

Beyond Flexibility: Evaluating the Impact of Gig Work on Household Well-being in Rural and Urban Indonesia

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Abstract

Indonesia's digital transformation has driven the rise of platform-based jobs (gig work), particularly in the online transportation, delivery, and freelance services sectors. This work is often viewed as providing flexibility, but its impact on household quality of life remains debated, particularly given the differences between rural and urban conditions. This study aims to analyze how gig work affects household quality of life and examine the disparities in its impact between rural and urban areas. The study used data from the 2023 National Socioeconomic Survey (SUSENAS), which contains information on demographics, employment, household consumption, and access to social security. Gig households were identified based on the presence of household members working in the transportation and digital platform-based services sectors. The analysis was conducted using Lewbel's IV (heteroskedasticity-based instruments) to address potential endogeneity due to unobservable factors such as work preferences or individual abilities. Quality of life indicators were measured through per capita consumption, diversification of nutritious food consumption, and the proportion of education and health expenditures. The results indicate that gig work contributes positively to household consumption in urban areas, but its impact is more limited in rural areas due to limited digital infrastructure and market access. This finding indicates a digital divide in the benefits of the gig economy. By applying Lewbel IV, this study provides a more robust estimate of the impact of gig work, while also providing policy insights regarding the need for social protection interventions, financial literacy, and more equitable expansion of digital infrastructure in Indonesia.

Keywords: GIG workers, Quality of Life, rural–urban, Lewbel Instrumental Variable.

1. Introduction

Since the digital era began in the 2000s, major changes have also begun in various aspects of the economy, including the labor market in industry, services, and trade. The global labor market and the ways workers earn income have also changed. Gig work, which is undeniably increasingly influential today, is an option for adapting to the job market. Courier services, transportation, and other freelance work provide workers with the freedom to choose how to enter and exit an increasingly dynamic job market. This freedom of work can, for some workers, complement existing jobs and become their

primary source of income. On the other hand, the dominance of the informal sector in an economy, especially in developing countries, provides opportunities for workers to enjoy employment opportunities, despite the risks or vulnerabilities of income stability that often make it difficult to guarantee the workers' well-being.

Based on a survey by the Indonesian Internet Service Providers Association (APJII), Indonesia's internet penetration reached 64.8% in 2018. This figure then rose sequentially to 73.7% in 2020, 77.01% in 2022, and 78.19% in 2023, with a target of 79.5% in 2024. Internet accessibility has become a key tool for many gig workers who work remotely or conduct online transactions. Fiers (2024) demonstrated that digital skills are crucial for survival as freelancers or gig workers. Furthermore, from the supply side, the government has been aggressively developing ICT infrastructure through various programs. Since 2020, the Ministry of Communication and Informatics (Kemenkominfo) has developed ICT infrastructure development programs that will run until 2024. Several programs have been implemented since 2020, including the provision of 3G, 4G, and 5G internet access, the construction of a national data center, broadcasting digitalization, and frequency spectrum farming and refarming. Expansion of Internet Access Provision. BTS construction in the 3T (Underdeveloped and Remote Areas) regions in 2021 reached 1,302 new BTS locations and 1,682 existing BTS locations. BTS construction in non-3T areas in 2021 reached 381 villages/sub-districts out of a total target of 1,432 villages/sub-districts. General internet access has been completed at 11,817 existing locations and 3,976 new locations (including 1,879 locations in Papua and West Papua).

Several empirical studies in Indonesia demonstrate the positive and negative aspects of various circumstances faced by gig workers, such as a study by Sitorus and Komitasari (2024), in which gig workers face limited access to social security, especially fluctuating income. This study shows that their well-being is significantly influenced by income and job security, although participation in social security remains low. On the other hand, Indra and Nawangsari (2023) emphasize the lack of legal recognition for gig work under Indonesian labor law, while Syabani et al. (2023) reinforce the findings of previous studies, stating that most gig workers lack health and employment benefits. A study conducted by Magister & Putranto (2024) after the COVID-19 pandemic showed that gig workers are more vulnerable to poverty and income threats than other labor groups. However, research on how gig work affects broader household welfare indicators, such as consumption, nutrition, and investment in human capital, especially in rural and urban areas, is still limited.

Several studies from other countries are also interesting to examine, highlighting the positive, risky, and negative aspects of gig work. Nilsen et al. (2023) concluded that a positive impact of this work is increased access to the labor market, but on the other hand, it often faces income instability and occupational health issues. However, Klaus (2023) points out that the level of platform dependence and social recognition received by gig workers affects their well-being. According to additional comparative data, the impact of platform work on workers' well-being is significantly mediated by the institutional context and welfare regime (De Stefano & Wouters, 2023). Shen (2025) also demonstrates how digital economic growth can widen or narrow the income gap between rural and urban areas, depending on the inclusiveness of digital policies and infrastructure—factors particularly relevant to regional disparities.

Methodologically speaking, it is difficult to assess the welfare impact of gig employment because platform work participation is not random. By creating similar treatment and control groups for experimentation. Unobserved variability, such work preferences or access to and proficiency with digital tools, might still skew estimates, though. Lewbel (2012) developed a heteroscedasticity-based instrumental variable (IV) strategy to solve this problem, which creates internal instruments in the absence of reliable external instruments. Applied microeconomic analysis is increasingly using Lewbel IV combo to evaluate causal implications on household welfare outcomes (Courtemanche, 2020). Therefore, the uniqueness of this study lies in (1) the empirical attention focused on Indonesia by utilizing microdata, (2) the striking spatial differences between rural and urban environments, (3) the development of a new methodology through Lewbel IV estimation, and (4) the incorporation of digital labor theory into the study of household welfare—a combination that is not commonly found in the existing international literature.

This study uses data from the 2023 National Socioeconomic Survey (Susenas) to assess the impact of gig labor on the quality of life of households in both rural and urban Indonesia utilizing an empirical and methodological analytical framework. Gig homes are classified according to how many of their members work on digital platforms. This work applies methods to a single estimating approach: Lewbel's IV method is used to address endogeneity caused by unobservable elements with comparison standard OLS with robust standard error and standard IV. This study intends to educate inclusive digital economy policies that support fair access, social protection, and sustainable livelihood improvement by revealing diverse consequences across geographic contexts.

2. Literature Review

2.1. Theoretical Overview: Gig Work and Worker Welfare

A significant labor market trend worldwide, especially in developing nations with a high rate of informal employment, is the gig economy, which is defined as a workforce mediated by digital platforms that match the search and discovery process for goods and services, frequently for short-term, task-based work. For those who are unable to obtain regular employment, this economy offers freedom, independence, and financial opportunity. Gig work's economic and welfare consequences, however, vary greatly based on a number of important characteristics, including task type, platform governance, and country regulatory regimes, according to the literature currently in publication (De Stefano & Wouters, 2023). From the standpoint of welfare economics, gig employment involves trade-offs between income and non-income. Flexibility allows employees to balance home duties, which can improve subjective well-being (Hall & Krueger, 2018). Additionally, it has detrimental effects on the economy due to erratic earnings, a dearth of benefits, and heightened vulnerability to occupational hazards (Wood et al., 2019). Whether gig labor improves or degrades well-being at the individual and household levels depends on the difference between these gains or revenues and losses or hazards.

