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Original Article

Does Job Training Work? Causal Evidence of the Kartu Prakerja Program's Impact on Labor Outcomes

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Abstract

The Indonesian government launched the Kartu Prakerja program to address skill shortages in the labor market, particularly through digital training, with the goal of increasing employability and income levels. This study investigates the impact of Indonesia's Kartu Prakerja program on workers' earnings, with a particular focus on the role of digital skills training in enhancing income. Utilizing 2023 Sakernas data and Propensity Score Matching (PSM) to control for selection bias, we find that participation is associated with an average increase in monthly earnings of approximately 3.3%. However, this aggregate effects masks significant heterogeneity. The benefits accrue primarily to lower-middle-income workers, women, urban residents, and formal sector employees. We hypothesize that these groups possess more supportive environments for applying new skills. Conversely, we find no significant effect for the poorest workers, rural residents, and those in informal employment, pointing to structural barriers that prevent them from converting skills into higher wages. These findings are robust to a series of sensitivity checks. In conclusion, while Kartu Prakerja provides measurable benefits, it predominantly assists those already in more advantageous positions, highlighting the need for more targeted designs to achieve equitable income growth.

Keywords: Active Labor Market Policy, Income Effect, Kartu Prakerja, Pre-Employment Card.

1. Introduction

In the modern era, Indonesia faces complex workforce challenges. The demographic boom offers enormous potential, with a workforce of 144.01 million by February 2024 (BPS, 2024) but creates pressure to provide adequate employment opportunities. Meanwhile, Industrial Revolution 4.0 and digitalization fundamentally change the structure of the labor market, creating a need for new skills while eliminating traditional jobs. This phenomenon creates a gap between the skills possessed by the workforce and industry needs, as reflected in the high rate of educated unemployment according to August 2024 TPT data (see Figure 1). Despite a growing number of individuals attaining higher education, many graduates find themselves unemployed or underemployed, suggesting that academic qualifications alone do not guarantee alignment with market needs.

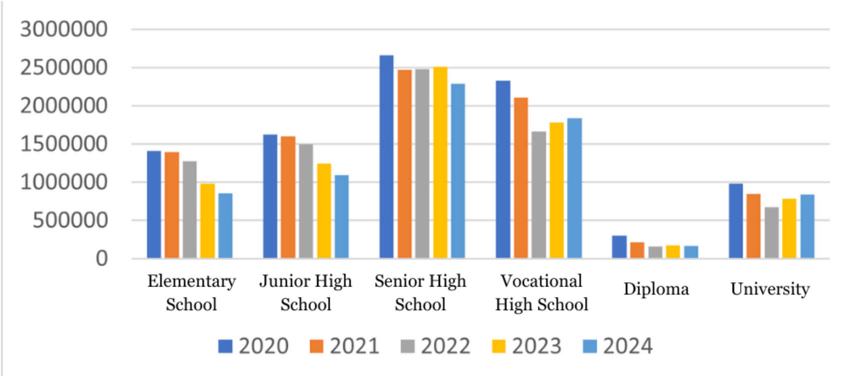

Figure 1. Unemployment according to highest level of education completed
Source: BPS 2024

To address this structural skills gap, the Indonesian government launched the Pre-Employment Card (Kartu Prakerja) program in 2020 as a national Active Labor Market Policy (ALMP). The initiative aims to enhance human capital through skilling, upskilling, and reskilling, preparing workers for technological transformation, while strengthening their competitiveness in an increasingly digital economy. This program is also designed to capitalize on the demographic dividend, ensuring that Indonesia's growing labor force remains adaptable and productive amid global economic changes.

While the Kartu Prakerja program is widely acknowledged as pioneering digital training and cash-transfer innovation, its effectiveness in improving participants' incomes remains an open empirical question. Early evaluations, such as those by Suryadi et. al. (2021) found that the program significantly improved employment prospects, particularly for previously unemployed individuals, but its effect on income was minor. This asymmetry between job placement and income outcomes has motivated extensive academic inquiry into whether a program's training components effectively translate into higher productivity and wages.

The recent literature presents divergent empirical findings. On one hand, studies such as (Ayyubi et al., 2023; Gunawan et al., 2024) highlight the program's success in improving employability, facilitating transitions from unemployment to formal employment, and strengthening economic resilience during the pandemic. Likewise, Muhyiddin et al. (2025) and Nguyen et al., (2023) emphasize that the program's market-based design, which combines welfare conditionality with digitalized training marketplaces, has enhanced efficiency and expanded access to vocational learning opportunities. On the other hand, quantitative assessments by Nugraha & Ariyanto (2025) and Yazid et al., (2024) reveal no significant or even negative short-term effects on participants' wages, indicating that the conversion of skill gains into income improvements remains limited. Complementary regional analyses, further demonstrate that outcomes vary substantially across provinces, reflecting disparities in digital literacy, training quality, and labor market structures (Khoirunnisa & Rumaisa, 2025).

