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Location is Destiny? Unravelling the Income Gap of Gig Workers in Indonesia with Blinder-Oaxaca Decomposition

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ABSTRACT

Purpose – The objective of this study is to analyze and identify key factors of the income gap between gig workers in urban and rural areas in Indonesia. Secondary data from the 2023 National Socioeconomic Survey (Susenas) was used in this study.
Design/methodology/approach – Data analysis was conducted by applying the Blinder-Oaxaca decomposition method to separate the sources of income inequality into components explained by differences in characteristics (endowments) and unexplained components (discrimination or non-observable factors). A robust regression model was also used to ensure the accuracy of the estimates.
Finding/Results – This study reveals that gig workers in urban areas have significantly higher incomes (around 12%) than their counterparts in rural areas. Most of this gap is due to differences in characteristics (explained component), particularly access to digital technology and education levels. However, the unexplained component is also significant, indicating differences in market value or discrimination against the same characteristics in both regions. Other factors such as full-time employment, white-collar jobs, male gender, and marital status also positively affect income levels.
Originality/Value – The value of this research lies in its primary focus on the long-term impact of spatial inequality among gig workers, as well as its comprehensive use of the Blinder-Oaxaca method in the context of the Indonesian gig economy to describe the sources of this inequality in detail

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1. Introduction

The development of the global digital economy has given rise to the phenomenon of the gig economy, characterised by the proliferation of platform-based freelance workers (Arriagada et al., 2023; Niederfranke & Drewes, 2017; Yousef, 2024). In Indonesia, this sector is growing rapidly and has become the backbone of digital transformation, supported by on-demand companies such as Gojek and Grab (Gunawan, 2024; Hamdoun, 2020). Although it offers flexibility and new job opportunities (Hsieh et al., 2023; Huang et al., 2020), the gig economy also faces fundamental challenges, particularly related to income instability and lack of social protection (Abd Samad et al., 2023; Lesala Khethisa et al., 2020; Yaroshenko et al., 2024).

A particular issue that has emerged is the significant income gap between gig workers located in urban and rural areas (Müller & Neumann, 2023), where workers in large cities such as Jakarta and Surabaya generally earn higher incomes (Rimbano et al., 2024; Wijayanti, 2023), while in rural areas opportunities and incomes are more limited (Fiseha & Oyelana, 2019). This situation has the potential to deepen existing regional economic disparities (Tamasauskiene & Dilius, 2020; Yuan et al., 2024).

Previous literature reviews have identified many factors that influence gig workers' income. Previous studies have discussed the role of individual characteristics such as gender (Cook et al., 2021; Foong et al., 2018; Miti et al., 2023; Sener et al., 2023), age (De Felice et al., 2022; Huđdek et al., 2021; Mohd Daud et al., 2024; Thomas, 2018), education (Bhatia et al., 2024; Herrmann et al., 2023; Orth, 2024; Van Slageren & Herrmann, 2024), and marital status (Vernon, 2010). In addition, structural aspects such as working hours (Checchi et al., 2016; Reynolds et al., 2024), training (Pérez et al., 2020; Zheng et al., 2024), access to technology, and weak labour regulations (Abdullah et al., 2024; Ghorpade et al., 2024) have also been recognised as key determinants. However, the majority of the literature tends to focus on the factors causing the gap in a partial manner without exploring in depth the sources and proportions of the spatial gap quantitatively, as well as its long-term impact on regional disparities and migration patterns (Ebeke, 2023; Yuan et al., 2024). Furthermore, recent research from Indonesia specifically demonstrates that digital platform adoption is not merely a function of access—it is shaped by deeper and often invisible spatial, infrastructural, and algorithmic factors that systematically exclude certain groups based on their location (Dwiputrianti et al., 2025).

The relationship between previous literature findings and the issues under study reveals both an analytical gap and a theoretical gap. Although the influence of individual and structural factors is well known, existing studies have largely treated location as a background variable rather than a structural condition that systematically alters the returns to individual characteristics. Recent evidence from digital labor markets suggests that remote platform work is spatially polarised: jobs are pulled to large cities, while rural areas systematically fall behind (Braesemann et al., 2022). This is driven by "agglomerative forces" linked to the unequal spatial distribution of skills, human capital, and opportunities—forces that pull platform work to places with institutions that foster specialisation and complex economic activities, leaving locations without such enabling institutions—in many cases, rural areas—behind (Braesemann et al., 2022). In the Indonesian context specifically, digital platforms not only provide access but also define their boundaries—determining who participates, under what conditions, and for whose benefit (Alauddin et al., 2025; Putri et al., 2023).

