

Occupational Mismatch and Income Effects in Indonesia's Gig Economy: A Gender Perspective

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Abstract

This study examines the relationship between occupational mismatch and income in Indonesia's gig economy, with particular attention to gender differences. Using nationally representative data from the 2020 Indonesian National Labor Force Survey, gig workers are identified based on self-employment status and digital engagement in work activities. To address potential endogeneity, this study employs a treatment-effects model using district-level mismatch rates as an instrumental variable. The results show a negative association between occupational mismatch and income, indicating that mismatched workers have lower income than their well-matched counterparts after accounting for selection bias. This finding is consistent across ordinary least squares (OLS), propensity score matching (PSM), and treatment-effects models, supporting the robustness of the results. Gender-disaggregated analysis further shows that the negative effect is statistically significant for male workers but not for female workers, indicating important gender heterogeneity. Quantile regression results show that income penalties are present across the income distribution for male workers and become more pronounced at higher income levels. In contrast, the estimated effects for female workers remain statistically insignificant across quantiles. These findings suggest that occupational mismatch in digitally mediated labor markets reflects structural constraints rather than efficient skill allocation. This study contributes to the literature by providing evidence on the distributional and gender-specific effects of occupational mismatch. It also offers policy implications for improving skill alignment and reducing regional labor-market disparities.

Keywords

Gender heterogeneity; gig economy; income effects; occupational mismatch

Introduction

The expansion of digital labor platforms has coincided with significant demographic and educational transitions in Indonesia. Between 1990 and 2021, the national workforce increased from 75.01 million to 140.15 million workers. This growth was accompanied by rising educational attainment, with approximately 1.5 million university graduates recorded in 2020 (BPS-Statistics Indonesia, 2021). Although these trends would traditionally be expected to support entry into formal employment, a growing share of educated workers has instead entered gig work. This type of work often requires limited formal credentials but places greater emphasis on platform literacy and task-specific adaptability. These developments raise important questions about labor-market allocation in digital work settings, where traditional signals such as education may play a more limited role in job matching.

In this context, occupational mismatch, defined as the misalignment between workers' educational backgrounds and job requirements, takes on new characteristics. In traditional labor markets, employment is often shaped by qualification-based hiring, while informal work is commonly associated with low-productivity activities. By contrast, labor allocation in gig work is increasingly influenced by algorithmic matching, customer ratings, and changing demand conditions. As a result, occupational mismatch may reflect not only inefficient human capital utilization but also information asymmetries and platform-based sorting. Classical labor economics theory predicts that mismatch leads to income penalties because skills are not optimally allocated (Arranz & García-Serrano, 2025; Eguia et al., 2023; Sun & Kim, 2022). However, emerging evidence suggests that overqualified workers in flexible digital labor markets may convert excess skills into productivity gains and higher income (Chaudhary et al., 2025; Jacobs et al., 2023).

This study departs from the conventional view that occupational mismatch necessarily reflects labor-market inefficiency. It instead examines how mismatch operates within digital labor markets. Existing research has predominantly focused on formal employment, leaving platform-based work relatively underexplored, particularly in developing economies. This issue is especially relevant in Indonesia, where digital platforms interact with large informal labor markets, surplus educated labor, and uneven access to economic opportunities. Rather than treating mismatch solely as a deviation from optimal labor allocation, this study considers whether mismatch in gig work may reflect adaptive labor-market strategies shaped by individual choices and platform-level mechanisms.

The gender dimension further complicates this relationship. In Indonesia, female labor force participation increased from 48.87% in 2015 to 54.52% in 2023 (BPS-Statistics Indonesia, 2015, 2023). This increase reflects changing social norms and the growing appeal of flexible work arrangements. Gig platforms may offer women opportunities for flexible scheduling and remote work, helping them balance paid work with domestic responsibilities. However, this flexibility may coexist with structural constraints. Previous studies suggest that women in platform-based work often face lower income, safety concerns, and potential algorithmic bias (Ajaiyeoba, 2025; Lott & Abendroth, 2020; Seo et al., 2021). In addition, caregiving responsibilities may shape labor supply decisions. Some women may therefore accept suboptimal job matches as a trade-off between income generation and household obligations (Díaz, 2022).

Despite these increasingly visible issues, empirical evidence on the interaction between occupational mismatch and gender in the gig economy remains limited, especially in developing countries. Existing studies primarily focus on formal or regulated labor markets (Addison et al., 2020; Hasibuan & Handayani, 2021), leaving informal and platform-based contexts relatively underexplored. Digital labor markets also require closer attention because technology reshapes access to employment and labor allocation processes (Ross et al., 2024). In addition, platform governance may reinforce inequality when algorithmic job assignment systems do not prioritize formal qualifications (Alacovska et al., 2024).

Building on these gaps, this study examines the effect of occupational mismatch on income among gig workers in Indonesia, with particular attention to gender differences. The study contributes to the literature in three ways. First, it provides empirical evidence on occupational mismatch in platform-based labor using nationally representative Indonesian microdata. Second, it extends the conceptual understanding of mismatch by situating it within digital labor markets, where allocation mechanisms differ from traditional employer-employee settings. Third, it provides a gender-disaggregated analysis of how mismatch and income dynamics differ between male and female workers.

Methodologically, this study applies a treatment-effects model to address endogeneity and selection bias. It also incorporates spatial variation in district-level mismatch to capture local labor-market conditions. This approach is relevant in the gig economy, where selection bias and unobserved heterogeneity are likely to be substantial. Overall, the study provides a clearer understanding of how occupational mismatch operates in digital labor markets.