Moreover, studies such as Yana (2021), highlights that the effectiveness of social protection and training initiatives like Kartu Prakerja largely depends on precise targeting, the relevance of the curriculum, and how well the training matches labor market needs. If training programs focus more on administrative completion rather than on job placement or wage growth, any income gains are often temporary and inconsistent. Overall, the existing body of research underscores that while the Kartu Prakerja program has made important strides in enhancing workforce participation and employability, its measurable impact on income and long-term labor productivity remains inconsistent. This mixed empirical evidence points to a crucial research gap: understanding the mechanisms through which digital training and conditional cash transfers can sustainably raise workers' earnings in diverse labor-market contexts. Accordingly, this study seeks to extend the current literature by systematically analyzing the relationship between the Kartu Prakerja program and income outcomes, thereby contributing to the broader discourse on active labor market policies and human capital development in Indonesia.

Despite growing empirical evidence on the Kartu Prakerja program, most existing studies have primarily focused on employment outcomes, such as participation, formal–informal transitions, or job matching, while income effects remain understudied and inconclusive. Several evaluations indicate that while the program enhances employability and absorption into the labor market, its direct effect on participants' income is either insignificant or inconsistent across demographic groups and regions (Ayyubi et al., 2023; Gunawan et al., 2024; Nugraha & Ariyanto, 2025). Moreover, methodological heterogeneity among previous studies, ranging from descriptive analyses and logistic regressions to quasi-experimental DiD estimations, often leaves unresolved questions of selection bias and counterfactual validity.

Another critical gap lies in the absence of a micro-level causal analysis using nationally representative post-pandemic data. Since the program's structure and participants' composition have evolved substantially by 2023, with more diverse cohorts joining via digital platforms, the need for updated evaluations using recent data is pressing. Furthermore, regional disparities in digital access and labor market structure may affect how program participation translates into income improvements, making it essential to analyze heterogeneity across provinces and demographic characteristics.

To address these limitations, this study employs Propensity Score Matching (PSM) using Sakernas 2023 microdata to estimate the average treatment effect on income between individuals who received the Kartu Prakerja (treatment group) and those who did not (control group). The PSM approach is particularly suitable for this context, as it allows controlling for observable characteristics (education, age, gender, region, and employment status) that may influence both program participation and income levels, thereby reducing selection bias and producing a more credible counterfactual comparison. This PSM approach directly measures the program's causal effect on income, addressing a key research gap in evaluating Kartu Prakerja's efficacy.

Accordingly, this study aims to achieve two primary objectives: first, to estimate the causal impact of the Kartu Prakerja program on participants' income using PSM analysis based on Sakernas 2023; second, to provide policy recommendations for enhancing the effectiveness of future labor market interventions and ensuring that human capital investments translate into sustainable income growth. By addressing these research gaps, this study contributes to the broader discourse on active labor market policies in developing economies, providing empirical evidence on the income effects of digital-based training and cash transfer programs in the post-pandemic era.

2. Literature Review

2.1. Prior Studies

Several studies have indicated the direct and indirect positive impacts of Kartu Prakerja on increasing participants' income, employability, and economic resilience. Gunawan et al., (2024) demonstrated that the program successfully increased opportunities for the transition from unemployment to formal employment through a training mechanism based on labor market needs. This increase in formal employment opportunities has implications for potential wage increases and reduced inequality between formal and informal sectors. Similarly, Ayyubi et al., (2023) found that youth participation in the Kartu Prakerja increased employment opportunities, especially for those previously unemployed due to the pandemic. Although most participants remained in the informal sector, this study confirms that the program contributed to increased household income and resilience during the crisis.

From a human resource development perspective, Yana (2021) highlights that training within the Kartu Prakerja plays a crucial role in improving individual quality and competence. Although broadly deemed “less effective” in developing human resources, field research indicates that the certificates and skills acquired by some participants helped them obtain new jobs or develop small businesses. Another study, Awinda & Syafitri (2025)also found a positive relationship between training participation and increased access to employment, which ultimately led to increased income.

Furthermore, Muhyiddin et al. (2025) viewed the Kartu Prakerja as an integral part of the national ALMP strategy, along with Wage Subsidy (BSU) and Job Loss Insurance (JKP) programs. According to them, a combination of these three programs successfully maintained income stability, improved workforce skills, and strengthened economic resilience during the pandemic. Nguyen et al. (2023) examined the Kartu Prakerja as a form of welfare conditionality and marketization that successfully expanded the involvement of private training providers and created a competitive market mechanism. Their findings suggest that these institutional reforms contributed to increased professionalism and efficiency in training delivery, which, in the long term, can strengthen the relationship between training and participants’ income.

Although various studies have found social benefits and improved skills, most empirical research has concluded that the program’s impact on wage increases is still limited. Based on a Difference-in-Differences analysis of 2022–2023 Sakernas data, Nugraha & Ariyanto (2025) found that participation in the Kartu Prakerja program did not significantly increase participants’ incomes, and even in the first year of implementation, it showed a significant negative effect on wages. These results indicate that, while training can improve knowledge and skills, the conversion of skills into increased income has not yet occurred widely.