The statement in the previous paragraph reinforces the assumption that the three intersecting features make Indonesia an extremely valuable case for studying spatial inequalities in the gig economy. First, the country has experienced one of the most rapid digital platform expansions in the Global South, with homegrown platforms like Gojek and Grab becoming integral to both urban and rural economies (Gunawan, 2024). Second, Indonesia exhibits persistent and wide regional economic disparities, with a Gini ratio that remains among the highest in Southeast Asia. Third, labour regulation in the gig sector remains nascent and fragmented, creating an environment where spatial inequality can operate with minimal institutional mitigation (Dwiputrianti et al., 2025). Without deliberate labour governance, Indonesia risks facing a *dual digital economy*—one sector benefiting from digital innovation, and another trapped in precarious, digitally mediated inequality (Dwiputrianti et al., 2025).

Thus, the urgency of this study lies not merely in applying a decomposition method, but in providing a theoretically grounded, spatially-aware decomposition that distinguishes between income gaps arising from differences in observable characteristics (endowments) and arising from differential returns to the same characteristics across spatial contexts—the latter capturing what labour economists term statistical discrimination in the gig context (Trautwein et al., 2025). This understanding is crucial for formulating targeted policies to prevent more serious long-term socio-economic consequences (Ebeke, 2023; Tamasauskiene & Dilius, 2020). To address this issue, this study applies a quantitative approach using the Blinder-Oaxaca decomposition method on data from the National Socioeconomic Survey *(Susenas)*. This approach allows the decomposition of the average income gap between urban and rural gig workers into two main components: a component that can be explained by differences in characteristics (endowments) and an unexplained component that reflects differences in returns to the same characteristics or discrimination. Thus, this approach not only confirms the existence of the gap but also provides a clear map of its sources, which forms the basis for more effective and inclusive policy recommendations to create a fair digital labour market.

2. Methodology

2. 1. Research Design

This study uses an inferential quantitative design with a causal-comparative (ex post facto) approach to compare wage gaps between workplaces. Data were collected secondarily from the 2022 National Socioeconomic Survey (Susenas) in 2022 with a total population of 756,890 individuals, where a sample of 16,804 workers (both gig workers defined as self-employed workers in the transportation/warehousing/other services sector who use the internet for marketing, as well as non-gig workers) was selected to represent the population. The analysis technique began with estimating the Mincer wage equation using Ordinary Least Squares (OLS) with classical assumption testing and outlier handling, followed by robust regression (moment method/MM) to ensure the robustness of the results. Next, the estimated coefficient results are input into the Blinder-Oaxaca decomposition to measure and separate the sources of wage gaps into 'explained' components (due to differences in observable characteristics) and 'unexplained' components (due to non-observable factors or discrimination). Furthermore, it can be expressed as in the following equation (1).

$$Yi = Ln\,Yi = \beta 0 + \beta 1Xi1 + \beta 2Xi2 + \cdots + \beta kXik + \varepsilon i \qquad (1)$$

Then, the variables used in this research are as followed in table 1 about operational definition of the variables.

Table 1. The Operational Definitions of Variables

Variables	Operational Definitions	Categories

Wages	Net wages or basic wages/salaries and allowances received	Continuous
Residential Area	Classification of residences based on administrative conditions	0=rural 1=urban
Gender	Classification of gender	0=female 1=male
Education	Highest level of education attained	0=elementary school and junior high school 1=senior high school, undergraduate, and postgraduate
Age	The age of the worker in years	Continuous
Marital Status	Marital status at the time of enumeration	0=married 1=not yet married
Training	Activities to develop skills or expertise	0=without training 1=training
Working Hours	The total of time spent working in one week	0=part-time workers (<35 hours per week) 1=full-time workers (>35 hours per week)

2. 2. Data Collection and Analysis Technique

The data used in this study is secondary data sourced from an official institution, namely the Central Statistics Agency (BPS), through the March 2023 National Socio-Economic Survey (Susenas) dataset. The population in this study consisted of 756,890 individuals, with a sample of 16,804 individuals identified as gig workers. Gig workers are defined as self-employed workers in the transportation, warehousing, or other service sectors who use the internet for marketing purposes. Sampling from this large population indicates that the technique used was sampling, not a census.

