% and *** Significant at 1%

3.1.2 The Impact of the Kartu Prakerja Program on the Decision to Become a Gig Worker

Figure 1 shows the kernel density plots of propensity scores before and after nearest neighbor matching for the outcome of becoming a gig worker. Prior to matching, the distributions of treated and control groups differ considerably, indicating covariate imbalance. After matching, the distributions converge substantially, reflecting improved balance and comparability. All treated units remain within the common support region (approximately 0.1 to 0.25), confirming that the matching procedure was effective in simulating a randomized design.



(a) Before Matching



(b) After Matching

Figure 1. Balance Check: Propensity Score Distribution for Gig Worker Participation Equation
Source: Processed from Sakernas, August 2024

Standardized bias testing is conducted to evaluate the extent of covariate bias reduction following matching. According to Baek et al. (2015), standardized bias values after matching should ideally be below 20%. As shown in Table 5, all covariates exhibit a significant reduction in bias after matching. Additionally, the p-values from the t-tests become insignificant, indicating no statistically significant differences between the treated and control groups after matching. These results confirm that the matching process created well-balanced groups. Finally, Table 6 presents overall matching quality. All indicators (pseudo R^2, mean bias, and median bias) significantly decrease after matching. The lower pseudo R^2 value after matching indicates that the ability of covariates to predict treatment assignment has been minimized, further validating the balance between groups (Caliendo & Kopeinig, 2005).

Table 5. Covariate Balance Before and After Matching (Outcome: Decision to Become a Gig Worker)

Covariate Variable	Before Matching		After Matching	
	Standardized Bias (%)	*p*-value (t-test)	Standardized Bias (%)	*p*-value (t-test)
Gender (X_1)				
1: male	13.0	0.006**	-1.8	0.723
Age (X_2)	1.4	0.765	0.8	0.871
Years of schooling (X_3)	10.5	0.026**	3.6	0.477
Marital status (X_4)				
1: married	5.2	0.263	-3.2	0.534
Area classification (X_5)				
1: urban	9.6	0.040*	-3.1	0.544
Migration status (X_6)				
1: migrant	5.4	0.240	6.2	0.244
Work experience (X_7)				
1: Has work experience	16.3	0.001**	-1.2	0.811

Source: Processed from Sakernas, August 2024
Note: ** Significant at 5% and * Significant at 10%

The impact of Kartu Prakerja Program on decision to become a gig worker can be shown in Table 7. Based on this table, the Kartu Prakerja Program significantly increases the probability of individuals becoming gig workers. Using nearest neighbor matching, the estimated ATT is 0.0598, indicating a 5.98 percentage point higher likelihood of becoming a gig worker among participants. Caliper and kernel matching also produce the same results (6.22% and 3.92%, respectively). These findings are consistent with Putri (2023), who found that Kartu Prakerja training increases the likelihood of participation in gig work.

To examine whether the impact is robust to omitted variable bias, Rosenbaum bounds sensitivity tests are conducted. The results in Table 8 show that, even if the odds of participating in the program were ten times higher due to an unobserved covariate, the positive effect of the Kartu Prakerja program on gig work participation remains robust. This supports the reliability of the PSM estimates.

Table 6. Summary of Matching Quality Using Nearest Neighbor Matching (Outcome: Decision to Become a Gig Worker)

Outcome Variable	Sample	Pseudo R^2	Mean Bias (%)	Median Bias (%)
Decision to become a gig worker (Y_1)	Before *matching*	0.011	8.8	9.6
	After *matching*	0.002	2.9	3.1

Source: Processed from Sakernas, August 2024

Table 7. ATT Estimation: Impact of Kartu Prakerja Program on Decision to Become a Gig Worker using Logit Model

Matching Method	ATT Value	Standard Error
Nearest neighbor matching	0.0598**	0.0200
Caliper/radius matching	0.0622**	0.0147
Kernel matching	0.0392**	0.0148

Source: Processed from Sakernas, August 2024
Note: ** Significant at 5%

Table 8. Rosenbaum Bounds Sensitivity Test for Gig Worker Participation Equation

Gamma (Γ)	Q^{+}_{MH}	Q^{-}_{MH}	p^{+}_{MH}	p^{-}_{MH}
1	3.1103	3.1103	0.0009***	0.0009***
2	2.5370	9.0858	0.0056***	0.0000***
3	5.9788	12.8029	0.0000***	0.0000***
4	8.5300	15.5826	0.0000***	0.0000***
5	10.6075	17.8391	0.0000***	0.0000***
6	12.3889	19.7593	0.0000***	0.0000***
7	13.9662	21.4440	0.0000***	0.0000***
8	15.3934	22.9540	0.0000***	0.0000***
9	16.7048	24.3292	0.0000***	0.0000***
10	17.9238	25.5968	0.0000***	0.0000***