Similar findings were presented by The Impact of the Kartu Prakerja Program on the Labor Force (Habsari et al., 2022; Yazid et al., 2024), which highlighted that while the Kartu Prakerja program increased labor force participation, particularly in the service and trade sectors, there is no strong evidence that the program increased real wages. Furthermore, Khoirunnisa & Rumaisa (2025) confirmed that the effectiveness of the Kartu Prakerja program varies across regions; areas with high unemployment rates, such as West Java, have not shown significant improvements in participants’ incomes. This is thought to be due to the digital literacy gap and differences in training quality between the providers.

In addition to implementation issues, structural challenges such as a mismatch between training skills and labor market needs also play a role. Hanum et al., (2022) emphasizes that the success of social programs, such as the Kartu Prakerja Program, depends heavily on accurate targeting and incentive design. If the program is too focused on cash distribution without ensuring that training aligns with the needs of the productive sector, income increases will tend to be temporary.

Methodologically, studies on the impact of the Kartu Prakerja employ a variety of approaches that enrich the understanding of a program’s effectiveness. Nugraha & Ariyanto (2025) used difference-in-differences (DiD) to estimate the causal impact on wages using national Sakernas data. Ayyubi et al. (2023) and Gunawan et al. (2024) applied a multinomial logit model to analyze labor transitions between formal, informal, and unemployed statuses. Both studies highlighted a significant selection bias due to differences in demographic characteristics between participants and non-participants, which was addressed using Lee's selectivity correction.

Nguyen et al., (2023) study used a mixed methods approach through in-depth interviews and online surveys with training providers and program participants to assess the effectiveness of marketization in the implementation of the Kartu Prakerja. Other studies, such as Muhyiddin et al (2025) and Yana, (2021), relied on descriptive qualitative methods with primary data sources through direct interviews with beneficiaries, enriching the analysis of perceptions, implementation, and social outcomes.

Geographically, most studies have focused on Java (particularly West Java and East Java) because the highest proportion of Kartu Prakerja participants resided in these regions. However, Asmara & Saleh (2025) highlighted that variations in impact across provinces are strongly influenced by structural labor market conditions, digital infrastructure, and participant literacy levels, which impact training effectiveness and income outcomes.

2.2. Kartu Prakerja

The Pre-Employment Card (Kartu Prakerja) initiative, inaugurated by the Indonesian government on April 11, 2020, represents a state-sponsored training program aimed at addressing employment challenges and mitigating the economic repercussions of the COVID-19 pandemic. This program operates as a digital training platform for adults within the job force, encompassing job seekers, individuals who have been laid off, and those seeking to enhance their skills, with the primary stipulation being that the participants are not engaged in formal education.

The program pursues a dual objective: to augment the skills and competitiveness of the workforce while simultaneously stimulating the economy. Participants were afforded access to skill-enhancement courses through registered partner platforms, with training incentives ranging from IDR 3.5 4.5 million. A notable feature of the program is post-training financial incentives, which are disbursed in phases following the completion of training and related assessments, amounting to between IDR 1.8 and 2.4 million. This comprehensive approach ensures that Kartu Prakerja not only facilitates skill development, but also provides a temporary financial safety net, thereby creating an incentive structure to encourage active participation and course completion.

3. Methods

3.1. Data

This study employs microdata from the 2023 National Labor Force Survey (Sakernas), disseminated by Statistics Indonesia (Badan Pusat Statistik, BPS). Sakernas provides extensive national data on employment status, income, education, demographics, and participation in government initiatives, rendering it an optimal resource for evaluating the impact of the Kartu Prakerja program on income outcomes.

This research focuses on individuals of working age (18–64 years), excluding those still engaged in formal education or not active in the labor market. Participants are categorized into two groups: (a) Treatment group: respondents who reported receiving benefits or participating in the Kartu Prakerja program. (b) Control group: comparable individuals who did not participate in the program.

The initial dataset underwent a rigorous cleaning process. Observations with missing critical data including income, Prakerja participation, education, or region were excluded. Furthermore, to ensure robustness, income outliers were identified and treated by Winsoring extreme values at the 99th percentile. Afterthese procedures, the final sample comprised approximately 36,113 observations, dependent on the availability of income and participation data across provinces. Income is defined as monthly earnings from the primary job, as reported in the Sakernas questionnaire, and adjusted to 2023 constant prices.

3.2. Analytical Method

The main aim of this research is to examine how participating in a Kartu Prakerja program affects the income of workers in Indonesia. We propose that Kartu Prakerja have the potential to boost income for workers in both the formal and informal sectors. To assess the causal effect of program participation on income, this study employs Propensity Score Matching (PSM), a quasi-experimental method that creates a counterfactual group with observable traits similar to the treatment group. PSM addresses selection bias that results from non-random participation in the program by pairing individuals with similar likelihood of enrolling in the program.

In the first stage, a logit model is estimated to calculate the probability that an individual receives the program, conditional on observable characteristics. The probability function is expressed as follows:

$$Prob(Treatment = 1 \mid X_i) = \Phi(\beta_0 + \textstyle\sum_{i=1}^{k} \beta_i X_{ij}) \quad (1)$$

Where $Prob(Treatment = 1 \mid X_i)$ denotes the probability that individual participates in the program, $\Phi(.)$ is the cumulative distribution function of the standard normal distribution, β_0 is the intercept, X_j is the vector of observed covariates for individual j, and β_i are the parameters to be estimated.