Data analysis was conducted in three main stages. First, the Mincer wage equation model was estimated using multiple linear regression with the Ordinary Least Squares (OLS) method. This stage was supplemented with classical assumption testing and outlier handling to ensure the reliability of the initial estimates. Second, to ensure the robustness of the results, re-estimation was performed using Robust Method of Moments (MM) regression. This method is useful for addressing assumption violations, such as heteroscedasticity, and minimising the influence of remaining outliers. Third, the main analysis to measure the gap was performed by applying the Blinder-Oaxaca decomposition method. This method utilises the coefficients from the estimated regression model to break down the average wage difference between urban and rural groups into two components, namely the 'Explained' component caused by differences in characteristics (endowments) and the 'Unexplained' component reflecting differences in coefficients (residual or discrimination factors).

3. Result and Discussion

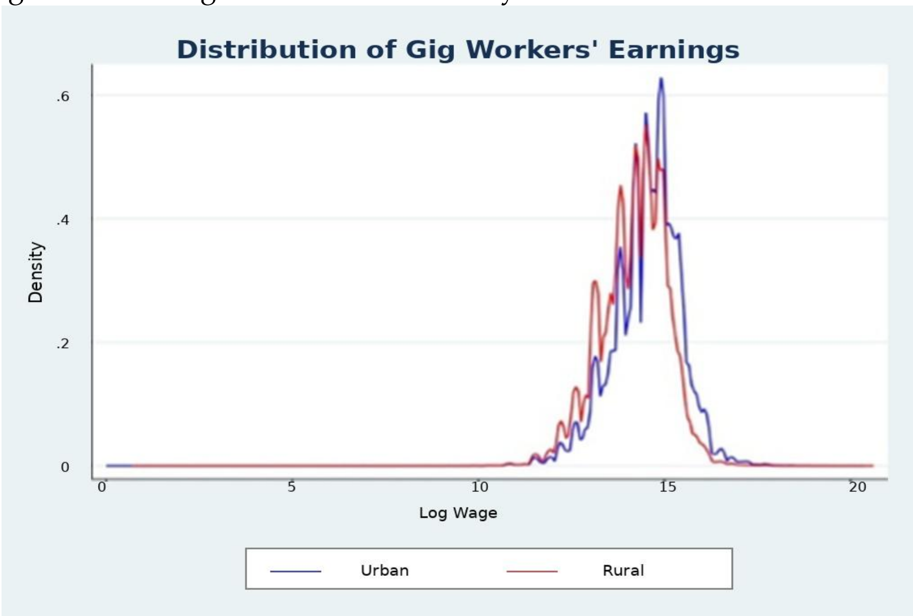
3. 1. Results

Based on the results of a robust regression analysis of the 2023 SAKERNAS data, the graph in Figure 1 reveals a systematic pattern in the determinants of gig worker earnings in Indonesia, considering the interaction between education level and geographical location. Consistently, gig workers in urban areas show higher regression coefficient values compared to their rural counterparts across every educational stratum (Basic, Intermediate, Higher). This reflects the structural advantages of the urban environment, including broader market access, adequate digital infrastructure, and a diversity of service demand. Meanwhile, a positive earnings gradation is also observed alongside increasing education levels, in both rural and urban settings, indicating the crucial role of developing technical skills and adaptive capacities on digital platforms. This pattern affirms that while geographical location creates an initial disparity, educational qualifications serve as a significant reinforcing mechanism for earnings

Figure 1. Determinants of Gig Workers' Income

Geographical disparity is found to vary according to education level, where the largest gap occurs at the basic education stratum (Δ = 0.1 between rural and urban), whilst at the higher education level this disparity narrows (Δ = 0.1). This finding implies that higher education can act as a compensating factor which mitigates spatial inequality, although it does not completely eliminate it. In terms of policy, this phenomenon highlights the urgency for location-based interventions: in rural areas, accelerating digital infrastructure development and vocational skills training are prerequisites for reducing the gap, whereas in urban areas, social protection is needed to prevent income stagnation for low-educated workers. Although the robust regression model has controlled for heteroscedasticity, generalising the findings requires consideration of contextual variables such as platform specialisation and work experience, which were not covered in this analysis. Furthermore, differences are also observed in the earnings of gig workers in both rural and urban areas. The density distribution of gig worker earnings is shown in Figure 2.