Source: Processed from Sakernas, August 2024
Note: *** Significant at 1%

3.2. Impact Analysis Using PSM: Equation for the Decision to Gig Workers' Earnings

Following the first analysis on the decision to become a gig worker, the second analysis of this study focuses exclusively on individuals already working as gig workers to assess the impact of the Kartu Prakerja Program on their hourly earnings. This separation of stages allows for clarity in the unit of analysis-shifting from all working-age individuals in stage one to only gig workers in stage two-and enables a more accurate estimation of program effects within the informal labor segment.

Among the 11,331 working-age individuals observed in the August 2024 Sakernas dataset, a total of 11,060 were identified as gig workers. Of these, only 586 individuals (5.17 percent) reported having participated in the Kartu Prakerja Program, while the remaining 10,745 individuals (94.83 percent) did not. Table 9 summarizes the background characteristics of participants and non-participants, including gender, age, education, marital status, area classification, migration status, and work experience. On average, program participants tend to be younger, more educated, more likely to have work experience, and reside in urban areas-patterns aligned with prior findings (Bappenas, 2021; Iskandar, 2022).

Table 9. Descriptive Statistics of Gig Workers' Characteristics by Participation in Kartu Prakerja Program (Outcome: Gig Worker Earnings)

Covariates Variable (X)	Category	Participation in Kartu Prakerja Program	
		No Participate	Participate
Gender (X_1)	0: female	2,461 (22.90%)	140 (23.89%)
	1: male	8,284 (77.10%)	446 (76.11%)
Average age (X_2)		40.78 years	36.62 years
Average years of schooling (X_3)		10.67 years	11.94 years
Marital status (X_4)	0: single/divorced	2,852 (26.54%)	144 (24.57%)
	1: married	7,893 (73.46%)	442 (75.43%)
Area classification (X_5)	0: rural	2,846 (26.49%)	132 (22.53%)
	1: urban	7,899 (73.51%)	454 (77.47%)
Migration status (X_6)	0: non-migrant	10,355 (96.37%)	547 (93.34%)
	1: migrant	390 (3.63%)	39 (6.66%)
Work experience (X_7)	0: no experience	4,141 (38.54%)	160 (27.30%)
	1: has experience	6,604 (61.46%)	426 (72.70%)

Source: Processed from Sakernas, August 2024

Table 10. The Number of Gig Workers and Mean Hourly Earnings by Kartu Prakerja Program Participation

Participation in Kartu Prakerja Program	Frequency of Gig Workers (%)	Mean Hourly Earnings (IDR)
No participate	10,745 (94.83%)	Rp27.716,21
Participate	586 (5.17%)	Rp19.998,86
Total	11,331 (100.00%)	

Source: Processed from Sakernas, August 2024

Table 10 shows that although only 5.17 percent of individuals in the sample participated in the program, a striking 83.48 percent of these participants are gig workers. This indicates that the program has been relatively successful in targeting informal labor segments. However, the average hourly earnings of gig worker participants (IDR 19,998.86) remain lower than those of non-participants (IDR 27,716.21). This suggests that while access to the program may be reaching the intended group, its short-term income-enhancing effects are not yet evident. These findings support the argument made by Pratomo et al. (2023), who caution that participation in the gig economy does not guarantee income security or upward mobility. Gig workers often face structural constraints such as unstable earnings, limited bargaining power, and intense competition, which may dilute the benefits of training. Therefore, enhancing the effectiveness of the Kartu Prakerja Program requires a more targeted approach that addresses the underlying vulnerabilities faced by informal workers.

3.2.1 Determinants of Kartu Prakerja Program Participation in Indonesia

Table 11. APE Estimates from the Logit Model in the Kartu Prakerja Program Participation Equation

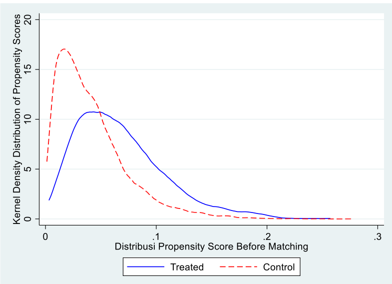
Covariate Variable	Observed Category	APE	Standard Error	*p*-value
Gender (X_1)	1: male	0.0015	0.0048	0.754
Age (X_2)		-0.0016	-0.0022	0.000***
Years of schooling (X_3)		0.0024	0.0052	0.000***
Marital status (X_4)	1: married	0.0203	0.0045	0.000***
Area classification (X_5)	1: urban	0.0101	0.0046	0.027*
Migration status (X_6)	1: migrant	0.0134	0.0104	0.196
Work experience (X_7)	1: has work experience	0.0292	0.0041	0.000***