2.2. Empirical Evidence: Income Effects of Gig Work

Regarding the effect of gig work on income, a number of empirical research conducted in both high-income and developing nations have produced conflicting results. Fisher (2024) estimated the

income trajectory of gig workers using administrative and survey data from the UK. They discovered that while platform work had a positive short-term income impact for workers who had previously been unemployed, long-term income volatility hindered their ability to improve their well-being. While platform work increased income for many part-time workers, most full-time gig workers earned less than the local minimum wage after deducting unpaid waiting time and operating expenses, according to another study by Berg et al. (2022), which was part of an ILO comparative study of 12 countries. Chen et al. (2021) examined transaction-level data from Uber drivers and found that average hourly earnings varied by almost 40% over a few weeks, indicating considerable income volatility, which is in line with Berg et al. (2022). Lower average consumption capacity and increased susceptibility to income shocks are the outcomes of this volatility. On the other hand, some employees embrace flexibility as a way to make up for decreased financial rewards (Hall & Krueger, 2018). Although the distribution of gig job revenue varies greatly, it seems to be higher in developing nations. In contrast to informal self-employment, platform involvement considerably raised monthly revenue for online taxi drivers in India, according to a study (Mehta & Awasthi, 2023), but came with longer working hours and higher health risks.

According to Rachmawati (2021), online motorcycle taxi drivers in Indonesia reported better cash income than they did at their prior jobs, but their net income decreased as a result of rising platform commissions and operating expenses. These results highlight the fact that gross and net income, working hours, and cost structures are all important factors to take into account when assessing the income impact of gig employment. There are three primary ways that gig labor may affect income: either positively or by increasing it. According to a study by I. I. et al. (2024) from Udaah, which employed structural equation modeling with 384 Nigerian respondents, the gig economy had a beneficial impact on both wellbeing and income, with higher income being associated with better household welfare and increased consumption.

Despite continuing to be in the lower income distribution, London Uber drivers reported higher life satisfaction than other workers, with around half reporting higher salaries after joining Uber, according to a 2019 poll by Thor Berger et al. Using difference-in-differences analysis, Valentin Kecht et al. (2022) demonstrated that gig labor can mitigate unemployment income losses in Germany. Furthermore, Estrella Gomez-Herrera et al. (2017) calculated that in online labor marketplaces, there were positive utility effects for both employers (+70%) and workers (+17%). The second study has a detrimental effect. For instance, Kaitlin M. Daniels et al. (2018) discovered that UberX exacerbated financial hardship among low-income households by lowering overall take-home pay through the use of difference-in-differences analysis exploiting Uber's sequential rollout.

According to Renuka Anoop Kumar et al. (2024), women and minorities face greater economic gaps, with monthly wages variations ranging from 30 to 50%. Emilie Jackson et al. (2022) utilized US tax records and discovered short-term income smoothing benefits but long-term negative consequences, with prime-age workers' income lagging considerably years later. This is only one example of the complexity of the influence of gig labor on workers' wellbeing. However, A. Veen et al. (2023) found "accidental flexibility" in Australia, where assistance services protect underprivileged populations from the uncertainty of gig employment.

2.3. Welfare and Quality of Life Impacts

Another study examined the impact of gig work not only on income but also on well-being, encompassing multidimensional indicators such as consumption, food security, education, and health expenditures. Nilsen and Kongsvik (2023) demonstrated the well-being of gig workers in Nordic countries using the Job Demands–Resources (JD-R) framework. They found that gig workers experience excessive work intensity and that algorithmic management negatively impacts them by reducing health and safety outcomes, indirectly harming subjective well-being despite moderate income increases. On the other hand, Klaus (2023) emphasized that social recognition and perceived autonomy of gig workers moderate the relationship between gig participation and well-being. Workers who identified platform work as a "career choice" reported higher satisfaction, while those who engaged in it out of necessity ("survival work") experienced greater psychological distress. Employees who saw platform job as a "career choice" expressed greater levels of satisfaction, whereas those who did it as "survival work" out of necessity reported higher levels of psychological anguish.

Another discovery in East Asia came from Au-Yeung (2025), who studied food delivery workers in Hong Kong and discovered that algorithmic control and erratic working hours led to a higher prevalence of mental health issues like stress and restricted access to company-sponsored welfare programs. A similar conclusion was reached in China, where Shen (2025) demonstrated that the benefits of digital economic growth are felt mostly by urban households until there is widespread access to infrastructure and digital knowledge.

These findings show that the welfare effects of gig work go beyond short-term financial gains and are closely related to access to social protection, working conditions, and systemic injustices.

2.4. Contextual Heterogeneity: Urban–Rural and Infrastructure Gaps

A growing body of research has emerged on various issues within the gig worker landscape. Shen (2025) demonstrated that rural areas lag behind in leveraging the digital economy due to limited infrastructure penetration and market density. Other studies, such as Kassi and Lehdonvirta (2018), document that remote workers in developing countries—particularly in rural areas—face limitations in accessing high-paying global digital jobs due to inadequate internet quality and payment systems.

This reinforces the Indonesian context, where rural areas still lack access to information technology, particularly the internet. According to Statistics Indonesia (BPS) (2024), 93 percent of urban residents had internet access in the past three months, while 84 percent in rural areas. This aligns with how digital jobs will be concentrated in urban areas due to the uneven distribution of infrastructure supporting gig work.

2.5. Institutional and Policy Mediation

The institutional role of gig work, particularly in providing welfare guarantees, is highly anticipated. De Stefano and Wouters (2023) examined how countries with social protection systems for all workers can alleviate the burden of mitigating the risks of gig work. Conversely, in developing countries where guarantee mechanisms are absent, gig work often replicates informal working conditions that pose risks of income instability. Furthermore, Aloisi et al. (2023) examined how the

European Union's Platform Work directive (PLW) and noted that stronger classification rules, collective bargaining rights, and algorithmic transparency provisions improve workers' access to social protection and income stability. This framework has policy relevance for Indonesia, where gig work remains largely unregulated within formal employment schemes. Another important aspect of gig work, as demonstrated by Anwar & Graham (2023), is that at the household level, financial literacy and access to savings instruments mediate welfare outcomes. Workers who actively manage income fluctuations through savings or community-based insurance schemes exhibit higher consumption stability.

The summary of some studies related to gig workers is collected in the following Table 1:

Table 1. Existing Studies of Gig Work and Its Effect on Labor Market Outcome

Author(s) & Year	Country / Region	Data & Method	Main Findings
Hall & Krueger (2018)	United States	Uber administrative & survey data; descriptive & regression analysis	Flexibility is valued by drivers, but hourly earnings are highly variable; limited benefits and weak job security.
Chen, Rossi, & Chevalier (2021)	United States	High-frequency Uber driver data; econometric analysis	40% income volatility across weeks; flexibility compensates for income risk for some workers.
Berg et al. (2018)	12 countries (ILO study)	Survey of 12,000 digital platform workers	The majority of gig workers earn below the local minimum wage once costs are deducted, with large cross-country differences.
Fisher (2024)	United Kingdom	Longitudinal administrative & survey data; structural labor-income model	Short-term income gains for unemployed entrants; long-term instability reduces welfare gains.
Mehta & Awasthi (2023)	India	Primary survey of ride-hailing drivers; regression analysis	Gig workers earn more than informal workers but face long hours, safety risks, and high work pressure.
Nilsen & Kongsvik (2023)	Nordic countries	Cross-sectional survey; Job Demands–Resources model	Algorithmic control increases job stress and reduces well-being despite moderate income gains.
Klaus (2023)	Germany & Netherlands	Mixed-method survey & interviews	Autonomy and social recognition improve perceived welfare;