Figure 2. Gig Workers' Wages Distribution Density Plot



Density plot 2 visualises the distribution of the logarithm of income (log wages) of gig workers in Indonesia, comparing patterns between urban and rural areas. Based on the plot, the income distribution of urban workers shows a peak (mode) located at a higher log wage value than rural workers, indicating a higher absolute average income in urban areas. In addition, the urban distribution curve tends to be flatter and extend to the right, reflecting wider income variability—a phenomenon that represents job diversification, competition levels, and income inequality in the urban gig ecosystem. In contrast, the income distribution in rural areas is concentrated in a lower log wage range with a sharper peak and shorter tail, indicating relative homogeneity in income levels but also limited economic opportunities. This pattern confirms the existence of systemic spatial disparities, where factors such as market access, digital infrastructure, and location-based service demand significantly shape the income inequality of gig workers.

Figure 3. Gig Workers Wage Distribution

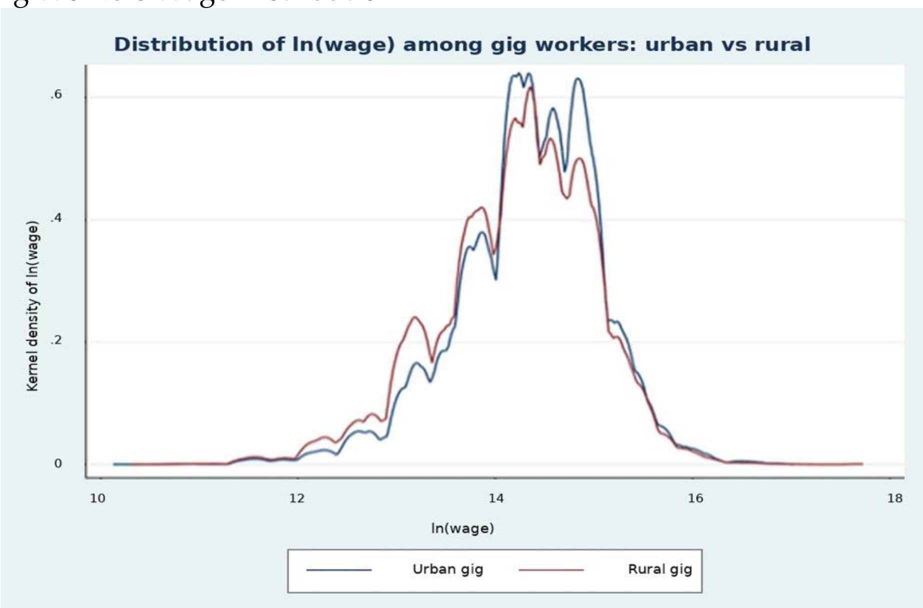


Figure 3 displays the distribution of the natural logarithm of earnings (ln(income)) for gig workers in cities (blue) and villages (red) using kernel density estimation. Both curves exhibit substantial overlap—indicating that many wage ranges are commonly occupied by both groups—however, the urban curve is slightly shifted to the right and possesses a thicker right tail. This rightward shift signifies that the average/geometric mean of gig wages in cities is higher than in villages.

The peak density (mode) for both is located around ln(income) ≈ 14.1–14.5, which, when converted, is roughly equivalent to Rp1.3–1.8 million per month (since e^14 ≈ 1.2 million and e^14.5 ≈ 2.0 million). In the range of 13–13.8 (≈ Rp0.4–1.0 million), the rural curve tends to be higher—indicating a greater proportion of low-wage workers in villages. Conversely, in the range >14.6 (≈ >Rp2 million), the urban curve is relatively higher—demonstrating a larger number of middle-to-high-income earners in cities.