The selection of covariates included in the vector X_j is grounded in labor economics theory and empirical evidence. Age and age squared were employed to illustrate the evolution of productivity and income throughout an individual's life. Typically, earnings increase with experience, although they may decline in the later years. Job experience reflects skills and knowledge acquired through work. Education level refers to formal skills, job opportunities, and earnings. It also affects a person's capability and motivation to participate in skill programs such as Kartu Prakerja.

Furthermore, the model controls demographic and socioeconomic characteristics such as gender, marital status, area of residence, and employment status. These factors affect access to jobs and opportunities, which can influence who joins a program. Employment status is included to determine the difference between formal and informal workers, as their pay and job security vary. By considering these factors, this study aims to control factors that affect both joining the program and income, supporting the study's method.

In the second stage, the causal effect of program participation on income is estimated using the Average Treatment Effect on the Treated (ATT):

$$ATT = E(\ln Y_1 - \ln Y_0 \mid D = 1) \quad (2)$$

where is the observed log income of the participants and is the estimated counterfactual income derived from matched non-participants. A statistically significant and positive ATT indicates that participation increases workers' income in percentage terms.

4. Results and Discussion

4.1. Research Results

Descriptive statistics in table 1 reflect the diverse composition of workers in Indonesia's labor market. The income distribution shows substantial variability, indicating differences in earnings across individuals and sectors. To address skewness in the income data, the natural logarithm of monthly earnings is used as the outcome variable in the subsequent analysis, ensuring a more statistically appropriate distribution for econometric estimation.

Table 1. The Variables' Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Income	2168252	1780664	53333	35000000
Log Income	14.29981	0.8129	10.88431	17.37086
Gender				
Men	0.6320	0.4823	0	1
Women	0.3679	0.4823	0	1
Age	35.846	10.0952	18	65
Age-squared	1386.872	782.203	324	4225
Marriage Status				
Marriage	0.7767	0.4165	0	1
Single	0.2233	0.4165	0	1
Education category				
Low education	0.1793	0.3836	0	1
Middle education	0.6166	0.4862	0	1
High education	0.2041	0.4031	0	1
Employment status				
Informal	0.4819	0.4995	0	1
Formal	0.5180	0.4997	0	1
Kartu Pra-Kerja				
Achieve	0.4332	0.4955	0	1
Not-achieve	0.5668	0.4955	0	1
Location				
Rural	0.4228	0.4940	0	1
Urban	0.5772	0.4940	0	1
Job experiences (Year)	6.9723	7.7548	0	47
Number of observations	36113			

Source: processed data, 2025

Referring to the table 1, the sample is dominated by male workers, which aligns with typical labor force participation patterns in developing economies. Most individuals are in their productive age range, and the inclusion of both age and its quadratic form helps to capture nonlinear patterns of productivity and earnings throughout the life cycle. The majority of the respondents were married, reflecting the demographic characteristics of Indonesia's working-age population.

In terms of human capital characteristics, a large proportion of workers possess an intermediate level of education, while a noticeable share has attained higher education. These educational variations are essential as they shape both access to skill enhancement programs and the potential for income improvement. Employment characteristics reveal a balance between formal and informal labor markets, pointing to the continued importance of informal work arrangements and the associated disparities in job stability and wage-setting structures.

Participation in the Kartu Prakerja program is fairly widespread across the sample, demonstrating the reach of the initiative as one of Indonesia's major labor market policies. Spatially, a larger share of individuals resides in urban areas, reflecting the concentration of employment opportunities in metropolitan regions. Job experiences levels vary considerably among workers, indicating diversity in skill accumulation and labor market exposure.

Overall, these descriptive patterns illustrate the heterogeneity of the workforce, highlighting the importance of controlling demographic, educational, occupational, and regional differences. Such variations justify the application of Propensity Score Matching to ensure robust and unbiased assessment of the income effects associated with participation in the Kartu Prakerja program.

Table 2. Main Estimation Results: Propensity Score Matching Analysis

Specification	Sample Size	ATT	Standard Error	t-statistic	Sig.
Full Sample Income	36,147	0.0332	0.0150	2.21	**
Income < 5 million	33,994	0.0114	0.0141	0.81	
Very Low Income (<2M)	18,337	-0.0205	0.0142	-1.45	
Lower-Middle Income (2-5M)	15,657	0.0133	0.0062	2.16	**
Middle Income (5-10M)	1,886	-0.0077	0.0115	-0.67	
High Income (>10M)	267	-0.0675	0.0602	-1.12	

*Notes: ATT = Average Treatment Effect on the Treated. ** indicates significance at 5% level.*

Source: processed data, 2025

Table 2 shows the Propensity Score Matching estimation provides evidence that participation in a Kartu Prakerja program has a measurable yet modest impact on workers' earnings. The full-sample ATT indicated a statistically significant income improvement of 3.32% (t = 2.21, p<0.05). Using the median monthly income of treated individuals in the sample, this effect corresponds to an estimated gain of approximately Rp70,000–Rp85,000 per month, which, while not transformative at the household level, reflects a positive return on public investment in workforce development.