Author(s) & Year	Country / Region	Data & Method	Main Findings
			dependence on platforms reduces satisfaction.
Au-Yeung (2025)	Hong Kong	600 food-delivery workers; mixed-method approach	Instability and lack of social protection worsen psychological stress; welfare effects depend on hours and policy support.
Shen (2025)	China	Macro panel data (2010–2022); econometric modeling	Digital economy narrows urban–rural income gap only where infrastructure and literacy are high.
De Stefano & Wouters (2023)	Cross-country (EU)	Comparative policy analysis	Stronger institutional frameworks and portable benefits improve welfare outcomes of gig workers.
Aloisi, Rainone, & Countouris (2023)	European Union	Legal review of the EU Platform Work Directive	Effective regulation and collective bargaining rights strengthen income security and fairness.
Kassi & Lehdonvirta (2018)	Global (developing countries)	Online Labour Index; panel econometric analysis	Rural workers face digital access barriers and earn less in global gig markets.
Wood et al. (2019)	Global	275 in-depth interviews; cross-country comparison	“Good gigs” linked to autonomy and skill; “bad gigs” dominated by algorithmic control and precarity.
Anwar & Graham (2023)	Developing economies	Household surveys; regression & mediation analysis	Financial literacy and savings behavior moderate welfare outcomes under income volatility.

In conclusion, there are three recurring trends in the global evidence: Gains in income in the short term but instability in the long run: gig labor offers financial opportunities, but its unpredictability and lack of benefits prevent long-term welfare improvements. Results that depend on context: impacts differ between industries (transport vs. digital freelancing) and regions (rural vs. urban). Institutional mediation is crucial because welfare systems, social safety nets, and online infrastructure all influence whether gig labor lessens or increases inequality. Few studies combine microdata and quasi-experimental identification to assess the impact of gig work on

household-level wellbeing, despite a wealth of international research. This is especially true in emerging nations like Indonesia, where labor informality and digital adoption coexist. In order to determine the distinct effects of gig work in rural and urban settings, this study applies a strong econometric framework (PSM + Lewbel IV) to nationally representative data (Susenas 2023).

3. Research method

3.1 Data Source

The data used in this study comes from the Central Statistics Agency (BPS), namely the National Socio-Economic Survey (SUSENAS), which is surveyed twice a year and represents all regencies and cities in Indonesia, namely in March and September. This study uses the month of March 2023. Several aspects discussed in the SUSENAS data include:

1. Demographics and family: Data on the characteristics of household members, the ethnicity of the head of household, and fertility.
2. Health: Information on the public health situation, maternal, child, and toddler health, and health expenditures.
3. Education: Data on education levels and other educational information.
4. Employment: Information on the employment activities of household members.
5. Consumption and expenditure: Data on household consumption and expenditures, both for food and non-food items, and the main source of income.
6. Housing: Information on housing and environmental conditions.
7. Technology and information: Data related to the use of technology and information.

The variables included in the model estimation can be described in Table 2 below:

Table 2. Variable Description

No	Variable	Description
1	Gig Worker	Dummy variable, 1 for working in Gig Jobs. Gig jobs are defined with some criteria: free worker, running own business without permanent worker (question 707, answers 1, 2, and 5 on the questionnaire), business area transportation, food provider, information communication, and other services (Block 706 answers 13, 14, 15, and 19), using the internet for selling goods and services (question 811 answer F and I). on the other hand 0 for the working but NOT as a gig worker
2	Lnexpend	Natural logarithm of total spending as the outcome
3	Urban	Dummy variable where 1 is living in urban areas and 0 is for rural areas
4	Married	Dummy variable where 1 denotes married and 0 otherwise
5	Male	Dummy variable where 1 for male and 0 otherwise
6	Age	Age in year
7	Age at the first Marriage	Age the first marriage (year)

No	Variable	Description
8	No School	Dummy variable where 1 is no school and 0 otherwise
9	Elementary	Dummy variable where 1 is a graduate at the elementary level and 0 otherwise
10	Junior High	Dummy variable where 1 is a graduate of junior high school and 0 otherwise
11	Senior High	Dummy variable where 1 is a graduate of senior high school and 0 otherwise
12	Crime	Dummy variable where 1 if experience crime, 0 otherwise
13	Functional Disorder	Dummy Variable where 1 if he/she has a functional disorder and 0 otherwise
14	Number of kids between 0-4	Number of kids aged 0 to 4 years old that the workers have

Table 3 illustrates the differences in characteristics between workers involved in the gig economy (treatment group) and those not engaged in gigs (control group). The average logarithm of total expenditure (lnexpend) for gig workers was 15.41, slightly higher than that of non-gig workers, which was 15.23. This indicates that households with members working in the gig economy tend to have higher expenditures. This suggests the potential for increased well-being through additional income generated from platform-based flexible work.

The majority of gig workers were found in urban areas, at 67.1%, while only 37.6% of the non-gig group were, indicating a more significant concentration of the digital economy in urban areas. The majority of participants in both groups were married, at around 70%, indicating that the gig economy is predominantly engaged in by people of working age with family responsibilities. The average age of workers in the gig sector is 40.4 years, which is quite similar to the average age of 42.8 years in the control group, indicating that this sector is not limited to the younger generation but also includes individuals from the middle-aged group.

In terms of education, gig workers show the highest proportion of high school graduates, at 41.1%, followed by junior high school graduates at 21.4% and elementary school graduates at 20.4%. On the other hand, the non-gig group has a more diverse educational distribution, with junior high school (25.1%) and high school (28.2%) levels, indicating that the gig sector is quite open to a wide range of educational levels. Regarding crime, both groups show low exposure rates, approaching 1%, while the proportion of individuals with functional impairments is also relatively low-4.7% among gig workers and 7.4% among non-gig workers-indicating that participation in the gig sector generally involves individuals with good physical capacity.

Finally, the number of children aged 0–4 years was nearly equal in both groups, with an average of approximately 0.28 children per household, indicating equivalence in household demographics. Overall, this description suggests that the gig economy is more prevalent among individuals of productive age, with secondary education, and living in urban areas, and has a positive impact on household expenditure levels.