The persistence of a significant unexplained component in the Blinder-Oaxaca decomposition—the portion of the urban-rural income gap that cannot be attributed to observable differences in education, working hours, or demographics—points to deeper structural mechanisms that transcend individual characteristics. In the context of Indonesia's gig economy, this unexplained residual likely reflects what recent literature identifies as algorithmic spatial discrimination (Dwiputrianti et al., 2025; Labib Fardany Faisal et al., 2019). Platform algorithms that determine job allocation, surge pricing, and performance ratings are often trained on historical data generated predominantly in urban areas, creating a feedback loop where rural workers systematically receive lower-paying tasks or fewer job offers despite identical qualifications.

This interpretation is consistent with the finding that white-collar gig workers enjoy a ~13% premium irrespective of location: such workers are less reliant on location-bound platform algorithms and more on portable skills tradable in digital marketplaces. Conversely, location-bound gig workers (e.g., delivery, ride-hailing) are subject to algorithmic management that embeds spatial biases—a phenomenon termed **"**algorithmic wage discrimination**"** where dynamic pricing systematically disadvantages peripheral areas. The absence of transparency in pay-setting mechanisms means that rural workers cannot discern whether lower wages stem from market fundamentals or algorithmic bias.

Furthermore, the unexplained component captures what labour economists term statistical discrimination in the gig context—a phenomenon where platforms use observable characteristics such as location, gender, or race as imperfect proxies for unobservable productivity signals (Orley & Rees, 1973; Phelps, 1972), leading to systematically different returns for identical individual characteristics across spatial contexts. Platforms may use location as a proxy for unobservable productivity signals—lower digital literacy, less reliable transport infrastructure, or weaker customer density—leading to a "spatial penalty" applied to all rural workers regardless of individual capabilities. This spatial stereotype perpetuates a self-reinforcing cycle: lower expected productivity in rural areas reduces platform investment in those markets, which in turn depresses actual productivity and wages (Botelho et al., 2025).

Figure 4. Gig Workers Residential Area

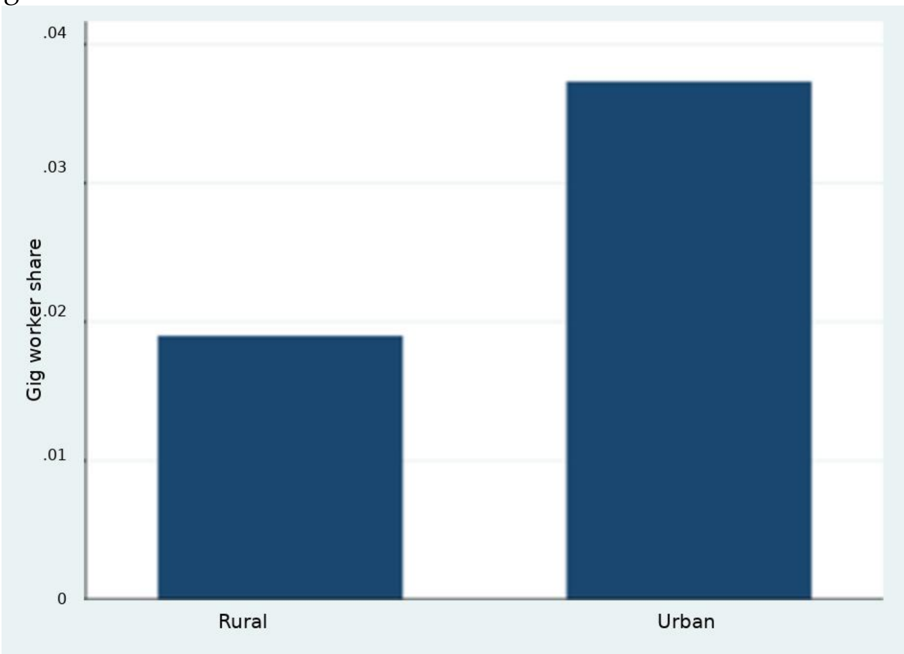


Figure 4 illustrates the proportion of gig workers (platform-based/self-employed workers) by residential area. In urban areas, the proportion stands at approximately 3.7–3.8%, whilst in rural areas it is approximately 1.9%—meaning there are nearly twice as many gig workers in cities compared to villages. Put differently, for every 100 workers, roughly 4 individuals in urban areas are gig workers, whereas in rural areas the figure is about 2.