Literature review

Theoretical and empirical background

Occupational mismatch, defined as the discrepancy between an individual's educational attainment and the skill requirements of a job, has attracted increasing attention in labor-market research. Rooted in classical human capital theory, mismatch has traditionally been viewed as a form of labor-market inefficiency associated with income penalties and productivity losses. This inefficiency is closely related to unequal job access, job-search frictions, and information asymmetries (Addison et al., 2020). Evidence from formal labor markets consistently shows that mismatched workers tend to earn lower income (Jacobs et al., 2022; Wicaksono et al., 2023), experience slower career progression (Sevilla et al., 2021; Voces & Caínzos, 2021), and report lower job satisfaction (Bedemariam & Ramos, 2021). Similar patterns are observed in developing countries such as India and Vietnam, where both overeducation and undereducation are associated with income penalties (Bahl & Sharma, 2024; Tran et al., 2025).

However, the expansion of digital labor markets calls for a re-evaluation of these traditional assumptions. In the gig economy, work is increasingly organized through short-term, task-based arrangements facilitated by digital platforms. Foundational studies suggest that digital platforms reshape labor relations through algorithmic coordination, fragmented work arrangements, and asymmetric power relations between workers and platforms (Graham et al., 2017; Schor et al., 2020). In these settings, labor allocation is influenced not only by formal credentials but also by reputation systems, algorithmic sorting, and real-time demand

matching (Duggan et al., 2023; Kadolkar et al., 2025). This transformation is especially relevant in Indonesia, where large informal labor markets coexist with rapid platform expansion (Faik et al., 2026; Prasetyo, 2024). Consequently, occupational mismatch may reflect inefficient human capital allocation, platform-driven sorting, and unequal access to digital opportunities (Pater et al., 2022).

Emerging evidence further suggests that mismatch in digital labor markets may not always generate income penalties. Overqualified workers may use excess skills, digital literacy, adaptability, and platform-specific competencies to improve visibility, client satisfaction, and income (McKenzie, 2022; Wood et al., 2019). In this context, occupational mismatch may function as an adaptive labor-market strategy rather than a purely inefficient outcome. Platform-based sorting, reputational accumulation, and selective participation may enable some mismatched workers to achieve higher income.

Human capital theory also highlights the role of age and work experience in shaping income outcomes. Mincer (1974) emphasized that accumulated experience contributes to productivity and income. In both conventional and digital work environments, older workers may exhibit stronger soft skills, discipline, professionalism, and emotional regulation (Cavanagh et al., 2020; Foweraker & Cutcher, 2020). These attributes contribute to productivity and job stability (Mori et al., 2024). In platform-based employment, such advantages may be reinforced through feedback systems and client ratings that reward consistency and service quality (Herrmann et al., 2023; Topel, 1991). These dynamics indicate that relevant skills in digital labor markets extend beyond formal education and include noncognitive and platform-specific competencies that are not fully captured by conventional mismatch measures (Calvo, 2024).

Signaling theory also helps explain labor allocation in the gig economy. In the absence of formal hiring mechanisms, workers rely on alternative signals, such as specialization, ratings, and work history, to convey credibility to clients. Task specialization may enhance perceived professionalism and reliability (Gussek & Wiesche, 2023), while reputation systems influence worker visibility and labor demand (Benson et al., 2020). However, these systems are not always transparent and may reproduce algorithmic bias, which can affect workers' long-term income prospects (Wood & Lehdonvirta, 2023). These dynamics show how information asymmetries and platform coordination shape labor outcomes beyond traditional signaling processes (Lukac & Grow, 2021).

Beyond individual-level explanations, labor-market segmentation theory emphasizes that mismatch is embedded within broader institutional and socioeconomic constraints (Doeringer & Piore, 1985). In platform-based labor markets, segmentation may emerge through algorithmic sorting, spatial inequality, and unequal access to digital infrastructure (Wood et al., 2019). Geographic and racial segregation may further intensify mismatch, as shown by Stoll (2005) in the context of urban labor markets in the United States. In developing Asia, search frictions and unequal digital access may contribute to skill misallocation and widening educational inequality (Chua & Chun, 2016). In Indonesia, these challenges are reinforced by regional disparities in infrastructure and labor-market opportunities (Siatan et al., 2024; Suparman & Muzakir, 2023).

Spatial mismatch theory further explains how geographic and infrastructural inequalities shape labor-market outcomes (Kain, 1968). Although digital platforms are expected to reduce geographic barriers, access to opportunities remains uneven because of disparities in digital connectivity and regional economic development. Studies in Indonesia indicate that available

platform-based jobs often do not match workers' qualifications, particularly in less-developed regions (Flores-Saviaga et al., 2020; Khoiruddin et al., 2024).

Household economics theory adds an important gender dimension to occupational mismatch. Becker (1993) argued that labor supply decisions are shaped by intra-household trade-offs and constraints. Women often face disproportionate caregiving responsibilities, commuting burdens, and time constraints that influence their participation in flexible forms of employment (Farré et al., 2023; Mukherjee & Sarkhel, 2025). Although rising educational attainment and declining birth rates have expanded women's labor-market participation (Klasen et al., 2021), marital status continues to affect employment outcomes (McKinnish, 2020). From a feminist economics perspective, these dynamics reflect time-use constraints and caregiving burdens that may encourage women to prioritize flexibility over job-skill alignment (Blecker & Braunstein, 2022). In platform-based work, such constraints may lead women to accept mismatched jobs as a rational response to household and structural limitations. At the same time, digital platforms may reproduce gender inequality through algorithmic bias and occupational segmentation (Ajaiyeoba, 2025; Gerber, 2022; Rani et al., 2022).

Hypotheses development

Drawing on the theoretical frameworks and empirical literature discussed above, this study formulates the following hypotheses on the determinants and effects of occupational mismatch in Indonesia's gig economy.

H1: Occupational mismatch is negatively associated with income among gig workers.

This hypothesis is grounded in classical human capital theory, which suggests that skill-job misalignment reduces productivity and income. In gig work, mismatch may reflect constraints in labor allocation rather than optimal skill utilization, thereby generating income penalties.

H2: Age is positively associated with income among gig workers.

Age reflects accumulated experience, soft skills, and behavioral traits, such as discipline and emotional regulation. These attributes are valued in platform-based work and may be reinforced through client ratings and algorithmic evaluation systems.

