
Designing Optimal Policies for Indonesia's Gig Economy through Agent-Based Modeling to Enhance Worker Welfare and Sustainable Growth

Iman Supriadi

Faculty of Economics and Business, STIE Mahardhika Surabaya

*Correspondence: iman@stiemahardhika.ac.id

Abstract

The growth of the gig economy in Indonesia has fostered a new form of employment relationship that is flexible yet highly vulnerable to social and economic uncertainties. A critical issue emerging within this context is the BPJS contribution policy, which potentially suppresses workers' income and distorts the equilibrium of the digital labor market. This condition calls for an analytical framework capable of capturing the dynamic interactions among policy interventions, worker behavior, and market mechanisms. This study aims to analyze the impact of BPJS contribution costs on gig workers' welfare, assess the role of price elasticity as a stabilizing factor, and design an optimal socio-economic policy that balances social protection with digital economic efficiency. The research employs an Agent-Based Modeling (ABM) approach involving three primary agent types: gig workers, digital platforms, and regulators. Simulations are conducted across 27 scenarios that vary BPJS contribution rates, income preferences, and price elasticity. Sensitivity analysis using Ordinary Least Squares (OLS) identifies the influence of each parameter on workers' average income. The simulation results reveal that an increase in BPJS contributions reduces worker income by approximately 0.9 units for every one-unit rise in fees, while price elasticity acts as a stabilizing mechanism maintaining market balance. A proportional contribution policy with flexible rates proves more effective than a fixed-rate scheme. The study concludes that the optimal policy for Indonesia's gig sector is a hybrid policy mix integrating proportional subsidies, flexible tariffs, and fiscal incentives for platforms, ensuring both worker welfare and systemic digital economic sustainability.

Keywords: gig economy, BPJS costs, agent-based model, price elasticity, worker welfare.

1. Introduction

The development of the digital economy has given rise to a new phenomenon known as the gig economy an employment ecosystem based on digital platforms where work relationships are flexible, temporary, and often lack formal contractual arrangements (Tan et al., 2020; Lata et al., 2022; Koutsimpogiorgos et al., 2020). This model has become a defining feature of the 21st-century economic transformation, where employment is no longer confined to conventional industrial relations but instead operates through algorithms and online systems (Bucos, 2023; Raimi, 2025; Ostoj, 2021). In Indonesia, the gig economy has experienced rapid growth through platforms such as Gojek, Grab,

Maxim, Shopee, and TikTok Shop, engaging millions of workers who rely on this demand-driven system for their livelihoods (Yasih, 2022; Ayu, 2024).

However, behind the narrative of digital progress lies a fundamental issue encompassing social, legal, and economic dimensions how to design policies that balance worker welfare with the sustainability of platform-based economies. This issue extends beyond academic discourse and has become part of the national political debate involving policymakers, digital business associations, and labor unions (Malik et al., 2021; Montgomery & Baglioni, 2020). Overly stringent regulations may suppress innovation and investment, while overly lenient regulations risk deepening inequality and social vulnerability (Kvart et al., 2025; Guo et al., 2021).

Within this context, the present study emerges from the urgency to develop an evidence-based policy tool capable of dynamically and realistically projecting the impact of policy interventions on worker welfare and national economic performance. One of the most promising approaches to achieve this objective is Agent-Based Modeling (ABM), a simulation method that represents the micro-level interactions among agents (workers, firms, and regulators) to generate complex macroeconomic dynamics (Jung et al., 2025; Douven, 2024; Axtell & Farmer, 2025).

The primary challenge in regulating the gig economy in Indonesia lies in the structural imbalance between labor market flexibility and worker social protection. To date, gig workers have not been fully recognized as formal employees and therefore lack comprehensive access to social security programs such as the Employment Social Security (BPJS Ketenagakerjaan) or the Old-Age Security Scheme (Indonesiana.id, 2025). On the other hand, platform companies reject the classification of gig workers as permanent employees, citing cost structures and partnership-based digital business models as their rationale (Arif et al., 2024).

This issue raises a highly complex policy question: to what extent will government interventions such as the mandatory BPJS contribution policy or the establishment of minimum service tariffs affect worker welfare, platform operating costs, and overall market equilibrium? Poorly calibrated policies may create counterproductive trade-offs, wherein increased social protection comes at the expense of reduced digital employment opportunities (Choudary, 2022; Chen et al., 2020). Therefore, a policy model is required that can systematically test and evaluate these scenarios prior to implementation. This study contributes to the ongoing policy debate concerning the adequacy and structural design of social protection schemes for gig workers in Indonesia, by providing simulation-based evidence on the welfare impacts of mandatory contribution policies.