This disparity is readily understood by the public: cities have denser markets, more stable internet and digital payment access, and a greater concentration of app-based services (ride-hailing, delivery, food, content/white-collar gigs) that require a critical mass of customers. In rural areas, demand is more dispersed, logistics costs are higher, and the digital network/supporting ecosystem is less developed than in urban centres.

Figure 5. Wages Rate Comparasion of Gig Workers

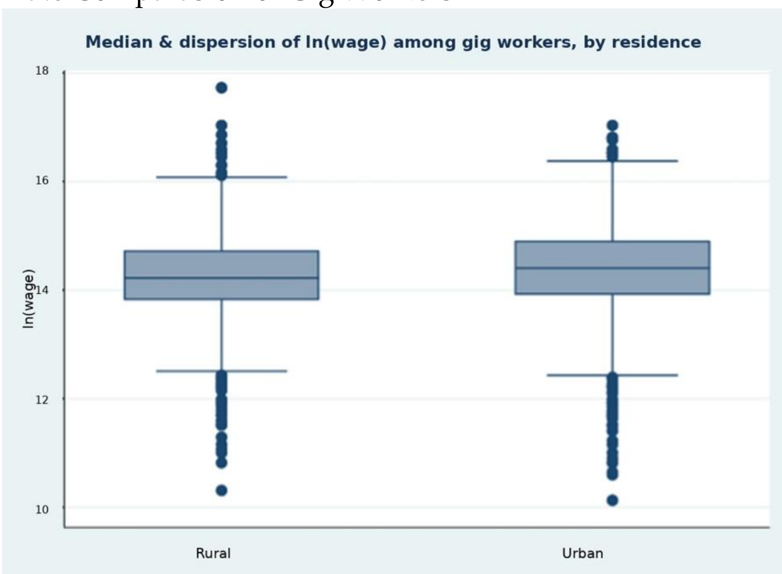


Figure 5 presents a boxplot comparing wage levels (on a natural logarithm/ln scale) of gig workers between rural and urban areas. The thick line within the box indicates the median (the central point). The median in urban areas is slightly higher than in rural areas—meaning the "typical" gig worker in cities earns a somewhat larger wage. Roughly converting from ln to Rupiah, the median for both groups falls within the range of approximately 1.4–1.6 million Rupiah per month, with urban areas tending towards the higher end of this range.

The box itself represents the middle 50% of each group (the interquartile range). The similar width on both sides indicates that the spread of mid-range wages in urban and rural areas is relatively comparable: the majority of workers fall within a range that is not too dissimilar. The "whiskers" and points outside the box show very low or very high values (outliers)—and these appear in both rural and urban data. This conveys a straightforward message: although the urban average/median is higher, variation within each respective region remains substantial; there are gig workers with both very low and very high wages in both location.