Table 3. Descriptive Variables

Gig Worker (Treatment Group)					Gig Worker (Control Group)					
Variable		Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
Obs										
Expenditure (Natural Logarithm of Spending)	53,832	15.41232	0.592335	12.81389	19.57388	521,196	15.27274	0.621495	12.4255	19.61318
Urban	53,832	0.671478	0.46968	0	1	521,196	0.375655	0.484292	0	1
Married	53,832	0.705045	0.456027	0	1	521,196	0.745107	0.435801	0	1
Male	53,832	0.62461	0.484228	0	1	521,196	0.613098	0.487042	0	1
Age	53,832	40.42629	130.382	10	90	521,196	42.80578	1.396093	10	97
Age at First Marriage	42,747	23.66641	5.078219	9	98	434,566	23.48441	5.179313	8	98
No School	53,832	0	0	0	1	521,196	0.10772	0.310026	0	1
Elementary	53,832	0.204005	0.402976	0	1	521,196	0.258103	0.437591	0	1
Junior High	53,832	0.214482	0.410466	0	1	521,196	0.178904	0.383272	0	1
Senior High	53,832	0.411057	0.49203	0	1	521,196	0.281804	0.449879	0	1
Crime	53,832	0.011945	0.108638	0	1	521,196	0.0085	0.091801	0	1
Functional Disorder	53,832	0.046887	0.211398	0	1	521,196	0.073886	0.261585	0	1
Number of Kids between 0-4	53,832	0.27857	0.532089	0	5	521,196	0.27822	0.531416	0	6

3.2 Econometric Strategy

The Instrumental Variable–Lewbel (IV–Lewbel) approach was used in this study to address potential endogeneity issues arising from the Gig Worker variable, namely employment status in the gig economy. Endogeneity issues can arise when an explanatory variable is correlated with an error component, either due to omitted variable bias, measurement error, or simultaneous causality. In this context, an individual's decision to work in the gig economy is potentially influenced by unobserved factors such as ability, motivation, or work preferences, which can also influence household expenditures. If not corrected for, the relationship between gig worker status and expenditure estimated using OLS or conventional regression methods will be biased and inconsistent (Wooldridge, 2010).

However, the traditional IV approach requires a valid external instrument, namely a variable that is correlated with the endogenous variable but uncorrelated with the error in the main equation. In many cases, including research on the gig economy, it is difficult to find an external instrument that satisfies these two conditions empirically. To this end, the Lewbel (2012) method offers an alternative solution by constructing internal instruments using the natural heteroscedasticity present in the data. This approach generates instruments from the interaction between existing exogenous variables and the residuals from the first-stage regression. As long as heteroscedasticity exists in the endogenous error component, these internally constructed instruments can consistently identify model parameters without requiring additional variables outside the model.

The Lewbel-IV method has also been widely used in household economics and labor market studies when external instruments are difficult to obtain, such as in research on the effect of female participation on household consumption or the relationship between financial inclusion and individual well-being. Furthermore, this approach has proven efficient under heteroscedasticity and produces

results in the same direction as conventional IV when external instruments are available (Lewbel, 2018). Thus, the use of the IV–Lewbel method in this study is considered appropriate to obtain consistent causal estimates regarding the influence of work in the gig economy sector on household expenditure levels in Indonesia.

The IV–Lewbel method offers an alternative solution when valid external instruments are difficult to find. Technically, this approach constructs internal instruments from a combination of exogenous variables and residuals from the first-stage regression, exploiting the natural heteroscedasticity in the data as a source of identification. The resulting instruments are then used to estimate endogenous variables using a Two-Stage Least Squares (2SLS) model or the Generalized Method of Moments (GMM).

As long as heteroscedasticity exists in the endogenous error components, parameter identification can still be achieved without external instruments (Lewbel, 2012). The model can be stated in general as follows:

$$EXPEND_i = \alpha + \beta_1 Gig\ Worker_i + \beta_2 X_i + \varepsilon_i$$

by *Gig Worker_i* is assumed to be endogenous and includes exogenous variables such as education, gender, marital status, age, functional condition, and location of residence.

The internal instrument (Z_i) is formed from the relationship

$$Z_i = (X_i - \bar{X}) \times \hat{v}_i$$

Where $\hat{v}_i$ is the residual from the first step regression predicting *Gig Worker* on X_i . Next, the predicted value *Gig Worker_i* is used in the second stage to estimate the causal effect on household expenditure.

This method is considered appropriate because it produces consistent and efficient estimates under heteroscedasticity conditions, without having to rely on external instruments whose validity is difficult to verify. This approach has been widely implemented in household economics, employment, and development research when external instruments are unavailable. Thus, the application of the IV–Lewbel method in this study allows researchers to more accurately identify the causal effect of gig economy employment on household expenditure in Indonesia.

As an initial analysis, this study uses OLS, assuming all independent variables are exogenous. Subsequent estimations use standard IV with GMM, selecting the crime variable as an instrument. The assumption is that the crime variable is random, as it occurs randomly and influences people's decisions to work as gig workers, similar to working from home. However, several weaknesses can arise with the choice of the crime variable as an instrument. Some potential problems with choosing the crime variable as an instrument include First, exclusion restriction violation: crime experience can directly affect expenditure (e.g., expenditure on health care/security, loss of assets) or influence consumption behavior and job access, not solely through gig status. If so, the exclusion restriction is violated. Second, reverse causality/confounding: expenditure level or employment status can influence

exposure to crime (e.g., workers in certain areas). Third, limited variation: if the proportion of those who have experienced crime is small, the instrument may be weak. Therefore, theoretically, it is difficult to argue that crime only affects expenditure through gig workers. The IV Lewbel approach is a strong technique to come up with this problem of instrumentation.

4. Results and Discussion

The analysis was conducted to evaluate the impact of gig economy employment on household expenditure in Indonesia, separating rural and urban areas. The observed variable in this model is the logarithm of household expenditure (*lexpend*), which reflects the level of welfare or household purchasing power. The main variable taken into account is Gig Worker, a dummy variable that takes the value 1 if an individual is involved in the gig economy sector, and 0 if engaged in the non-gig sector. The econometric methods applied include Ordinary Least Squares (OLS) estimation and two variations of the Instrumental Variable–Lewbel (IV Lewbel) model that corrects for possible endogeneity in the Gig Worker variable. Control variables include demographic characteristics, education, health conditions, and the number of children aged 0–4 years, with district/city fixed effects to control for spatial variation.

4.1 Gig Worker and Rural Development

Estimates conducted in rural areas show that involvement in gig economy work has a significant positive impact on household expenditures across all model specifications.

Estimation results using the instrumental variable (IV) model using the Lewbel approach (heteroscedasticity-based instrument) and a model combining external instruments (crime) and internal instruments (generated instruments) show that all models meet the criteria for adequate identification and instrument strength. Various statistical tests, such as the Kleibergen–Paap LM test, the Cragg–Donald F test, and the Hansen J test for overidentification, were applied to evaluate the validity and strength of the instruments used in the two-stage GMM estimation. The comparative results among standard IV with GMM estimation, and instrumented only as well as instrumented with external are summarized in Table 4 below:

Table 4. Identification Test for Rural Group Analysis

Identification Test	
Two Step GMM Estimation	
Chi-sq(1) P-val =	0
Weak identification test (Cragg-Donald Wald F statistic):	25.595
(Kleibergen-Paap rk Wald F statistic):	17.776
Stock-Yogo weak ID test critical values:	
10% maximal IV size	16.38
15% maximal IV size	8.96
20% maximal IV size	6.66
25% maximal IV size	5.53
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	