Source: Processed from Sakernas, August 2024
Note: * Significant at 10% and *** Significant at 1%

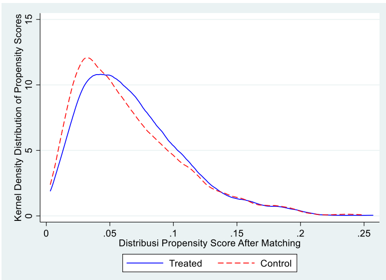
Table 11 displays the factors influencing gig workers' participation in the Kartu Prakerja Program. The estimation results suggest that older gig workers are significantly less likely to participate, with each additional year of age reducing the probability by 0.16 percentage points. Years of schooling positively and significantly increase the likelihood of participation. Marital status, location of residence, and work experience are all positively associated with participation. These findings are consistent with studies by Suryadarma & Suryahadi (2020), which highlight the role of education, urban access, and human capital in explaining program engagement.

3.2.2 The Impact of the Kartu Prakerja Program on the Gig Workers' Earnings

Figure 2 illustrates the distribution of propensity scores before and after matching for gig worker earnings. Prior to matching, notable differences between treated and control groups indicate covariate imbalance. After matching, the distributions align more closely—especially within the 0.1 to 0.25 range—suggesting improved comparability. All observations remain within common support, indicating effective reduction of selection bias through matching.



3.1. Before Matching



3.2. After Matching

Figure 2. Balance Check: Propensity Score Distribution for Gig Worker Earnings Equation
Source: Processed from Sakernas, August 2024

Table 12 presents the covariate balancing results before and after PSM using the nearest neighbor algorithm. Prior to matching, several covariates exhibited substantial standardized bias and statistically significant t-test results. After matching, the standardized biases for all covariates fell well below the 20% threshold commonly used to indicate adequate balance (Austin, 2009; Rubin, 2001). Furthermore, the *p*-values of t-test became statistically insignificant, indicating that the treatment and control groups became similar in observable characteristics. This strengthens the credibility of the causal effect estimates derived from the matched sample.

Table 12. Covariate Balance Before and After Matching (Outcome: Gig Worker Earnings)

Covariate Variable	Before Matching		After Matching	
	Standardized Bias (%)	*p*-value (t-test)	Standardized Bias (%)	p-value (t-test)
Gender (X_1)				
1: male	−0.9	0.836	−1.7	0.777
Age (X_2)	−40.3	0.000***	−0.8	0.879
Years of schooling (X_3)	40.9	0.000***	0.5	0.924
Marital status (X_4)				
1: married	5.2	0.235	−4.0	0.484
Area classification (X_5)				
1: urban	10.8	0.015**	4.5	0.438
Migration status (X_6)				
1: migrant	13.7	0.000***	8.2	0.189
Work experience (X_7)				
1: Has work experience	25.3	0.000***	−2.0	0.720

Source: Processed from Sakernas, August 2024
Note: ** Significant at 5% and *** Significant at 1%

Table 13 provides a summary of overall matching quality. All indicators improved considerably after matching: the pseudo R^2 declined from 0.050 to 0.002, the mean bias from 19.6% to 3.1%, and the median bias from 13.7% to 2.0%. These reductions indicate that the explanatory power of the covariates in predicting treatment assignment was effectively neutralized after matching, suggesting successful balancing of covariates. According to Caliendo and Kopeinig (2005), lower post-matching values in these indicators support the internal validity of the estimated treatment effects.

Table 13. Summary of Matching Quality using Nearest Neighbor Matching (Outcomes: Gig Worker Earnings)

Outcome Variable	Sample	Pseudo R^2	Mean Bias (%)	Median Bias (%)
Hourly earnings of gig workers (Y_2)	Before *matching*	0.050	19.6	13.7
	After *matching*	0.002	3.1	2.0

Source: Processed from Sakernas, August 2024

Table 14 reports the estimated ATT of the Kartu Prakerja Program on gig workers' hourly earnings using the tobit model with three matching methods: nearest neighbor, caliper/radius, and kernel. Across all methods, the ATT is negative and statistically significant at the 1% level. Specifically, the program is associated with a decrease in hourly earnings by −22.22% (nearest neighbor), 18.89% (caliper), and 18.96% (kernel). These findings suggest that program participation is correlated with lower earnings among gig workers. This result is consistent with Pratomo et al. (2023), who found that the program may not benefit informal workers in terms of income, possibly due to a mismatch between generic training and the specific needs of gig economy participants. Supporting literature notes that gig workers often face unstable income streams, lack of social protections (Woodcock et al., 2019), and highly competitive markets that lead to excessive working hours and income volatility (Hafeez et al., 2022; Anwar et al., 2021; Taylor et al., 2023; Horton et al., 2016).