Figure 6. Added Variable Plot

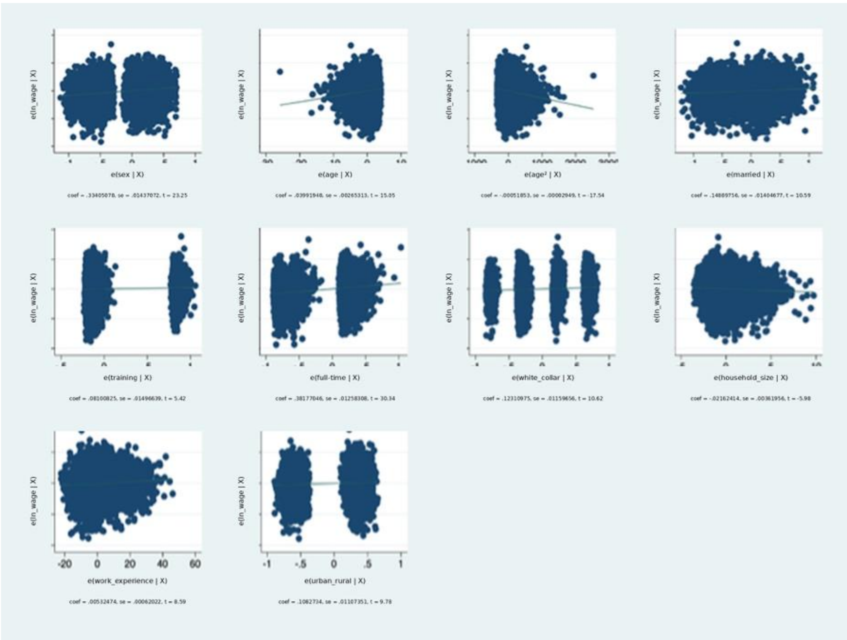


Figure 6 displays added-variable plots (partial regression) for each factor against ln(wage) after "removing" the influence of other factors. The green line in each panel represents the slope of the partial coefficient; an upward slope indicates the factor is positively correlated with wage, whilst a downward slope indicates a negative correlation. As the Y-axis uses a log scale, the coefficient can be interpreted approximately as the percentage change in wage.

The main results are easily digestible. Working full-time (≥35 hours) demonstrates the strongest effect: a slope of approximately 0.382, equivalent to ≈ +46% in wages compared to non-full-time workers (ceteris paribus). Males also receive a substantial premium (≈ +40%). The white-collar factor (office/professional service work) is associated with ≈ +13%, marital status with ≈ +16%, training with ≈ +8%, and urban residence provides a premium of ≈ +11%. Work experience adds a small but consistent increase (≈ +0.5% per year).

For age, the slope is positive for "age" (≈ +4% per year) but negative for "age^2", indicating a concave downward relationship: wages tend to rise with increasing age then slow down/decrease after a peak around 38–39 years. Household size (number of household members) is negatively correlated (≈ -2% per additional member), which could be interpreted as the pressure of household dependents on effective productivity/work hours.

Overall, these patterns are consistent with a straightforward narrative for the public: effective working hours, type of work (white-collar), urban residence, and accumulated experience are closely linked to higher gig wages. Males and married individuals also tend to have higher wages, whilst the prime age group enjoys increases until the late 30s before the effect diminishes (Dong et al., 2024; Luo & Tharumarajah, 2025). On the other hand, larger households are associated with slightly lower incomes.

3. 2. Discussion

Indonesia presents a highly valuable case for studying spatial inequality in the gig economy due to three interacting features. First, the country has experienced one of the fastest expansions of digital platforms in the Global South, with local platforms such as Gojek and Grab becoming an integral part of both urban and increasingly rural economies. Second, Indonesia exhibits persistent and extensive regional economic disparities, reflected in a Gini ratio that remains among the highest in Southeast Asia (Permana, 2025). Third, labor regulations in the gig sector are still in their early stages and fragmented, creating an environment where spatial inequality can occur with minimal institutional mitigation (Heeks, 2017).

The current situation of gig workers in Indonesia reflects a significant geographical gap between urban and rural areas (Labib Fardany Faisal et al., 2019; Putri et al., 2023; Sudirman & Disemadi, 2023). Not only do urban gig workers constitute a proportion of the workforce nearly twice as large as their rural counterparts, but they also enjoy a higher average income, with a difference of approximately 12%. At first glance, this gap aligns with traditional labor market theory, where denser markets in urban areas, supported by robust digital infrastructure and concentrated demand, naturally yield higher returns (Moretti, 2012). However, in the context of the platform economy, this phenomenon requires further examination as it challenges the promise of digital platforms as “spatial equalizers.” The findings of this study initially support the “spatial mismatch” hypothesis proposed by Kain (1968) and later restated by Zenou (2016) and Brueckner & Martin (1997), extended into the digital realm: rural workers are not only disconnected from physical jobs but also from access to platform-mediated markets. Conversely, in rural areas, gig workers face challenges like dispersed demand, an underdeveloped digital ecosystem, and higher operational costs, consequently limiting both opportunities and income levels.