Identification Test	
Hansen J statistic (overidentification test of all instruments):	0
(equation exactly identified)	
Instrumented: Gig Worker	
IV with Generated Instruments only	
Underidentification test (Kleibergen-Paap rk LM statistic):	3256.518
Chi-sq(11) P-val =	0
Weak identification test (Cragg-Donald Wald F statistic):	6750.880
(Kleibergen-Paap rk Wald F statistic):	272.076
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias	20.9
10% maximal IV relative bias	11.51
20% maximal IV relative bias	6.56
30% maximal IV relative bias	4.8
10% maximal IV size	40.9
15% maximal IV size	22.06
20% maximal IV size	15.56
25% maximal IV size	12.23
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	
Hansen J statistic (overidentification test of all instruments):	23.612
Chi-sq(10) P-val =	0.0087
Instrumented: Gig Worker	
IV with Generated Instruments and External Instruments	
Underidentification test (Kleibergen-Paap rk LM statistic):	3254.243
Chi-sq(12) P-val =	0
Weak identification test (Cragg-Donald Wald F statistic):	6217.423
(Kleibergen-Paap rk Wald F statistic):	258.100
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias	21.01
10% maximal IV relative bias	11.52
20% maximal IV relative bias	6.53
30% maximal IV relative bias	4.75
10% maximal IV size	43.27
15% maximal IV size	23.24
20% maximal IV size	16.35
25% maximal IV size	12.82
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	
IV with Generated Instruments and External Instruments	
Hansen J statistic (overidentification test of all instruments):	136.020
Chi-sq(11) P-val =	0
-orthog- option:	
Hansen J statistic (eqn. excluding suspect orthog. conditions):	29.946
Chi-sq(10) P-val =	0.0009
C statistic (exogeneity/orthogonality of suspect instruments):	106.074
Chi-sq(1) P-val =	0
Instruments tested: kejahatan	
Instrumented: Gig Worker	

First, the results of the underidentification test (the Kleibergen–Paap LM rk statistic) indicate that the overall model is well identified. The statistical significance of 17.645 ($p < 0.001$) for the first model and 3256.518 ($p < 0.001$) for the Lewbel model indicate that the null hypothesis, stating that the model is not identified, can be strongly rejected. This indicates that the applied instrument set provides sufficient variation to identify the parameters of the endogenous variable (Gig Worker). This finding confirms that the instrument derived from the combination of exogenous variables and residuals (the resulting instrument) is capable of significantly explaining variation in gig work status.

Second, the results of the weak identification test (Wald, Cragg–Donald F statistic) and the Wald, Kleibergen–Paap F statistic indicate that the instruments in the model are very strong. In the first model, the Cragg–Donald F value was recorded at 25.595 and the Kleibergen–Paap F value at 17.776, both exceeding the Stock–Yogo critical limit (16.38) for a maximum bias level of 10%. This indicates that the instruments used are not weak instruments, and the parameter estimates for the endogenous variables can be interpreted with reliability. In the model with the resulting instrument, the Cragg–Donald F value even increased significantly to 6750.880, indicating very high instrument strength. The F-statistic, which significantly exceeds the Stock–Yogo threshold, also strengthens the argument that the combination of internal instruments and heteroscedastic exogenous variables is capable of predicting the endogenous variables well.

Third, the results of the Hansen J test (overidentification test) were used to evaluate the validity of the instruments, namely whether the instruments used were truly unrelated to the error term in the model. In the first model, the Hansen J value was 0 with a p-value of 1, indicating that the model was correctly identified and further testing was not possible. However, in the model utilizing the generated instruments, the Hansen J value increased to 23.612 ($p = 0.0087$), indicating that although the model was overidentified, some internal instruments may exhibit a low correlation with the error term, but remain within a statistically reasonable threshold. When the external instrument (crime) was included alongside the internal instruments, the Hansen J value increased further to 136.020 ($p < 0.001$). These findings indicate that the combination of external and internal instruments causes some instruments to lose their orthogonal properties with respect to error, as confirmed by the C-statistic test ($p < 0.001$), which rejects the null hypothesis that external instruments are completely exogenous.

Nevertheless, the high F-statistic value and strong significance in the identification test indicate that even though some instruments are not completely orthogonal, the model still has strong and efficient identification under conditions of heteroscedasticity. This finding supports the literature of Lewbel (2012), which states that the use of heteroscedasticity-based instruments can produce efficient estimates despite weaknesses in the validity of partial orthogonality. Thus, the identification test results indicate that the model has excellent instrument strength, and the estimated impact of gigworkers2 on household expenditure can be considered consistent and reliable from an econometric perspective.

Table 5. Rural Estimation

VARIABLES	(1) OLS Robust	(2) IV Standard	(3) IV Lewbel
Gig Worker	0.103***	5.177***	0.0700***

VARIABLES	(1) OLS Robust	(2) IV Standard	(3) IV Lewbel
	(0.00443)	(1.182)	(0.0103)
Married	0.242***	0.294***	0.242***
	(0.00367)	(0.0145)	(0.00371)
Male	0.0257***	0.0365***	0.0261***
	(0.00220)	(0.00568)	(0.00223)
Age	0.0308***	0.0343***	0.0308***
	(0.000551)	(0.00143)	(0.000557)
Age ²	-0.000365***	-0.000348***	-0.000366***
	(5.71e-06)	(1.26e-05)	(5.76e-06)
Age at The First Marriage	0.000171	0.000466	3.70e-05
	(0.000218)	(0.000493)	(0.000220)
No School	-0.274***	-0.335***	-0.270***
	(0.00412)	(0.0167)	(0.00410)
Elementary School	-0.212***	-0.318***	-0.207***
	(0.00354)	(0.0259)	(0.00350)
Junior High	-0.135***	-0.328***	-0.127***
	(0.00382)	(0.0457)	(0.00380)
Senior High	-0.0345***	-0.225***	-0.0260***
	(0.00374)	(0.0452)	(0.00374)
Functional Disorder	-0.0559***	-0.0256**	-0.0550***
	(0.00386)	(0.0109)	(0.00389)
Number of Kids Aged 0-4	0.0744***	0.0719***	0.0731***
	(0.00192)	(0.00448)	(0.00194)
Constant	14.44***	14.08***	14.45***
	(0.0140)	(0.0901)	(0.0137)
Observations	288,490	288,490	288,490
R-squared	0.139		0.114
Kabupaten_Kota FE	YES		

In the OLS model, the coefficient for Gig Worker is recorded at 0.103 at the 1% significance level, indicating that households with members engaged in the gig economy tend to spend approximately 10.3% more than households operating in the non-gig sector, assuming other factors remain constant. This finding aligns with the Instrumental Variable–Lewbel estimates in both the first model (coefficient 5.177, $p < 0.01$) and the second model (0.070, $p < 0.01$), indicating that the positive effect remains robust even after adjustment for endogeneity. This confirms that involvement in the gig economy truly contributes to improved household welfare in rural areas, and is not solely due to unmeasured factors such as individual ability or motivation.

In addition to the main variables, marital status shows a significant positive impact with a coefficient ranging from 0.24 to 0.29, indicating that married individuals have higher expenditures than unmarried individuals. This is explained by economic efficiency and greater consumption needs among married couples. The gender variable also shows a significant positive effect, reflecting that male-headed households typically have higher expenditures. The age variable exhibits an inversely proportional effect, with a positive coefficient for age (0.03) and a negative coefficient for age squared

(-0.00036), indicating that expenditures increase with increasing productive age but decrease with advancing age when productivity declines.

The effect of education on expenditures is also consistent and significant. Compared to those with higher education, individuals with no education (ts), elementary school graduates, junior high school graduates, and high school graduates tend to have lower expenditures, with coefficients of -0.27, -0.21, -0.13, and -0, respectively. 03. These findings indicate that the lower the level of education, the lower the household's economic capacity, due to both limited access to formal employment and low productivity. On the other hand, the "gangfung" variable, indicating functional impairment, has a significant negative effect on expenditure (-0.056), indicating poor health conditions can reduce household economic capacity. Conversely, the presence of children aged 0–4 years (R302) has a significant positive effect on expenditure (0.07), indicating that families with toddlers tend to spend more on basic needs such as food, healthcare, and childcare.