H3: Job-specific experience is positively associated with income among gig workers.

Experience with platform-specific tasks may improve productivity and familiarity with digital systems. It may also contribute to greater efficiency, stronger reputation scores, and better income opportunities.

H4: Specializing in a single job is positively associated with income among gig workers.

Task specialization may improve productivity and signal reliability, thereby increasing income through better matching outcomes.

H5: Higher levels of mismatch in a worker's residential area increase the likelihood of experiencing occupational mismatch.

This hypothesis reflects structural labor-market conditions in which local imbalances and limited matching efficiency influence individual job allocation.

H6: Marital status is positively associated with the likelihood of experiencing occupational mismatch.

From a household economics perspective, marital status may influence labor supply decisions and job selection, particularly through work–family trade-offs.

H7: Residing in rural areas is positively associated with the likelihood of experiencing occupational mismatch.

Rural residence may reflect spatial and digital constraints, including limited job availability and weaker labor-market matching. These constraints may increase the probability of mismatch.

To synthesize the theoretical framework and guide the empirical analysis, Figure 1 illustrates the relationships among occupational mismatch, its determinants, and income outcomes in the gig economy.

Figure 1: Conceptual Framework of Occupational Mismatch and Income

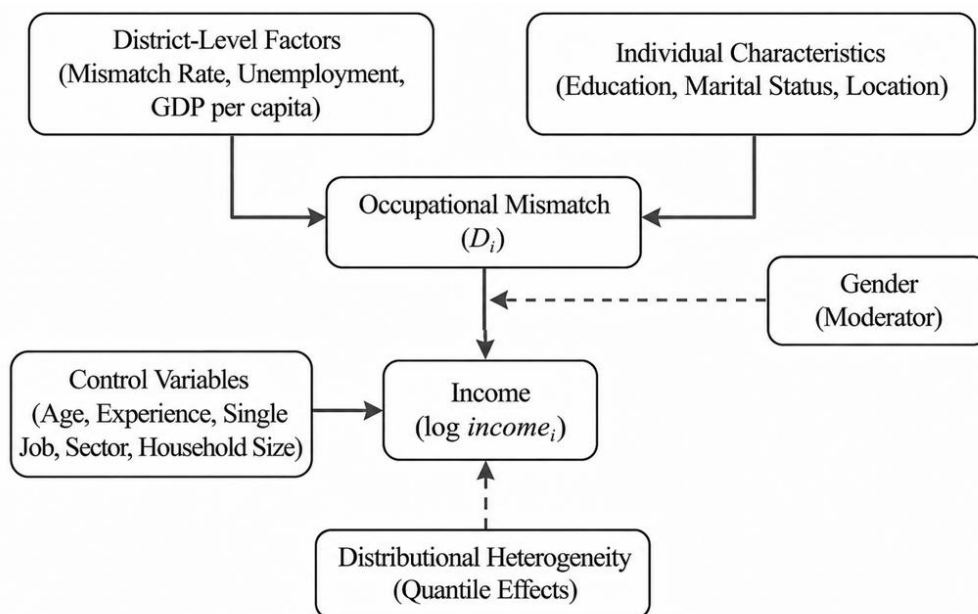


Figure 1 illustrates the conceptual framework of this study. Occupational mismatch (D_i) is influenced by district-level factors, including mismatch rates, unemployment, and GDP per capita. It is also shaped by individual characteristics, such as education, marital status, and location. Together, these factors determine the likelihood of experiencing a mismatch. Occupational mismatch is expected to affect income (log income_i), the primary outcome variable. Control variables, including age, experience, jobholding status, sector, and household size, are included to account for observable differences in income. The framework also captures heterogeneity in the mismatch–income relationship. Gender is modeled as a moderating factor, while distributional heterogeneity is examined through quantile effects across the income distribution.

Method

Data source and sample selection

This study uses data from the 2020 Indonesian National Labor Force Survey, or *Survei Angkatan Kerja Nasional* (SAKERNAS), an annual nationally representative survey administered by Statistics Indonesia (*Badan Pusat Statistik* [BPS]). SAKERNAS provides detailed individual-level information on employment status, income, education, demographic characteristics, and digital engagement. These data are well-suited for analyzing gig work dynamics and occupational mismatch.

Gig workers are identified using two criteria. First, they classify themselves as self-employed or freelancers. Second, they report using the internet as a primary tool in their work. This operational definition reflects the main characteristics of digitally mediated gig work. Applying these criteria yields a final sample of 17,288 gig workers, consisting of 12,387 male workers and 4,901 female workers. This gender-disaggregated sample enables a comparative analysis of occupational mismatch and income outcomes across demographic groups.

Although this definition captures the core features of digitally mediated gig work, it may also include a broader group of self-employed individuals who use the internet in their economic activities. To improve conceptual clarity, this study focuses on workers whose income-generating activities are closely linked to digital platforms or online-mediated transactions. In Indonesia, these activities include online freelancing, digital services, and platform-based work arrangements. These forms of work differ from conventional informal self-employment in task allocation, client interaction, and income-generation mechanisms. This distinction is important because gig work is shaped by platform-mediated matching, flexible contracts, and algorithmic coordination. These features influence labor-market outcomes differently from traditional informal employment.

Empirical framework and model specification

To estimate the causal effect of occupational mismatch on income among gig workers, this study employs a treatment-effects model grounded in the potential outcomes framework. This approach addresses potential endogeneity in the mismatch status. Endogeneity may arise when unobserved characteristics, such as intrinsic ability, digital skills, or personal motivation, influence both the likelihood of mismatch and income outcomes. If unaddressed, this issue may bias estimates from conventional regression models.