However, when disaggregated, the program's benefits appear to be concentrated in the lower-middle income group (2–5 million IDR/month). This group experienced a significant ATT of 1.33% (t = 2.16, p<0.05). By contrast, workers in the very low-income segment (<2 million IDR) experience a negative but statistically insignificant change in income (ATT = –2.05%), suggesting that structural disadvantages may hinder their ability to convert newly acquired skills into earnings. Similarly, the middle- and high-income groups show negative and statistically insignificant estimates, implying that additional training brings little marginal wage progression when workers are already near productivity-based wage ceilings.

Table 3. Determinants of Program Participation by Income Groups

Variable	Very Low	Lower-Middle	Middle	High
Age	0.0424***	0.0120	-0.0005	-0.0034
Age-squared	-0.0005***	-0.0002	-0.0001	-0.0001
Higher Education	0.3233***	0.2694***	0.1820	0.0559
Middle Education	-0.0196	-0.0108	0.1210	0.4865
Urban Area	0.0650**	0.1288***	-0.0504	0.0742
Female	-0.0383	0.0594	-0.0787	-0.1263
Unmarried	-0.3080***	-0.3249***	-0.3824**	-0.2313
Job experiences	-0.0018	-0.0007	-0.0008	0.0043
Pseudo R^2	0.0077	0.0058	0.0047	0.0126
Observations	18,337	15,657	1,886	267

*Notes: Coefficients from logistic regression models for program participation. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

Source: processed data, 2025

Table 3 presents the determinants of program participation across income groups, revealing several important patterns. Higher education has emerged as a consistently strong predictor of participation, particularly for lower-income groups. For the very low-income group, having higher education increased the log-odds of participation by 0.323 ($p<0.001$), while for the lower-middle-income group, the effect was 0.269 ($p<0.001$). This strong education effect persists throughout the middle-income group (coefficient = 0.182), although it loses statistical significance, likely due to the smaller sample size.

Urban residence significantly predicts program participation for lower-income groups, with coefficients of 0.065 ($p<0.05$) for very low-income and 0.129 ($p<0.001$) for lower-middle-income participants. This pattern reflect that digital infrastructure and accessibility is vital in program uptake, especially for the key beneficiaries.

A notable finding across all income groups is the consistent negative association between unmarried status and program participation. The coefficients are statistically significant and substantial in magnitude: -0.308 ($p<0.001$) for very low-income, -0.325 ($p<0.001$) for lower-middle-income, -0.382 ($p<0.05$) for middle-income, and -0.231 for high-income participants. This finding suggests that marital status and potentially associated family responsibilities significantly influence program participation decisions.

Age showed a nonlinear relationship with participation, particularly for the very low-income group, where both age (0.042, $p<0.001$) and age-squared (-0.0005, $p<0.001$) were significant, indicating that participation initially increased with age but eventually declined.

Table 4. Balance Diagnostics: Standardized Mean Differences Before and After Matching

Variable	Sample	Treated Mean	Control Mean	Standardized Bias (%)	Bias Reduction (%)	t-test p-value
Age	Unmatched	35.95	35.52	4.3	-	0.000
	Matched	35.95	35.46	4.8	-12.9	0.000
Age-squared	Unmatched	1389.8	1368.5	2.7	-	0.013
	Matched	1389.1	1348.0	5.2	-92.4	0.000
Secondary Education	Unmatched	59.39%	63.61%	-8.7	-	0.000
	Matched	59.41%	61.59%	-4.5	48.3	0.000
Higher Education	Unmatched	22.42%	17.84%	11.4	-	0.000
	Matched	22.43%	22.03%	1.0	91.2	0.407
Female	Unmatched	38.62%	37.36%	2.6	-	0.017
	Matched	38.61%	36.87%	3.6	-36.8	0.002
Urban Residence	Unmatched	57.88%	56.09%	3.6	-	0.001
	Matched	57.89%	57.12%	1.6	56.9	0.182
Formal Employment	Unmatched	51.40%	51.32%	0.2	-	0.875
	Matched	51.42%	52.26%	-1.7	-881.2	0.147
Unmarried	Unmatched	19.90%	25.14%	-12.5	-	0.000
	Matched	19.88%	19.63%	0.6	95.2	0.587
Job Experiences	Unmatched	6.93	6.86	0.8	-	0.452
	Matched	6.92	6.67	3.2	-287.4	0.005

Source: processed data, 2025

The propensity score matching procedure demonstrated a satisfactory overall balance quality, supporting the validity of the causal inference approach. As presented in Table 4, the matching achieved substantial improvement in the covariate balance between the treatment and control groups. The pseudo R^2 value decreased from 0.007 in the unmatched sample to

0.001 in the matched sample, indicating that observable characteristics have minimal predictive power for treatment assignment after matching, which is a key condition for satisfying the conditional independence assumption (Stuart, 2010). The overall mean bias was reduced by 69.4%, from 5.2% to 2.9%, which is well below the recommended threshold of 5% for an adequate balance. Furthermore, the B-value of 8.9 falls comfortably below the critical threshold of 25, and the R-value of 1.10 remains within the acceptable range of 0.5 to 2, collectively indicating successful covariate balancing.