Table 14. ATT Estimation: Impact of Kartu Prakerja Program on Gig Worker Earning using Tobit Model

Matching Method	ATT Value	Standard Error
Nearest neighbor matching	-0.2222***	0.0536
Caliper/radius matching	-0.1889***	0.0406
Kernel matching	-0.1896***	0.0409

Source: Processed from Sakernas, August 2024
Note: *** Significant at 1%

To examine potential sensitivity to omitted variable bias, Rosenbaum bounds sensitivity tests are conducted. Table 15 presents results from Rosenbaum bounds sensitivity analysis to test the robustness of the estimated treatment effects against unobserved confounding. The analysis increases the gamma (Γ) value from 1 to 10. At all levels of Γ, both upper-bound (*sig*$^+$) and lower-bound (*sig*$^-$) p-values remain highly significant ($p < 0.001$). This indicates that even under extreme assumptions of hidden bias, the negative effect of the Kartu Prakerja Program on gig worker earnings remains statistically robust. Therefore, the findings are unlikely to be driven by unobserved variables, confirming the internal validity of the ATT estimates derived through PSM and Tobit modeling.

Table 15. Rosenbaum Bounds Sensitivity Test for Earnings Equation (Tobit Model)

Gamma (Γ)	sig$^+$	sig$^-$	t^+_{hat}	t^-_{hat}	CI$^+$	CI$^-$
1	0.0000***	0.0000***	9.57733	9.57733	9.5620	9.5955
2	0.0000***	0.0000***	9.33201	9.8413	9.3157	9.8595
3	0.0000***	0.0000**	9.18817	10.0032	9.1741	10.0223
4	0.0000***	0.0000***	9.0948	10.1218	9.0766	10.1423
5	0.0000***	0.0000***	9.0199	10.2138	8.9999	10.2382
6	0.0000***	0.0000***	8.9610	10.2909	8.9391	10.3138
7	0.0000***	0.0000***	8.9109	10.3498	8.8890	10.3820
8	0.0000***	0.0000***	8.8660	10.4106	8.8416	10.4395
9	0.0000***	0.0000***	8.8275	10.4591	8.8071	10.4936
10	0.0000***	0.0000***	8.7948	10.5037	8.7726	10.5347

Source: Processed from Sakernas, August 2024
Note: *** Significant at 1%

3.3. Sectoral Impact Analysis of the Kartu Prakerja Program

Although the Kartu Prakerja Program is intended to enhance recipients' skills and well-being, the main findings of this study reveal that participation in the program is associated with a general decline in earnings among gig workers. This prompts further analysis of the potential heterogeneity of program impacts across economic sectors, given that each sector has distinct labor market characteristics, including job types, skill requirements, income structures, and work flexibility. By categorizing gig workers based on their primary employment sectors and estimating the program's impact separately for each group, this analysis aims to identify which sectors genuinely benefit from the program and which experience no significant or even negative effects. These sectoral findings are crucial for informing more context-sensitive training policies that better respond to the specific needs of different sectors within the gig economy labor market.

Table 16. Sectoral Impact of the Kartu Prakerja Program on the Decision to Become a Gig Worker

Sector	Observations	ATT	Standard Error	*p*-value
Transportation and storage (8)	8,219	0.026	0.027	0.348
Information & communication (10) and financial & insurance services (11)	767	-0.018	0.035	0.613
Real estate (12)	306	0.400	0.173	0.022**
Business services (13)	886	0.044	0.040	0.212
Education services (15)	556	0.059	0.117	0.615
Health services (16)	492	-0.381	0.208	0.068*
Other services (17)	5,168	0.400	0.034	0.022**

Source: Processed from Sakernas, August 2024
Note: * Significant at 10% and ** Significant at 5%