Unlike ordinary least squares (OLS), which assumes exogenous treatment assignment, the treatment-effects model explicitly addresses self-selection. It jointly estimates the probability of occupational mismatch and the corresponding income outcome. Compared with propensity score matching (PSM), which adjusts only for observable characteristics, the treatment-effects approach also accounts for unobserved heterogeneity (Cerulli, 2014; Smith, 2022). This feature makes the model suitable for labor-market analysis, where latent traits may influence both occupational sorting and income. The treatment-effects framework is specified as follows:

$$\log(Y_i) = D_i Y_i(1) + (1 - D_i) Y_i(0) \quad (1)$$

where $\log(Y_i)$ represents observed income, D_i denotes mismatch status, $Y_i(1)$ is the potential income if the individual is mismatched, and $Y_i(0)$ is the potential income if matched. Because individuals can only be observed in one state at a given time, the observed outcome reflects either $Y_i(1)$ or $Y_i(0)$, depending on the realized value of $D_i \in \{0,1\}$.

The parameter of interest is the Average Treatment Effect on the Treated (ATT), defined as follows:

$$ATT = E[Y_i(1) - Y_i(0) | D_i = 1] \quad (2)$$

This parameter measures the expected difference in income between mismatched and matched conditions among individuals who actually experience mismatch. Given the likely correlation between D_i and unobserved components in the income equation, OLS estimates may be biased because of nonrandom selection into mismatch status.

The coefficients obtained from the treatment-effects model are not directly comparable to those from conventional OLS estimation. OLS estimates average associations across the full sample, whereas the treatment-effects model estimates the ATT for individuals who experience occupational mismatch. Therefore, differences in coefficient magnitudes between OLS and treatment-effects estimates should be interpreted as reflecting methodological differences and selection correction, rather than inconsistencies in the underlying relationship.

Income equation

The income equation builds on the standard Mincerian income framework, which links income to human capital factors such as education and work experience. The outcome equation models the natural logarithm of monthly income, $\log(\text{income}_i)$, as a function of occupational mismatch and individual, job, and regional covariates. The income variable refers to self-reported monthly income from primary work activities. This measure is appropriate for gig workers, given their predominantly self-employed status. The logarithmic transformation is applied to reduce right-skewness in the income distribution and to allow coefficient interpretation in approximate percentage terms. The income equation is specified as follows:

$$\log(\text{income}_i) = \alpha + \beta_1 D_i + \beta_2 \text{Age}_i + \beta_3 \text{Age}_i^2 + \beta_4 \text{Experience}_i + \beta_5 \text{SingleJob}_i + \beta_6 \text{SedondaryEdu}_i + \beta_7 \text{TertiaryEdu}_i + \beta_8 \text{Married}_i + \beta_9 \text{Rural}_i + \beta_{10} \text{HH_Size}_i + \beta_{11} \text{Industry}_i + \beta_{12} \text{Service}_i + \beta_{13} \text{Gender}_i + \beta_{14} \text{Unemployment}_i + \beta_{15} \ln(\text{GDP}_{pc})_i + \varepsilon_i \quad (3)$$

The key explanatory variable is occupational mismatch, represented by the binary variable D_i . This variable equals 1 if an individual is either overeducated or undereducated for their current occupation, and 0 otherwise. It captures the treatment effect of mismatch on income. Age (Age_i) and its squared term (Age_i^2) are included to capture potential nonlinear effects of labor-market experience on income. Job-specific experience (Experience_i), measured in months, reflects the accumulation of skills in the current role. Job structure is captured by SingleJob_i , which equals 1 if the individual holds only one job and 0 if the individual holds multiple concurrent jobs.

Additional controls are included to improve model specification and reduce omitted-variable bias. These include educational attainment ($SecondaryEdu_i$ and $TertiaryEdu_i$), marital status ($Married_i$), household size ($HHSize_i$), residential location ($Rural_i$), and sector of employment ($Industry_i$ and $Service_i$). The model also incorporates district-level characteristics, including the unemployment rate ($Unemployment_j$) and GDP per capita ($\ln(GDPpc_j)$). In the full-sample specification, gender ($Gender_i$) is included as a control variable. Finally, the model includes an error term, ε_i , to account for unobserved factors affecting individual income. Together, these variables provide a comprehensive framework for estimating how occupational mismatch relates to income in the gig economy.

Mismatch variable construction

The variable D_i , indicating occupational mismatch, is constructed by comparing each worker's reported education level with the modal education level for their occupation. This comparison is based on mappings from Indonesia's Standard Classification of Occupations (*Klasifikasi Baku Jabatan Indonesia* [KBJI]) and the National Qualification Framework (*Kerangka Kualifikasi Nasional Indonesia* [KKNI]). A mismatch occurs when a worker's educational attainment is either above or below the modal level for a given occupation. This definition is consistent with the international literature (Huertas & Raymond, 2024; Salas-Velasco, 2021; Sitorus & Wicaksono, 2020). The approach captures vertical mismatch, which has direct implications for productivity and income outcomes.

Although this approach is widely used, it primarily relies on formal educational attainment. As a result, it may not fully capture the skills required in digitally mediated labor markets. Gig work often depends on digital competencies, adaptability, and noncognitive skills, such as communication, problem-solving, and client management. These skills are not directly reflected in formal education levels. Therefore, the mismatch measure used in this study should be interpreted as an approximation of skill-job misalignment rather than a comprehensive measure of worker capability. This limitation is especially relevant in platform-based work, where performance is often evaluated through reputation systems and task-based outcomes rather than formal qualifications.

Selection equation and Instrumental Variable (IV)

To account for endogenous mismatch selection, occupational mismatch is modeled as a latent variable, D_i^* , observed as:

$$D_i = \begin{cases} 1, & \text{if } D_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The selection equation is specified as follows:

$$D_i^* = \gamma_0 + \gamma_1 DistrictMismatch_j + \gamma_2 SecondaryEdu_i + \gamma_3 TertiaryEdu_i + \gamma_4 Married_i + \gamma_5 Rural_i + \gamma_6 Unemployment_j + \gamma_7 \ln(GDPpc_j) + \mu_i \quad (5)$$

where $DistrictMismatch_j$ is the instrumental variable, defined as the proportion of mismatched workers in district j . This variable captures the local prevalence of mismatch and reflects structural labor-market imbalances. It is expected to be strongly correlated with an individual's probability of experiencing a mismatch, thereby satisfying the relevance

condition. Districts with higher aggregate mismatch are more likely to exhibit labor-market frictions, such as limited job-matching efficiency and constrained occupational mobility. These conditions may increase the likelihood of individual mismatch.