Several covariates exhibited exceptional balance improvement through the matching procedure. Higher educational attainment showed a 91.2% reduction in standardized bias, declining from 11.4% to 1.0%, with the post-matching difference becoming statistically insignificant (p = 0.407). Similarly, marital status demonstrated a 95.2% bias reduction, from -12.5% to -0.6%, with the matched difference no longer significant (p = 0.587). Urban residence also achieved substantial improvement with a 56.9% bias reduction, falling from 3.6% to 1.6%, with non-significant group differences (p = 0.182). These results indicate that the matching procedure successfully addressed the initial systematic differences in the key demographic and socioeconomic characteristics.

However, some residual imbalances warrant consideration when interpreting these results. Age and its quadratic term showed increased bias after matching, with standardized differences increasing from 4.3% to 4.8% and from 2.7% to 5.2%, respectively. Job experience also exhibited an increased bias, escalating from 0.8% to 3.2% and retaining statistical significance (p = 0.005) in the matched sample. The sex composition showed a similar pattern, with bias increasing from 2.6% to 3.6%, while it remained statistically significant (p = 0.002). These persistent imbalances suggest that age- and work-related factors may not be fully balanced between the treatment and control groups, potentially introducing confounding factors in the estimated treatment effects.

The variance ratio diagnostics indicated generally acceptable distributional similarity for most covariates, although age, age squared, and job experience showed ratios outside the ideal range [0.97, 1.03]. This suggests some differences in the shape of the distributions of these continuous variables, which could affect the comparability of the treatment and control groups across the full support of these covariates. Despite these limitations, the overall balance metrics support the use of matched samples for causal inferences. The substantial bias reduction for most covariates, combined with the low pseudo-R^2 and acceptable B-value, suggests that the matching procedure created sufficiently comparable groups for estimating treatment effects. Yet, the residual imbalances in age and job experience necessitate cautious interpretation of the results, particularly for subgroup analyses in which these factors may crucial. Future analyses should consider sensitivity checks using alternative matching specifications or covariate adjustments in the outcome model to tackle such imbalances.

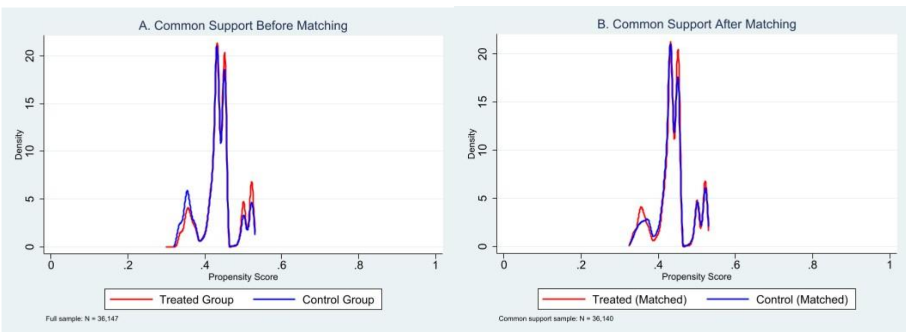

Figure 2. Before and After Matching
Source: processed data, 2025

Figure 2 also details both propensity score density curves before and after matching showed a good overlap between the treated and control subjects. After matching, the curves become more compact across most of the score range, indicating that the ATT estimates are calculated within a sufficient region of common support. This means that outcome comparisons are made across individuals with similar participation probabilities, as required by PSM-based inference.

Table 5. Subgroup Analysis: Treatment Effects on Log Earnings

Subgroup	ATT	SE	t-stat	p-value	Treated N	Total N	Sig.
Female	0.073	0.026	2.78	0.005	5,849	13,310	**
Male	0.014	0.016	0.85	0.393	9,809	22,832	
Urban	0.039	0.020	1.95	0.051	9,194	20,861	*
Rural	0.008	0.022	0.36	0.722	6,467	15,284	
Low Education	-0.018	0.030	-0.59	0.555	2,767	6,484	
Medium Education	0.030	0.019	1.58	0.114	9,314	22,286	
High Education	0.056	0.035	1.58	0.114	3,582	7,377	
Formal Sector	0.064	0.022	2.90	0.004	8,104	18,717	**
Informal Sector	0.002	0.020	0.11	0.911	7,558	17,429	

Source: processed data, 2025

The analysis reveals substantial heterogeneity in treatment effects across demographic and socioeconomic subgroups, as detailed in Table 5. The digital training program demonstrates particularly strong and statistically significant effects for female participants, with an Average Treatment Effect on the Treated (ATT) of 0.073 ($p = 0.005$), indicating a 7.3% increase in earnings. This effect size was substantially larger than the 1.4% increase observed for male participants, which failed to achieve statistical significance ($p = 0.393$). The pronounced gender differential suggests that the program may be particularly effective in addressing gender-specific barriers in the labor market or that women experience higher returns to the acquired digital skills. This finding aligns with emerging literature on digital training programs in developing contexts, where women often demonstrate stronger responsiveness to skill-enhancement interventions due to initial skill deficits and structural barriers in traditional labor markets (Acevedo et al., 2020).