Table 16 presents the results of a heterogeneity analysis of the Kartu Prakerja Program's impact on the decision to become a gig worker, based on employment sectors, using the PSM method to address potential selection bias. The findings reveal that the program's effects vary across sectors: some show positive but statistically insignificant impacts, while the health services sector exhibits a marginally significant negative effect. In contrast, the real estate and other services sectors show significant positive effects, indicating that the program contributes to increased participation in gig work within those sectors. Due to limited observations, the information, communication, and financial sectors were combined, and the merged result showed no significant impact. These findings align with Sitorus and Kornitasari (2024), who emphasize that income stability and employment protection play a more critical role in shaping gig workers' well-being than participation in training programs alone. Likewise, IDinsight (2025) highlights the importance of tailoring training and social protection policies to the unique working conditions and demographic characteristics of gig workers in Indonesia, such as gender, working hours, and digital access. Overall, the results suggest that the Kartu Prakerja Program's impact on the decision to enter gig work is not uniform across sectors, underscoring the need for more sector-sensitive policy design.

Table 17 presents the estimation results of the heterogeneous impact of the Kartu Prakerja Program on gig workers' earnings across different economic sectors, using the natural logarithm of hourly earnings as the outcome variable and the PSM approach to control for individual-level differences between participants and non-participants. The analysis reveals that in most sectors, participation in the program is correlated with a decline in hourly earnings among gig workers. Statistically significant negative impacts are found in the transportation and storage sector and the other services sector, indicating that program participation is associated with a substantial reduction in earnings in these areas. A similar, though not statistically significant, downward trend is observed in the combined information, communication, and financial sectors, which were merged due to small sample sizes and similar characteristics as technology- and skill-intensive service sectors. Other sectors such as real estate, business services, and education also show negative effects, though not statistically significant, while the health sector records a negligible and insignificant positive impact. These findings align with Ayyagari et al. (2013), who emphasize the importance of aligning capacity-building programs with sector-specific needs and market structures—suggesting that a mismatch between training content and sectoral demands may limit the effectiveness of such interventions. Overall, the results in Table 17 highlight that the impact of the Kartu Prakerja Program on gig workers' earnings is not only sectorally diverse but also predominantly negative, underscoring the need for further evaluation of training relevance and improvements in program design to better support the welfare of gig workers.

Table 17. Sectoral Impact of the Kartu Prakerja Program on Gig Workers' Earnings

Sector	Observations	ATT	Standard Error	*p*-value
Transportation and storage (8)	5,594	-0.173	0.055	0.002***
Information & communication (10) and financial & insurance services (11)	709	-0.288	0.178	0.107
Real estate (12)	218	-1,261	0.921	0.173
Business services (13)	798	-0.194	0.158	0.220
Education services (15)	378	-0.175	0.282	0.535
Health services (16)	285	0.006	0.659	0.993
Other services (17)	3,208	-0.212	0.103	0.040**

Source: Processed from Sakernas, August 2024
Note: ** Significant at 5% and *** Significant at 1%

4. Conclusion and Recommendations

Based on the results and discussions presented, this study yields three main conclusions aligned with its objectives. First, individuals who are more likely to participate in the Kartu Prakerja Program tend to be male, in the productive age group, possess a secondary level of education (senior high school or equivalent, or an average years of schooling at the secondary level), be married, reside in urban areas, have prior work experience, and are non-migrants. Second, the Kartu Prakerja Program has been shown to significantly increase the likelihood of individuals transitioning into gig work. Third, however, this increased tendency to become a gig worker is not accompanied by an increase in earnings. In fact, the analysis reveals that hourly earnings of gig workers who participated in the program are lower than those of non-participating gig workers. These findings suggest that although the program facilitates transitions into flexible work arrangements, its impact on workers' welfare remains suboptimal. Therefore, further evaluation is necessary to ensure the program is better targeted, particularly in reaching vulnerable gig workers and enhancing their social protection.

Based on these findings, several policy recommendations can be proposed. The government should maintain and expand the coverage of the Kartu Prakerja Program, as it has proven effective in promoting participation in the gig economy. However, it is essential to improve the relevance and specificity of training curricula to better align with the skill demands of gig-sector jobs, such as digital literacy, online marketing, and microfinance management, in order to enhance the program's impact on gig worker earnings. Moreover, the eligibility criteria for program participants should be reassessed to ensure more accurate targeting, particularly with regard to the poverty status of potential beneficiaries. Future research is also encouraged to further examine the types and content of training delivered. Subsequent studies could explore the effectiveness of Kartu Prakerja training across different sectors—especially the digital technology sector, which may have a greater need for skill upgrading—and assess the program's long-term impact on gig workers' earnings.

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