The exclusion restriction assumes that *DistrictMismatch_j* affects individual income only through its impact on mismatch status rather than through a direct effect on income. Although this assumption is plausible, it may be challenged by regional factors such as local economic conditions. To mitigate this concern, the selection equation incorporates individual characteristics, including education (*SecondaryEdu_i*, *TertiaryEdu_i*) and marital status (*Married_i*). It also includes district-level controls, such as unemployment rates (*Unemployment_j*) and GDP per capita ($\ln(\text{GDPpc}_j)$). These controls reduce the likelihood that the instrumental variable captures broader regional economic effects that directly influence income.

The income and selection equations are jointly estimated using maximum likelihood estimation (MLE). This estimation assumes bivariate normality between the error terms, ε_i and μ_i , with a correlation coefficient ρ . A statistically significant ρ result indicates the presence of selection bias and justifies the use of the treatment-effects framework.

Although the exclusion restriction cannot be fully verified empirically, the empirical strategy is designed to reduce potential bias through individual and regional controls. Moreover, the consistency of the results across ordinary least squares (OLS), propensity score matching (PSM), and treatment-effects estimations supports the robustness of the findings. Therefore, the results should be interpreted as evidence consistent with a causal interpretation rather than definitive proof of causality.

Robustness testing

This study uses two robustness checks. First, a conventional ordinary least squares (OLS) regression is estimated using the same specification. The OLS results show a smaller and less precise income premium associated with occupational mismatch. This pattern suggests the presence of selection bias and unobserved heterogeneity, supporting the use of the treatment-effects model.

Second, propensity score matching (PSM) is used to compare mismatched and matched gig workers with similar observable characteristics. Workers are matched based on key covariates included in the model. The matched-sample results are qualitatively consistent with the treatment-effects estimates. This consistency suggests that the observed income differentials are not driven solely by observable worker characteristics.

Several limitations should be acknowledged. First, the cross-sectional SAKERNAS 2020 data cannot capture dynamic labor-market processes, such as job mobility or persistent income differences. The results may also partly reflect labor-market conditions during the COVID-19 period. Second, the education-based mismatch measure may not fully capture digital and noncognitive skills relevant to platform-based work. Third, although the instrumental-variable strategy addresses endogeneity, the exclusion restriction cannot be fully tested. District-level mismatch may also be correlated with unobserved regional factors affecting income. Therefore, the results should be interpreted with caution.

Result and discussion

Descriptive statistics

Table 1 summarizes the descriptive statistics of Indonesian gig workers by gender. Female workers report a higher incidence of occupational mismatch than male workers, at 25.10% compared with 20.18%. This pattern suggests that women are more likely to work in jobs that do not align with their formal qualifications. Female workers also show a higher rate of single-job engagement, at 91.65% compared with 87.97% among men, indicating more limited income diversification.

Table 1: Descriptive Statistics

Variable	Male (<i>n</i> = 12,387)		Female (<i>n</i> = 4,901)	
	Frequency (<i>n</i>)	Percentage (%)	Frequency (<i>n</i>)	Percentage (%)
Mismatch				
Yes	2,500	20.18	1,230	25.10
No	9,887	79.82	3,671	74.90
Single job				
Yes	10,897	87.97	4,492	91.65
No	1,490	12.03	409	8.35
Marital status				
Married	9,635	77.78	3,553	72.50
Otherwise	2,752	22.22	1,348	27.50
Residence				
Rural	4,608	37.20	1,509	30.79
Urban	7,779	62.80	3,392	69.21
Education				
Basic education	5,069	40.92	1,591	32.46
Secondary education	5,788	46.73	2,290	46.73
Tertiary education	1,530	12.35	1,020	20.81
Job sector				
Agriculture	1,474	11.90	83	1.69
Industry	2,524	20.38	781	15.94
Service	8,389	67.72	4,037	82.37
Variables	Mean	SD	Mean	SD
Income	IDR 2,837,763 (USD 195)	IDR 3,145,240 (USD 216)	IDR 2,425,478 (USD 166)	IDR 2,648,216 (USD 182)
Log income	14.65	0.57	14.49	0.57
Age	39.17	11.07	38.37	10.63
Working experience	7.81	8.02	6.35	7.26
Household size	3.98	1.46	3.87	1.47
Mismatch in district	0.19	0.06	0.20	0.06
Unemployment	6.93	2.82	6.96	2.84
Ln GDP per capita	10.48	0.71	10.53	0.70

Note: SD = standard deviation. Income values are reported in Indonesian rupiah (IDR), with approximate USD equivalents in parentheses. USD conversions are based on the 2020 average exchange rate of approximately USD 1 = IDR 14,582.

Female workers are more concentrated in urban areas, at 69.21% compared with 62.80% among men, and are more likely to work in the service sector. Despite having a higher share of tertiary education, at 20.81% compared with 12.35% among men, female workers still experience higher mismatch rates. This suggests that higher educational attainment does not necessarily translate into better job-matching outcomes for women in gig work.

Male workers report a higher average monthly income than female workers, at IDR 2.84 million, or approximately USD 195, compared with IDR 2.43 million, or approximately USD 166, for female workers. Male workers are also slightly older and have more work experience. Household size is relatively similar across groups, suggesting that income differences are unlikely to be driven by household composition.

At the regional level, the average district-level mismatch rate is slightly higher among women, at 0.20 compared with 0.19 among men. Unemployment rates and regional GDP per capita are broadly similar across gender groups. These patterns suggest that gender disparities in mismatch and income are more likely related to structural differences in labor-market participation than to geographic variation alone.