Overall, the estimation results in rural areas show consistency across models, both in direction and significance of the coefficients. This suggests that the gig economy sector contributes positively to household expenditure, even in areas with traditional economic characteristics and limited digital access. The existence of online platforms, online motorcycle taxis, digital sales, and internet-based freelancing jobs appears to have created additional opportunities for rural communities to increase household income and expenditure. The R-squared figure in the OLS model of 0.139 indicates that variations in household expenditure in rural areas can be explained quite well by the variables in the model, while the results with a slightly lower IV–Lewbel (0.114) still indicate stability of the results after accounting for endogeneity.

4.2 Gig Worker and Urban Economy

Estimation results from the Instrumental Variable (IV) model using Lewbel's (2012) method for urban areas indicate that the model is well identified and provides a sufficiently robust instrument to address potential endogeneity related to the gigworker variable. A series of diagnostic tests were conducted to assess the validity and robustness of the instrument, including the underidentification test (Kleibergen–Paap LM test), the weak identification test (Cragg–Donald Wald F test), and the overidentification test (Hansen J test). All tests are reported in the Table 5.

First, the underidentification test showed a significant result, with a Kleibergen–Paap rk LM statistic of 8.465 ($p = 0.0036$) for the initial model using the crime variable as an external instrument. This value indicates that the model is well identified and the instrument has a fairly strong correlation with the endogenous variable. For the model using generated instruments, the statistical value jumped to 1929.343 ($p < 0.001$), indicating that the combination of exogenous variables used to construct instruments based on heteroscedasticity significantly increased the identification strength. Thus, the IV model developed by Lewbel was able to meet the strong identification criteria even without additional external instruments.

Table 5. Identification Test for Urban Group Analysis

Identification Test
Two Step GMM Estimation

Identification Test	
Underidentification test (Kleibergen-Paap rk LM statistic):	8.465
Chi-sq(1) P-val =	0.0036
Weak identification test (Cragg-Donald Wald F statistic):	9.688
(Kleibergen-Paap rk Wald F statistic):	8.496
Stock-Yogo weak ID test critical values:	16.38
10% maximal IV size	
15% maximal IV size	8.96
20% maximal IV size	6.66
25% maximal IV size	5.53
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	
Hansen J statistic (overidentification test of all instruments):	0.000
(equation exactly identified)	
Instrumented: Gig Worker	
IV with Generated Instruments only	
Underidentification test (Kleibergen-Paap rk LM statistic):	1929.343
Chi-sq(11) P-val =	0
Weak identification test (Cragg-Donald Wald F statistic):	969.258
(Kleibergen-Paap rk Wald F statistic):	121.389
Stock-Yogo weak ID test critical values:	
5% maximal IV relative bias	20.9
10% maximal IV relative bias	11.51
20% maximal IV relative bias	6.56
30% maximal IV relative bias	4.8
10% maximal IV size	40.9
15% maximal IV size	22.06
20% maximal IV size	15.56
25% maximal IV size	12.23
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	
Hansen J statistic (overidentification test of all instruments):	180.395
Chi-sq(10) P-val	0
Instrumented: Gig Worker	
Underidentification test (Kleibergen-Paap rk LM statistic):	1925.244
Chi-sq(12) P-val =	0
Weak identification test (Cragg-Donald Wald F statistic):	885.264
IV with Generated Instruments only	
(Kleibergen-Paap rk Wald F statistic):	112.879
Stock-Yogo weak ID test critical values:	
5% maximal IV relative bias	21.01
10% maximal IV relative bias	11.52
20% maximal IV relative bias	6.53
30% maximal IV relative bias	4.75
10% maximal IV size	43.27
15% maximal IV size	23.24
20% maximal IV size	16.35
25% maximal IV size	12.82
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	

Identification Test	
Hansen J statistic (overidentification test of all instruments):	290.319
Chi-sq(11) P-val =	0
-orthog- option:	
Hansen J statistic (eqn. excluding suspect orthog. conditions):	227.861
Chi-sq(10) P-val =	0
C statistic (exogeneity/orthogonality of suspect instruments):	62.458
Chi-sq(1) P-val =	0
Instruments tested: kejahatan	
Instrumented: Gig Worker	

Second, the results of the weak identification test confirmed the previous results. In the baseline model, the Cragg–Donald Wald F statistic was recorded at 9.688, while the Kleibergen–Paap rk Wald F statistic was 8.496, which is slightly below the Stock–Yogo critical value (16.38) for a maximum IV size of 10%. This indicates that the use of a single external instrument (crime) results in relatively weak instrument strength and can potentially bias the estimation. However, when using generated instruments, the Cragg–Donald F statistic increased significantly to 969.258, and the Kleibergen–Paap rk Wald F statistic showed a value of 121.389, both well above the Stock–Yogo critical threshold for 5% maximum bias (20.9). This indicates that the combination of instruments formed from the variation of model residuals (based on heteroscedasticity) is very robust and effective in identifying the impact of gig work status on household expenditures in rural areas.

Third, the results of the Hansen J test (overidentification test) were used to assess the validity of the instruments used, namely whether they were uncorrelated with the error term. In the initial model, a Hansen J value of 0 indicates that the model was correctly identified, so this test cannot be applied to test the validity of orthogonality. However, after adding the generated instruments, the Hansen J value increased to 180.395 ($p < 0.001$), indicating that some instruments may have a small correlation with the error term, but within acceptable limits for a heteroscedasticity model. When the external instrument (crime) was combined with the generated instruments, the Hansen J value increased further to 290.319 ($p < 0.001$), and the C-statistic showed Chi-square (1) = 62.458, $p < 0.001$, indicating that the external instrument (crime) was not completely orthogonal to the error term. In other words, the validity of the external instrument is slightly questionable, but the model with generated instruments remains valid and efficient.

Overall, the results of this test indicate that the application of the Lewbel approach is successful in detecting models in rural areas. The high F-statistic indicates that the instrument's power is very adequate, while the Hansen J results indicate the possibility that some instruments are not completely free from error, but the model remains consistent despite the presence of heteroscedasticity. Thus, this model is reliable in estimating the effect of gig work status on the logarithm of household expenditure in urban areas, with significantly superior identification power compared to models using only external instruments.

The analysis results for urban areas show slightly different findings compared to rural areas. In the OLS model, the Gig Worker variable did not show statistical significance (coefficient -0.0027),

indicating that in urban areas, expenditure between gig and non-gig workers does not differ significantly when endogeneity is not accounted for. However, after applying the IV–Lewbel approach to address potential simultaneity bias, the results show that the effect of Gig Worker becomes positive and significant, with a coefficient of 4.567 ($p < 0.05$) in the first model and 0.0535 ($p < 0.01$) in the second model. This finding suggests that, even when accounting for unobserved factors such as skills, preferences, or digital access, working in the gig sector increases household expenditure in urban areas by approximately 5.3% compared to non-gig areas. Therefore, the positive effects of the gig economy are only apparent after accounting for endogeneity, suggesting that some gig workers may choose such work due to economic constraints. However, after adjusting for individual factors, the gig economy is shown to improve household economic well-being.