Nevertheless, income variation within each region is remarkably high. The graph illustrated in Figure 5 (Wage Rate Comparison) indicates that, in both urban and rural settings, there are gig workers with both very low and very high incomes. The decomposition analysis refines this picture, while individual factors like gig type and working hours are crucial, their "decisiveness" is itself conditioned by spatial context. For instance, the ~46% premium for full-time work is significantly amplified in urban "thick markets" where sustained demand makes such specialization viable. This reflects what Braesemann et al. (2022) term "agglomerative forces" in digital labor markets—the tendency of platform-based work to concentrate in large cities, creating a spatial polarisation that systematically disadvantages rural areas. The global evidence from online labor platforms confirms that remote work is pulled to regions with institutions that foster specialization, leaving locations without such enabling infrastructure—predominantly rural areas—falling behind (Liu et al., 2025). Moreover, Rani et al. (2025) demonstrate that despite adopting similar pricing strategies, earnings disparities among online freelancers persist across regional boundaries, with workers in developing countries incurring unpaid labour time as a discernible cost to access more lucrative opportunities. Thus, while residing in a city provides an 11% premium, it is the spatial-conditional returns to other characteristics that truly stratify economic outcomes.

Overall, this picture confirms that Indonesian gig workers operate within a highly dynamic yet still non-inclusive ecosystem, one where the promise of digital empowerment is constrained by spatial realities (Dwiputrianti et al., 2025). Although gig workers form the backbone of the digital economy, they face tangible inequalities in access and outcomes, exacerbated by demographic factors (Trautwein et al., 2025). This leads us to a critical conclusion: in its current form, Indonesia's gig economy risks creating a "dual digital economy" (Dwiputrianti et al., 2025), with an urban sector benefiting from innovation and higher returns, and a rural sector trapped in precarious, low-wage arrangements. To avert this, a spatially-aware governance framework is required. First, targeted investment in rural digital infrastructure must be coupled with "digital literacy for gig work" programs that go beyond basic internet use (Zheng et al., 2024). Second, platform accountability must be enhanced through regulations that mandate transparency in algorithm-driven pay and prohibit spatial wage discrimination (Lata et al., 2025; Rao et al., 2025). Finally, social protection schemes must be decoupled from formal employment status and made portable, ensuring that all workers, regardless of location, have a safety net (Dwiputrianti et al., 2025).

4. Conclusion and Suggestion

This study conclusively demonstrates a significant and systematic earnings gap between urban and rural gig workers in Indonesia, with urban workers earning approximately 12% more on average. Through the application of the Blinder-Oaxaca decomposition, this research reveals that while a substantial portion of this disparity is explained by observable characteristics—such as superior digital infrastructure, higher educational attainment, and greater market connectivity in urban areas—a significant unexplained component persists, indicating that differential returns to the same characteristics, potentially reflecting structural discrimination or unobserved market inefficiencies, also play a critical role. These findings underscore that geographic location remains a powerful determinant of economic opportunity within Indonesia's digital economy, reinforcing the thesis that the gig economy, while transformative, can also perpetuate existing spatial inequalities. The implications are twofold: from a policy perspective, there is an urgent need for targeted interventions aimed at leveling the digital playing field through strategic investment in rural digital infrastructure. Rural digital infrastructure must be accompanied by minimum wage benchmarks adjusted for location for platform workers to prevent platforms from extracting rents through spatial arbitrage. The role of policymakers in this regard is necessary to enact the ongoing Indonesian omnibus law on job creation, which explicitly prohibits wage discrimination based on geographic location. Next, the implication for platforms is that they are required to audit their algorithmic pricing mechanisms for spatial bias, in accordance with the framework. Transparency reports detailing earnings by district, type of task, and worker characteristics will enable independent verification of whether unexplained components reflect actual market conditions or systematic algorithmic discrimination. Theoretically, this research affirms that traditional labor economic frameworks remain highly relevant for analyzing modern platform-based work, providing a nuanced understanding that moves beyond merely identifying a wage gap to explicating its precise sources.

5. Limitations and Future Research

The study's limitations are including its reliance on national survey data (Susenas) which, while comprehensive, lacks platform-specific variables such as user ratings, precise working hours, and platform type that are known to influence earnings. Furthermore, the cross-sectional nature of the data provides only a temporal snapshot, preventing analysis of how the gig economy and its associated earnings gaps evolve dynamically. Consequently, future research should address these limitations through longitudinal studies that trace earnings trajectories over time, employ platform-specific data for more granular analysis of algorithmic management's influence on wage differentials, and adopt mixed-methods approaches incorporating qualitative interviews to uncover the lived experiences and social factors that explain the "unexplained" component of the wage gap, thereby providing critical insights that pure quantitative data cannot capture.

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Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Deepseek in order to conceptualization of initial ideas. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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