Treatment effect results by gender

Table 2 reports the estimates from the treatment-effects model with a two-step selection specification. The model corrects for potential endogeneity between mismatch status and income. For the full sample, occupational mismatch is associated with a statistically significant reduction in log income of 0.115 ($SE = 0.043$, $p < .01$). This corresponds to an income penalty of approximately 10.9% after accounting for selection bias.

When disaggregated by gender, the negative effect remains statistically significant for male workers (coefficient = -0.132 , $SE = 0.048$, $p < .01$). For female workers, the estimate is smaller and not statistically significant (coefficient = -0.075 , $SE = 0.090$, $p = .403$). These results suggest that the income consequences of occupational mismatch are not uniform across gender. The penalty is stronger among male gig workers, while the effect among female workers is statistically indistinguishable from zero. The direction of the results is consistent with the ordinary least squares (OLS) and propensity score matching (PSM) estimates reported in Tables 3 and 4.

The gender difference may reflect variations in job structure and labor-market constraints. Female gig workers are more concentrated in service-oriented and urban-based activities, where task flexibility may reduce the extent to which mismatch translates into income losses. In such contexts, mismatch may reflect broader job-allocation processes rather than binding skill constraints. This interpretation is consistent with prior studies showing that digital platforms may partially relax traditional matching frictions (Lott & Abendroth, 2020; Seo et al., 2021). At the same time, unobserved characteristics, such as digital skills, adaptability, and preferences for flexible work, may influence both mismatch status and income outcomes. Platform-based evaluation systems may also shape these outcomes, although concerns about algorithmic bias remain relevant (International Finance Corporation, 2021; Munoz et al., 2024).

Table 2: Treatment Effects of Occupational Mismatch on Income

Variables	Full Sample	Male	Female
Mismatch (treatment)	-0.115*** (0.043) [.008]	-0.132*** (0.048) [.007]	-0.075 (0.090) [.403]

Variables	Full Sample	Male	Female
Age	0.011*** (0.002) [$< .001$]	0.007*** (0.002) [.006]	0.015*** (0.004) [.001]
Age squared	-0.00009*** (0.00002) [.002]	-0.00005* (0.00003) [.088]	-0.0001** (0.00005) [.022]
Work experience	0.007*** (0.0006) [$< .001$]	0.006*** (0.0007) [$< .001$]	0.009*** (0.001) [$< .001$]
Single-job status	0.054*** (0.013) [$< .001$]	0.067*** (0.015) [$< .001$]	0.023 (0.028) [.410]
Secondary education	0.081*** (0.010) [$< .001$]	0.097*** (0.013) [$< .001$]	0.047** (0.018) [.011]
Tertiary education	0.386*** (0.037) [$< .001$]	0.444*** (0.041) [$< .001$]	0.275*** (0.075) [$< .001$]
Married	0.076*** (0.011) [$< .001$]	0.139*** (0.014) [$< .001$]	-0.021 (0.019) [.273]
Rural	0.009 (0.010) [.337]	0.019 (0.011) [.101]	-0.011 (0.019) [.565]
Household size	-0.007** (0.002) [.014]	-0.006* (0.003) [.051]	-0.007 (0.005) [.213]
Industry sector	0.040** (0.017) [.018]	0.075*** (0.018) [$< .001$]	-0.107* (0.064) [.094]
Service sector	0.061*** (0.015) [$< .001$]	0.058*** (0.016) [$< .001$]	0.013 (0.061) [.832]
Gender	0.182*** (0.009) [$< .001$]	—	—
Unemployment	0.009*** (0.001) [$< .001$]	0.007*** (0.001) [$< .001$]	0.014*** (0.003) [$< .001$]
Log GDP per capita	0.079*** (0.006) [$< .001$]	0.089*** (0.007) [$< .001$]	0.056*** (0.011) [$< .001$]
Selection equation			
District mismatch (IV)	0.464* (0.253) [.067]	0.438 (0.300) [.144]	0.526 (0.482) [.275]
Observations	17,288	12,387	4,901

Note: Standard errors are reported in parentheses, and p-values are reported in brackets. All models include individual-level controls (age, work experience, education, marital status, household size, and job sector) and district-level controls (unemployment rate and GDP per capita). IV = instrumental variable. An em dash (—) indicates that the variable is not included in the corresponding specification. *** $p < .01$, ** $p < .05$, * $p < .10$.

Most control variables in the income equation show the expected signs and are statistically significant across specifications. Age and work experience are positively associated with income, while the negative coefficient on age squared indicates diminishing returns. Educational attainment is also positively associated with income, particularly tertiary education, consistent with the Mincerian framework.

In the full-sample specification, the gender coefficient is positive and statistically significant. This indicates that male workers have higher income on average after controlling for observable characteristics. Single-job status is positively associated with income in the full sample and among male workers, but it is not statistically significant among female workers. Household size has a negative and marginally significant association with income, whereas rural residence is not statistically significant.

In the selection equation, district-level mismatch is positively associated with the likelihood of being mismatched. The coefficient is statistically significant in the full sample (coefficient = 0.464, $SE = 0.253$, $p < .10$), supporting the relevance of the instrument. However, it is not statistically significant in the gender-specific subsamples, possibly because of reduced statistical power. The inclusion of district-level controls helps account for broader regional labor-market conditions. Nevertheless, the exclusion restriction cannot be fully verified empirically. Therefore, the estimates should be interpreted with caution.

Overall, the results indicate that occupational mismatch in the gig economy is associated with lower income, particularly among male workers. For female workers, the effect is weaker and not statistically significant. These findings suggest that the consequences of mismatch depend on labor-market structure, gender-specific constraints, and the nature of platform-based work. They also indicate that a mismatch should not be interpreted as a uniform indicator of labor-market inefficiency.