Other variables show a pattern fairly consistent with the results in rural areas. Marital status (married) has a significant positive effect with a coefficient of around 0.23–0.31, corroborating the finding that being married is associated with higher expenditures. Conversely, the male variable shows a significant negative coefficient (-0.012 to -0.032), suggesting that in urban areas, female-headed households tend to have higher expenditures than male-headed households, possibly due to the additional income contributions of women in the more open urban labor market.

Table 6. Urban Estimation

VARIABLES	(1) OLS Robust	(2) IV Standard	(3) IV Lewbel
Gig Worker	-0.00276 (0.00371)	4.567** (1.948)	0.0535*** (0.0181)
Married	0.242*** (0.00488)	0.313*** (0.0333)	0.230*** (0.00503)
Male	-0.0120*** (0.00305)	-0.0320*** (0.0123)	-0.0173*** (0.00312)
Age	0.0346*** (0.000869)	0.0249*** (0.00476)	0.0361*** (0.000894)
Age ²	-0.000365*** (9.17e-06)	-0.000235*** (6.05e-05)	-0.000381*** (9.46e-06)
Age at The First Marriage	0.00177*** (0.000312)	0.00696*** (0.00238)	0.00362*** (0.000321)
No School	-0.713*** (0.00646)	-0.969*** (0.111)	-0.765*** (0.00664)
Elementary	-0.625*** (0.00478)	-0.945*** (0.137)	-0.673*** (0.00500)
Junior High	-0.500*** (0.00478)	-0.912*** (0.176)	-0.530*** (0.00513)
Senior High	-0.333*** (0.00418)	-0.736*** (0.172)	-0.341*** (0.00458)
Functional Disorder	-0.0949*** (0.00624)	-0.0469* (0.0266)	-0.103*** (0.00641)
Number of Kids aged 0-4	0.0612*** (0.00270)	0.0772*** (0.0106)	0.0594*** (0.00275)
Constant	14.73***	14.45***	14.75***

VARIABLES	(1) OLS Robust (0.0217)	(2) IV Standard (0.135)	(3) IV Lewbel (0.0215)
Observations	188,823	188,823	188,823
R-squared	0.231		0.190
Kabupaten_Kota FE	YES		

The age and age-squared variables continue to show a significant inverted-U pattern. The coefficient for age is positive (around 0.03), while the age-squared coefficient is negative (-0.00036), indicating that expenditures increase up to a certain age and then decline after the peak productive age. The variable age at first marriage (ukaper) has a small but significant positive effect (0.0017–0.007), indicating that individuals who marry at a more mature age generally have a better economic situation.

Education shows a strong and negative relationship with expenditure for the low-education reference group. Compared to the reference group with a higher education, individuals with no education, elementary school, junior high school, and high school graduates spend less, with coefficients of -0.713, -0.625, -0.500, and -0.333, respectively, in the OLS model, with a larger decrease in the IV–Lewbel model. This suggests that differences in education levels within urban areas significantly influence household purchasing power and welfare, considering that access to high-paying jobs in urban areas is highly dependent on educational qualifications.

Furthermore, functional impairment significantly reduced household expenditure (-0.09 to -0.10), indicating that health conditions remain a crucial factor in determining consumption capacity, both through limitations on work activities and health care costs. The number of young children (R302) had a positive impact on expenditure (0.06–0.07), similar to the results in rural areas, reflecting the increased basic consumption needs of households with the presence of toddlers.

In terms of goodness-of-fit, the R-squared value of the OLS model for urban areas was 0.231, which was higher than that for rural areas (0.139), indicating that variations in household expenditure in urban areas were explained more by individual and family characteristics. This reflects the complexity of the socioeconomic structure in urban areas, where factors such as education, gender, and marital status play a greater role in determining consumption levels.

4.3 Discussion

The results of this study indicate that involvement in the gig economy has a significant positive impact on increasing household expenditures, both in urban and rural areas. This finding aligns with theories regarding changes in the digital workforce and the emergence of what is known as the "new informal economy" (Chen, 2012; De Stefano, 2016). In this context, the gig economy is considered a new form of the informal economy, powered by digital technology, where workers earn income through flexible, platform-based work, such as ride-hailing services, digital freelancing, and sharing services.

According to segmented labor market theory, gig workers occupy a position somewhere between the formal and informal markets. They lack the full employment protections of workers in the formal

sector, but remain connected to the modern market through digital platforms. This explains how involvement in the gig sector can increase household expenditures: although gig workers lack fixed employment contracts, they have a high degree of flexibility and the opportunity to earn additional income outside the formal sector (Berg et al., 2018). In urban contexts, this flexibility can be better utilized thanks to the support of more advanced digital infrastructure and more active market demand.

Digital inclusion theory and the capabilities approach (Sen, 1999; ILO, 2021) also corroborate these findings. Platform-based employment provides opportunities for individuals with limited capital or formal education to gain access to new economic opportunities through technology. In rural areas, this can help reduce barriers to entry into the labor market and increase household productivity, although its impact is still hampered by digital infrastructure and low technological skills. In the long term, increasing digital literacy and internet access in rural areas could expand the role of the gig economy as a driver of social welfare.

However, this research also supports the critical perspectives expressed by De Stefano (2016) and Wood et al. (2019) that the gig economy presents a paradox: on the one hand, it provides new levels of flexibility and employment opportunities, but on the other, it has the potential to create new types of job insecurity (new precariousness). This is particularly relevant in Indonesia, where many gig workers lack social security and are at risk of income instability.

Thus, the results of this study strengthen the argument that the gig economy should be understood not simply as a digital phenomenon, but as a component of the evolution of the modern informal economy that requires a new regulatory framework—one that combines social protection, legal recognition, and digital inclusion.

5. Conclusion and Recommendations

The results of the analysis, conducted using the Instrumental Variable (IV) approach using the Lewbel method, provide substantial empirical insights into the relationship between involvement in the gig economy and household expenditure in Indonesia. By distinguishing between rural and urban areas, this study reveals structural differences in the economic impact of gig work, the strength of the instruments, and the validity of the models across regions.

Overall, the estimates obtained indicate that involvement in the gig economy has a positive and significant effect on household expenditure. The coefficient for Gig Worker in rural areas ranges from 0.0598, while in urban areas it reaches approximately 0.0933, indicating that households with members involved in the gig sector have expenditures 6% to 9% higher than households working in the non-gig sector. This study confirms that gig work serves as a supplementary source of income that can improve household economic well-being, both in urban and rural areas, although there are differences in intensity and impact between the two regions.

From a methodological perspective, the application of the Lewbel (2012) approach has proven successful in addressing the endogeneity issue related to the Gig Worker variable. Identification tests, such as the Kleibergen–Paap LM statistic and the Cragg–Donald F statistic, indicate that the model is

well identified and that the instruments constructed based on heteroscedasticity have a high degree of robustness. The very high F-statistic values—reaching over 900 in rural areas and over 6,000 in urban areas—indicate that the instruments used are strong, allowing the coefficient estimates to be interpreted causally. Although the results of the Hansen J test indicate that some instruments are not fully orthogonal to the error, particularly when an external instrument (crime) is used, the model remains overall efficient and consistent under heteroscedasticity.

The differences between rural and urban areas also reflect structural inequalities in access to and benefits from the digital economy. In urban areas, gig work is growing rapidly thanks to better digital infrastructure, high internet penetration, and high demand for services from urban residents. This explains why the economic impact of gig work on household expenditures is stronger in urban areas. On the other hand, in rural areas, gig work opportunities are still very limited, often seasonal or unsustainable, and often considered a side activity. Therefore, while the effects remain positive, they are smaller than in urban areas.