Geographic disparities in program effectiveness are equally noteworthy. Urban residents experience a marginally significant 3.9% earnings increase ($p = 0.051$), while rural participants show a negligible and non-significant 0.8% effect ($p = 0.722$). This urban-rural divide likely reflects differences in labor market structures, with urban areas offering more diverse employment opportunities that enable participants to capitalize on newly acquired digital skills. Rural labor markets, often characterized by agricultural predominance and limited formal employment opportunities, may provide fewer avenues for translating digital skills into earnings improvements. Additionally, infrastructure limitations in rural areas, including internet connectivity and digital device access, may constrain the practical application of training content.

The educational gradient in treatment effects reveals a clear pattern of increasing returns with higher educational attainment. Participants with low education levels experience a non-significant -1.8% effect ($p = 0.555$), suggesting that foundational literacy and numeracy skills may be necessary prerequisites for benefiting from digital training. Medium-educated individuals show a positive but non-significant 3.0% effect ($p = 0.114$), while highly educated participants demonstrate a substantial 5.6% earnings increase, albeit with marginal statistical significance (p = 0.114) due to smaller sample size. This pattern supports the hypothesis of skill complementarity, whereby digital training yields higher returns when combined with stronger foundational human capital (Heckman et al., 2014).

The formal-informal sector dichotomy presents one of the most striking contrasts in program effectiveness. Formal sector workers experience a robust 6.4% earnings increase (p = 0.004), while informal sector participants show virtually no effect (0.2%, p = 0.911). This divergence likely reflects structural differences in how skills are valued and compensated across sectors. Formal sector employment typically offers clearer pathways for skill-based advancement, standardized compensation structures, and greater opportunities to apply digital skills in workplace tasks. Conversely, the informal sector's irregular income patterns, limited career ladders, and different skill requirements may diminish the economic returns to digital training.

The subgroup analysis collectively suggests that the program's effectiveness is strongly moderated by participants' position in the labor market and their baseline human capital. The most significant benefits accrue to individuals with existing advantages—those in formal sector employment, urban locations, and with higher educational attainment. This pattern raises important questions about the program's ability to benefit the most marginalized populations and suggests potential mechanisms of cumulative advantage in skill acquisition programs. From a policy perspective, these findings indicate that while the program shows overall effectiveness, its impact is unequally distributed, potentially exacerbating existing inequalities unless complemented with targeted interventions for disadvantaged subgroups. Future program iterations might consider differentiated approaches for different beneficiary segments, with additional support mechanisms for those facing structural barriers to translating skills into economic gains.

Table 6. Robustness Check

Matching Method	ATT	SE	t-stat	p-value	Treated N	Control N	Total N	Sig.
Nearest Neighbor (Main)	0.037	0.015	2.47	0.014	15,656	20,484	36,140	**
Kernel Matching (Robustness)	0.005	0.009	0.58	0.562	15,656	20,484	36,140	

Source: processed data, 2025

The robust analysis reveals significant sensitivity in treatment effect estimates to methodological choices. As shown in Table 6, the main specification using nearest neighbor matching indicates a statistically significant 3.7% earnings increase (ATT = 0.037, p = 0.014). However, the alternative kernel matching approach yields a substantially smaller and non-significant effect of 0.5% (ATT = 0.005, p = 0.562).

This discrepancy highlights critical methodological considerations. Nearest neighbor matching, while widely used, may produce fewer stable estimates due to its reliance on limited matches per observation. The method's susceptibility to data sorting order and potential for poor matches in sparse propensity score regions could explain the larger effect size. In contrast, kernel matching employs weighted averages across all control units within a specified bandwidth, typically generating more conservative and stable estimates through smoother weighting functions.

The substantial difference between estimates suggests that the program's effects may be more limited or heterogeneous than initially apparent. The sensitivity to matching methodology indicates that the treatment effect is not robust across different estimation approaches, necessitating cautious interpretation of the program's overall effectiveness.

These findings underscore the importance of methodological transparency and multiple robustness checks in program evaluation. The contrasting results call for further investigation into whether the program benefits specific subpopulation rather than generating broad-based impacts. Future analyses should employ additional matching algorithms and explore treatment effect heterogeneity to provide a more comprehensive understanding of program impacts.

4.2. Discussion

This study provides a nuanced resolution to the contentious debate in the literature regarding the efficacy of Indonesia's Kartu Prakerja program. Our findings reveal that the program's impact is neither universally positive nor negative but is fundamentally contingent upon the socioeconomic positioning of participants within the larger labor market structure.

The modest aggregate effect of a 3.32% income increase aligns with studies that acknowledge the program's potential, such as those by Ayyubi et al., (2023); Gunawan et al., (2024); and Suryadi et al., (2021), who highlighted its role in employment transitions. However, the concentration of these benefits within the lower-middle income bracket and the null-to-negative effects for the very poor substantiate the critiques of Nugraha & Ariyanto (2025) who questioned its impact on real wages. This bifurcated outcome suggests a troubling pattern of cumulative advantage, where the program yields significant returns for those already better positioned such as formal sector workers, urban residents, and the higher-educated while offering little to the most vulnerable. This phenomenon of the "Matthew Effect" in skill acquisition provides a compelling explanation for the contradictory findings in the literature, demonstrating that both optimistic and pessimistic view can coexist by applying to different segments of the beneficiary population. In simple terms, individuals who enter the program with more skills and resources tend to acquire even more, while those who start the least often fail to benefit resulting in the gap between groups widening rather than narrowing.