These results are consistent with evidence from Indonesia's formal labor market, where overeducation is often associated with income penalties (Hasibuan & Handayani, 2021; Yoselina et al., 2024). However, neutral or context-specific effects have also been documented (Wulandari & Damayanti, 2021). Given that overeducation rates in Indonesia range from 25.79% to 27.90% and vary by education, gender, and region (Boto-García & Escalonilla, 2022; Sitorus & Wicaksono, 2020), mismatch should be interpreted within its institutional and technological context. Importantly, the estimated effects reflect income differentials rather than broader welfare outcomes, as gig work may involve income volatility and limited social protection.

Robustness test results using OLS and PSM

To assess the consistency of the main findings, this study employs two robustness checks. First, a conventional ordinary least squares (OLS) regression with robust standard errors is estimated as a baseline comparison. Table 3 reports the OLS estimates of the relationship between occupational mismatch and income. The results show a negative and statistically significant association in the full sample (coefficient = -0.070 , $SE = 0.014$, $p < .01$). This suggests that mismatched workers have approximately 7% lower income than their well-matched counterparts.

When disaggregated by gender, the negative effect remains statistically significant for male workers (coefficient = -0.085 , $SE = 0.016$, $p < .01$). For female workers, the estimate is smaller and not statistically significant (coefficient = -0.038 , $SE = 0.030$, $p = .210$). This pattern indicates that the income penalty associated with mismatch is mainly driven by male workers, consistent with the heterogeneity observed in the treatment-effects estimates.

Table 3: Robustness Check Using Ordinary Least Squares (OLS)

Variables	Full Sample	Male	Female
Mismatch	-0.070^{***} (0.014) [$< .001$]	-0.085^{***} (0.016) [$< .001$]	-0.038 (0.030) [.210]
Age	0.011^{***} (0.002) [$< .001$]	0.007^{***} (0.002) [.008]	0.015^{***} (0.0048) [.001]
Age squared	-0.00009^{***} (0.00003) [.003]	-0.00005 (0.00003) [.107]	-0.0001^{**} (0.00006) [.029]
Work experience	0.007^{***} (0.0006) [$< .001$]	0.006^{***} (0.00072) [$< .001$]	0.009^{***} (0.001) [$< .001$]
Single-job status	0.054^{***} (0.013) [$< .001$]	0.067^{***} (0.014) [$< .001$]	0.023 (0.029) [.415]
Secondary education	0.075^{***} (0.009) [$< .001$]	0.090^{***} (0.010) [$< .001$]	0.046^{***} (0.017) [.009]
Tertiary education	0.351^{***} (0.020) [$< .001$]	0.408^{***} (0.024) [$< .001$]	0.245^{***} (0.035) [$< .001$]
Married	0.077^{***} (0.011) [$< .001$]	0.140^{***} (0.013) [$< .001$]	-0.020 (0.019) [.286]
Rural	0.009 (0.009) [.325]	0.018^* (0.011) [.093]	-0.010 (0.018) [.576]
Household size	-0.007^{**} (0.002) [.014]	-0.006^{**} (0.003) [.049]	-0.007 (0.005) [.220]
Industry sector	0.040^{**} (0.016) [.013]	0.075^{***} (0.017) [$< .001$]	-0.107^* (0.064) [.095]
Service sector	0.061^{***} (0.015) [$< .001$]	0.058^{***} (0.016) [$< .001$]	0.013 (0.062) [.831]
Gender	0.182^{***} (0.009) [$< .001$]	—	—
Unemployment	0.009^{***} (0.001) [$< .001$]	0.007^{***} (0.001) [$< .001$]	0.014^{***} (0.003) [$< .001$]
Log GDP per capita	0.079^{***} (0.006) [$< .001$]	0.090^{***} (0.007) [$< .001$]	0.055^{***} (0.012) [$< .001$]
Constant	12.999^{***} (0.086) [$< .001$]	13.108^{***} (0.101) [$< .001$]	13.324^{***} (0.169) [$< .001$]
Observations	17,288	12,387	4,901

Note: Dependent variable: log monthly income. Robust standard errors are reported in parentheses, and p values are reported in brackets. All models include individual-level and district-level controls. An em dash (—) indicates that the variable is not included in the corresponding specification. *** $p < .01$, ** $p < .05$, * $p < .10$.

Most control variables show the expected signs. Age and work experience are positively associated with income across all specifications, while the negative coefficient on age squared indicates diminishing returns. Educational attainment is also positively associated with income, especially tertiary education, consistent with the Mincerian framework. In the full-sample model, the gender coefficient is positive and statistically significant, indicating that male workers have higher income on average after controlling for observable characteristics. Single-job status is positively associated with income in the full sample and among male workers, but it is not statistically significant among female workers. Household size has a negative and marginally significant association with income, whereas rural residence is not statistically significant. District-level variables, including unemployment and GDP per capita, are positively associated with income. These results provide a useful baseline, although OLS does not account for potential selection into mismatch. Therefore, alternative estimation strategies are needed.

Table 4: Robustness Check Using Propensity Score Matching (PSM)

Outcome Variable	Treatment	Coefficient	SE	z	p	95% CI
Log income	Mismatch (1 vs. 0)	-0.2164***	0.0376	-5.75	< .001	[-0.2902, -0.1426]

Note: SE = standard error; CI = confidence interval. *** $p < .01$, ** $p < .05$, * $p < .10$.

Next, propensity score matching (PSM) is employed to construct a more comparable sample of mismatched and matched workers based on observable characteristics. The matching procedure includes age, work experience, single-job status, gender, marital status, and region as covariates. As shown in Table 4, mismatch has a negative and statistically significant effect on income. The Average Treatment Effect on the Treated (ATT) is -0.216 ($SE = 0.038$, $p < .01$), indicating that mismatched workers have substantially lower income than their well-matched counterparts after matching.

The PSM estimate is larger than the OLS estimate, suggesting differences in how selection is addressed across methods. Whereas OLS relies on linear conditioning on covariates, PSM constructs a more comparable control group based on observed characteristics. However, PSM does not account for unobserved heterogeneity, which may still influence both mismatch status and income outcomes.