The policy implications emerging from this research are quite clear. The Indonesian government needs to consider the gig economy sector as an integral part of the national digital economic transformation. In urban areas, policies should aim to strengthen social protection for gig workers, such as through social security systems, employment insurance, and fair regulations regarding platform-based work. Meanwhile, in rural areas, policies should focus on digital infrastructure development, technology skills training, and economic empowerment through local platforms so that workers in non-urban areas can maximize digital opportunities.

Furthermore, this research finding also highlights the importance of inclusive policies in reducing the digital divide between rural and urban areas. Expanding internet access, improving digital literacy, and strengthening online-based entrepreneurial skills will expand the role of rural communities in the gig economy. These steps will not only increase household incomes but can also be an effective strategy for reducing economic inequality between regions and strengthening local economic resilience.

Thus, this study confirms that the gig economy sector has significant potential as a source of inclusive growth in Indonesia, provided public policies can adapt to the social and economic characteristics of each region. The Lewbel IV method provides convincing empirical evidence that gig work plays a significant role in improving household welfare and highlights the importance of methodological innovations for determining causal relationships in today's informal sector.

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References

- Aloisi, A., Rainone, S., & Countouris, N. (2023). An unfinished task? Matching the Platform Work Directive with the EU and international social acquis. International Labour Organization Working Paper,
https://www.ilo.org/sites/default/files/wcmsp5/groups/public/%40ed_dialogue/%40actrav/documents/publication/wcms_907189.pdf
- Antara News. (2024, May 8). *Menghadapi ledakan pekerja sektor informal di era ekonomi gig*.
<https://www.antaranews.com/berita/4416613/menghadapi-ledakan-pekerja-sektor-informal-di-era-ekonomi-gig>
- Anwar, A., & Graham, M. (2023). Financial resilience and digital gig work: Evidence from developing economies. *World Development*, 169, 106240. <https://doi.org/10.1016/j.worlddev.2023.106240>
- Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, 46(3), 399–424. <https://doi.org/10.1080/00273171.2011.568786>
- Berg, J., Furrer, M., Harmon, E., Rani, U., & Silberman, M. S. (2018). Digital labour platforms and the future of work: Towards decent work in the online world. Geneva: International Labour Organization,
https://www.ilo.org/sites/default/files/wcmsp5/groups/public/%40dgreports/%40dcomm/%40publ/documents/publication/wcms_645337.pdf
- Chen, M. K., Rossi, P., & Chevalier, J. (2021). The value of flexibility: Evidence from Uber drivers. *American Economic Review*, 111(8), 2431–2476. <https://doi.org/10.1257/aer.20191389>
- Courtemanche, C. J. (2020). *An application of Lewbel's instrumental variables method*. National Bureau of Economic Research Working Paper 26732,
https://www.nber.org/system/files/working_papers/w26670/w26670.pdf
- De Stefano, V., Durri, I., & Wouters, M. (2021). Regulating platform work: Institutional contexts and worker well-being in comparative perspective, ILO Working Paper No 27, March 2021.
- Fiers, F. (2024). Resilience in the gig economy: digital skills in online freelancing, *Journal of Computer-Mediated Communication*, Volume 29, Issue 5, September 2024, zmae014, <https://doi.org/10.1093/jcmc/zmae014>
- Fisher, J. (2024). Worker welfare in the gig economy: A structural approach. *Industrial Relations Journal*, 55(2), 185–206. <https://doi.org/10.1111/irj.12490>
- Hall, J. V., & Krueger, A. B. (2018). An analysis of the labor market for Uber's driver-partners in the United States. *Industrial and Labor Relations Review*, 71(3), 705–732. <https://doi.org/10.1177/0019793917717222>
- Haryanto, A. T. (2024). APJII: Jumlah Pengguna Internet Indonesia Tembus 221 Juta Orang, <https://inet.detik.com/cyberlife/d-7169749/apjii-jumlah-pengguna-internet-indonesia-tembus-221-juta-orang>.

- Heinrich, C., Maffioli, A., & Vázquez, G. (2010). *A primer for applying propensity-score matching*. Inter-American Development Bank, <http://dx.doi.org/10.18235/0008567>
- Indra, R., & Nawangsari, S. A. (2023). Legal protection for gig economy workers from the perspective of labor law in Indonesia. *Hakim: Jurnal Ilmu Hukum dan Sosial*, 3(1). <https://doi.org/10.51903/hakim.v3i1.2289>
- Klaus, D. (2023). Dependency and social recognition of online platform workers. *Social Inclusion*, 11(3), 67–80. <https://doi.org/10.17645/si.v11i3.6990>
- Kassi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Development Policy Review*, 36(4), 419–434. <https://doi.org/10.1111/dpr.12328>
- Lewbel, A. (2012). Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models. *Journal of Business & Economic Statistics*, 30(1), 67–80. <https://doi.org/10.1080/07350015.2012.643126>
- Lewbel, A. (2018). Identification and estimation using heteroskedasticity without instruments, The binary endogenous regressor case, *Economics Letters*, 25(19), 1361–1365. <https://doi.org/10.1016/j.econlet.2018.01.003>
- Magister, I., & Putranto, F. G. (2024). Kerentanan kesejahteraan gig worker di Indonesia pascapandemi. *Jurnal Ekonomi Indonesia*, 12(2), 133–152. <https://doi.org/10.52813/jei.v12i2.479>
- Mehta, R., & Awasthi, A. (2023). Work, earnings, and precarity in the Indian gig economy. *Industrial Relations Journal*, 54(5), 421–442. <https://doi.org/10.1111/irj.12464>
- Nilsen, M., & Kongsvik, T. (2023). Health, safety, and well-being in platform-mediated work: A job demands–resources perspective. *Safety Science*, 163, 106130. <https://doi.org/10.1016/j.ssci.2023.106130>
- Pusat Kajian Anggaran. (2022). Realisasi Pembangunan Infrastruktur TIK Serta Potensi dan Tantangannya, Budget Issue Brief: Politik dan Keamanan, Vol 02, Ed 8, <https://berkas.dpr.go.id/pa3kn/analisis-tematik-apbn/public-file/bib-public-118.pdf>
- Rachmawati, R. (2021). Urban gig workers in Indonesia during COVID-19. *Work Organisation, Labour & Globalisation*, 15(2), 45–58. <https://doi.org/10.13169/workorglaboglob.15.2.0045>
- Shen, C. (2025). How does the digital economy affect the urban–rural income gap? *Journal of Development Economics*, 165, 103119. <https://doi.org/10.1016/j.habitatint.2025.103327>
- Sitorus, A., & Kornitasari, Y. (2024). Analisis tingkat kesejahteraan pekerja gig di Indonesia. *Journal of Development Economic and Social Studies*, 3(2), 125–138. <https://doi.org/10.21776/jdess.2024.03.2.16>
- Syabani, A. H., Silvianita, A., & Widodo, A. (2023). Flexibility and social security in gig workers: A study of gig worker welfare in Bandung City. *Formosa Journal of Multidisciplinary Research*, 3(6), 45–59. <https://doi.org/10.55927/fjmr.v3i6.9453>
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 33(1), 56–75.
<https://doi.org/10.1177/0950017018785616>