The profound heterogeneity in effects underscores the powerful role of structural labor market constraints in mediating the conversion of skills into income. The stark formal-informal sector dichotomy, where formal workers experienced a robust 6.4% earnings increase compared to no effect for informal workers, challenges the core assumption of human capital theory that skills directly translate to higher pay. Instead, it suggests that the institutional context of employment with its standardized wage structures and clear advancement pathways is a prerequisite for realizing the returns to training.

Similarly, the urban-rural divide and the positive educational gradient reveal that pre-existing advantages, such as better infrastructure and stronger foundational knowledge, are crucial for leveraging digital training. This structural mediation effect resolves the apparent paradox in the literature between studies that found improved competencies (Yana, 2021) and those that found limited economic returns, as the acquisition of skills does not automatically overcome labor market segmentation and demand-side constraints.

A notable and promising exception to this pattern is the significant 7.3% earnings boost for female participants, which suggests the program may be particularly effective in circumventing gender-specific barriers in the traditional labor market, a dimension that merits greater exploration in future research. Further complicating this narrative is the evidence of significant selection bias in program participation. The strong predictive power of higher education and urban residence on enrollment indicates a "creaming" effect, where the most resourceful and accessible individuals are more likely to self-select into the program. This selection pattern likely influences the varying conclusions across impact evaluations, as studies with different sample compositions would capture different segments of the beneficiary population.

The consistently strong negative association between unmarried status and participation across all income groups is a novel finding that points to an underappreciated barrier, potentially related to household dynamics or care responsibilities, which the current digital delivery model does not adequately address. From a methodological standpoint, the sensitivity of our results to different matching algorithms echoes the diversity of approaches in literature from Difference-in-Differences to multinomial logit models and underscores the fragility of the estimated treatment effect. This methodological caution, coupled with the residual imbalances in covariates like age and job experience after matching, highlights the inherent challenges in establishing causal claims and suggests that the program's benefits may be highly localized rather than broadly generalized.

The collective findings necessitate a revision of the program's theory of change. The data indicates that solely providing skills from the supply side is inadequate to achieve equitable economic outcomes in a segmented labor market. While the program's market-driven strategy effectively expands training availability, it appears to exacerbate existing disparities by favoring individuals who already possess complementary resources (Nguyen et al., 2023).

To enhance the program's impact and equity, it is crucial to move away from a uniform approach. Future iterations should incorporate customized curricula that address the specific needs of informal and rural workers, implement proactive strategies to eliminate participation barriers for marginalized groups, such as the unmarried, and establish stronger institutional linkages to ensure that the skills acquired align with actual market demand. Ultimately, the Kartu Prakerja represents a significant innovation in Indonesian ALMP, demonstrating notable successes in expanding access to skills training and providing immediate benefits to participants. However, its effectiveness as a tool for inclusive development depends on its ability to address not only individual skill deficiencies but also the structural factors that influence their economic relevance.

5. Conclusion

This study evaluates the effectiveness of the Kartu Prakerja program on participants' income using PSM. This study demonstrates that the Kartu Prakerja initiative yields complex and diverse effects, which account for the conflicting conclusions observed in existing research. While the program exerts a modest positive impact on overall earnings, this effect obscures significant distributional consequences. The benefits of the program are disproportionately accrued by groups already in advantageous positions—such as formal sector employees, urban residents, and individuals with higher education—while it proves less effective for the most vulnerable groups, including the extremely poor, rural inhabitants, and informal sector workers. This pattern of accumulating advantage suggests that the program, in its current form, may inadvertently perpetuate existing disparities in Indonesia's labor market.

The findings challenge the assumption that skills training automatically leads to increased earnings, instead of revealing how structural factors influence economic returns. The pronounced divide between formal and informal sectors and the urban-rural gap underscores how labor market institutions and opportunity structures fundamentally affect the program's success. Furthermore, participation trends reveal systematic obstacles that hinder the most marginalized groups from accessing and benefiting from the program.

These results have significant policy implications. To enhance both effectiveness and equity, future iterations of the program require substantial redesign: developing tailored approaches for formal and informal sector workers; establishing targeted support systems for vulnerable groups; and strengthening connections between skills training and labor market demand. While the program's market-driven training approach shows potential for scalability, it necessitates additional structural interventions to ensure inclusive outcomes.

For researchers, this study underscores the importance of examining beyond average treatment effects to explore varied impacts across different population subgroups. Future assessments should employ mixed methods approaches to better understand the mechanisms behind these differential effects and identify strategies to reach those currently excluded. The success of the Kartu Prakerja as a tool for inclusive development will ultimately depend on its capacity to address not only individual skill gaps but also the structural barriers that determine their economic value in a segmented labor market.

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