Heterogeneity of mismatch effects across the income distribution

To examine heterogeneity in the effect of occupational mismatch, this study estimates quantile regressions at the 10th, 25th, 50th, 75th, and 90th percentiles of log monthly income. The models are estimated separately for male and female gig workers. The results are presented in Figure 2 and Table 5.

The results show a consistently negative association between mismatch and income among male workers. At the lower quantiles (Q10–Q25), the effects are only marginally significant. From the median onward, the coefficients become statistically significant and more stable. The estimates range from approximately -0.065 at Q50 to -0.070 at Q90. This pattern suggests persistent income penalties among middle- and higher-income male workers.

For female workers, the coefficients are also negative across quantiles, but none are statistically significant. This suggests that occupational mismatch does not systematically affect income among female gig workers. This pattern may reflect structural differences in labor-market participation, including constraints on job selection, task allocation, and non-income considerations in labor-supply decisions.

Figure 2: Quantile Plot Across Income Distribution and Gender

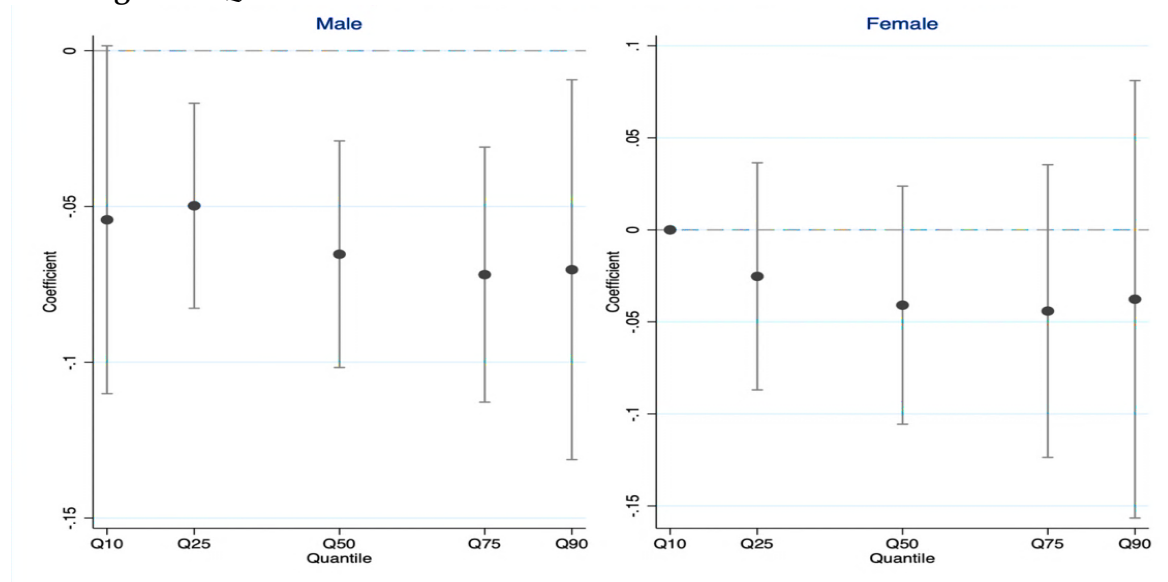


Table 5: Quantile Regression Results: Effect of Mismatch on Log Income

Quantile	Coefficient (Mismatch)	SE	<i>p</i>
Male workers			
Q10	-0.0542*	0.0284	.057
Q25	-0.0497*	0.0167	.057
Q50	-0.0653***	0.0185	< .001
Q75	-0.0718***	0.0208	< .001
Q90	-0.0702**	0.0310	.024
Female workers			
Q10	0.0000	—	—
Q25	-0.0252	0.0314	.422
Q50	-0.0409	0.0329	.215
Q75	-0.0441	0.0405	.277
Q90	-0.0377	0.0606	.534

Note: Dependent variable: log monthly income. SE = standard error. An em dash (—) indicates that the estimate is not statistically identifiable at the corresponding quantile. *** $p < .01$, ** $p < .05$, * $p < .10$.

The quantile regression results complement the average effects reported in the previous models. They show that the income penalty associated with mismatch is more pronounced and statistically identifiable among male workers, especially at higher points of the income distribution. These findings reinforce the conclusion that occupational mismatch represents an economically meaningful constraint. They also highlight the importance of gender-specific dynamics in shaping its labor-market consequences.

Conclusion and policy implications

This study provides evidence from Indonesia that occupational mismatch in the gig economy is associated with income penalties rather than gains, particularly among male workers. This negative relationship is consistently observed across ordinary least squares (OLS), propensity score matching (PSM), and treatment-effects models. These results indicate that mismatch remains an economically relevant factor in shaping income outcomes. In contrast, the effect is not statistically significant among female workers, suggesting gender differences in how mismatch translates into labor-market outcomes.

The quantile analysis shows that the income penalty associated with a mismatch is not uniform across the income distribution. Among male workers, the negative effect appears across quantiles and becomes more pronounced at the median and upper segments. Among female workers, the coefficients are consistently negative but not statistically significant. This suggests that mismatch is not a primary determinant of income variation for female gig workers. Overall, these findings show that the impact of mismatch is both distributionally heterogeneous and gender-specific.

These findings should be interpreted with caution. The analysis relies on education-based measures of mismatch, which may not fully capture digital competencies and noncognitive skills relevant to platform-based work. In addition, the cross-sectional data limit the ability to capture dynamic adjustments in mismatch and income over time. Therefore, the results should be interpreted as conditional associations rather than definitive causal relationships.

Future research could use longitudinal or panel data to examine how mismatch evolves over time and how workers move across different segments of the gig economy. Such approaches would provide deeper insight into the persistence and dynamics of mismatch in digital labor markets. From a policy perspective, the findings highlight the importance of labor-market interventions that respond to the characteristics of digital work. These include strengthening digital and transferable skills, promoting gender-responsive platform ecosystems, and reducing regional disparities in access to economic opportunities. Such efforts are essential for supporting more inclusive and adaptive labor-market outcomes amid ongoing digital transformation.

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