A growing body of literature on the gig economy has examined this phenomenon from diverse perspectives, including human resource management, labor policy, ethics, sustainability, and digitalization. However, most studies remain limited to conceptual, descriptive, or partial policy analyses, without incorporating computational experimental approaches capable of revealing dynamic interactions among actors and systemic policy implications. Meijerink & Keegan, (2019) introduced an ecosystem-based HRM approach emphasizing the interconnections among workers, customers, and platforms, although its focus remains primarily on organizational governance. Jin & Liu-Lastres, (2024) applied a micro–meso–macro framework to assess the impact of the gig economy on the

hospitality sector, yet the study did not allow for dynamic causal analysis. Furthermore, Silva & Moreira, (2022) identified research fragmentation through bibliometric analysis, while Asfahani et al., (2023) and Tan et al., (2020) highlighted career sustainability and ethical dilemmas without incorporating comprehensive quantitative or experimental models.

Mehta, (2020) examined labor dynamics in India within the context of technological change, emphasizing the gig economy's potential as an alternative source of employment, though the study remained qualitative and did not evaluate the long-term policy consequences on national growth. Srihita et al., (2025), through bibliometric coupling, identified key research themes on workers, innovation, and welfare but maintained an exploratory orientation without empirical policy testing. Vu & Nguyen, (2024) added the dimension of worker vulnerability to climate risks, while Muldoon & Sun, (2024) compared platform transportation regulations across six countries without developing dynamic policy models. Alauddin et al., (2024) identified twelve thematic impacts of digital platforms on gig workers, whereas Webster & Zhang, (2025) emphasized the policy silence regarding migration issues in Sweden. Anwar et al., (2023) and Hickson, (2023) connected the gig economy to global capitalism and structural dominance but lacked quantitative approaches. Similarly, Koutsimpogiorgos et al., (2020) and Van Doorn et al., (2020) discussed regulatory challenges and migrant worker protection, yet neither developed comprehensive empirical analyses or simulation-based policy models.

A synthesis of previous studies reveals several research gaps that form the foundation for this study's development. Methodologically, most prior research remains confined to qualitative, conceptual, or descriptive approaches, without utilizing simulations grounded in complex adaptive systems. To date, no study has applied Agent-Based Modeling (ABM) to assess the impact of public policy on the gig economy while considering the dynamic interactions among workers, platforms, regulators, and consumers. Analytically, previous studies have tended to separate the focus between worker welfare (Meijerink & Keegan, 2019; Hickson, 2023) and market or innovation dynamics (Silva & Moreira, 2022). This study integrates both dimensions through simulations that connect micro-level welfare indicators with macroeconomic outputs. From a policy perspective, the regulatory discourse remains largely normative (Tan et al., 2020; Koutsimpogiorgos et al., 2020) and lacks experimental testing of alternative schemes such as mandatory BPJS contributions, minimum tariffs, or tax incentives. This study offers a new theoretical synthesis by integrating Institutional Regulation Theory, Labour Market Equilibrium, and Complex Adaptive Systems within the context of Indonesia's digital economy. To the best of our knowledge, no prior study has employed Agent-Based Modeling (ABM) to simulate the welfare impact of BPJS contribution policies within Indonesia's gig economy ecosystem.

The study is grounded in the policy dilemma between social protection and digital economic flexibility. The government seeks to prevent the exploitation of gig workers, whereas platform companies emphasize efficiency and competitiveness two equally vital aspects of sustainable economic development. The Agent-Based Modeling (ABM) approach provides an innovative solution through experimental simulations in a virtual environment functioning as a policy laboratory, enabling policymakers to test policy interventions without real economic risks. This study aims to design and

simulate optimal policies that balance worker welfare, platform profitability, and national economic growth. Specifically, it develops an agent-based model to represent the interactions among workers, digital platforms, and government actors, and evaluates the effects of policies such as mandatory BPJS contributions, minimum tariff regulations, and tax incentives on welfare outcomes and digital labor market stability. Theoretically, this research advances the digital economy literature through the lens of complex adaptive systems, while practically offering an evidence-based foundation for adaptive policymaking in response to digital disruption in Indonesia.

2. Research method

2.1. Research Approach

This study employs a quantitative approach grounded in computational simulation using the Agent-Based Modeling (ABM) method. This approach is chosen for its capacity to represent complex interactions among heterogeneous actors gig workers, platform firms, and government agencies while enabling the analysis of emergent behaviors within a dynamic digital economic system (Gill et al., 2021; White, 2023; Bertani et al., 2020). Unlike conventional top-down macroeconomic models, ABM adopts a bottom-up perspective, where aggregate system behavior emerges from the interactions among individual agents who follow specific behavioral rules and preferences (Reissl, 2022; Tieleman, 2021; Zehra & Urooj, 2022). This model is particularly well-suited for analyzing the impact of policy interventions on socio-economic phenomena that are adaptive, non-linear, and driven by micro-level decision-making processes.

2.2. Type and Design of Research

This research adopts a computational simulation experiment (computational policy experiment) designed to evaluate the impact of policy interventions on worker welfare and national economic growth. The research design consists of three interrelated stages. The first stage involves the design of agents and their environment, including the specification of agent types Gig Workers, Platforms, and Regulators along with their attributes, behaviors, and patterns of interaction. The second stage entails the construction of the simulation model, in which the model is developed based on behavioral rules and microeconomic decision functions, and subsequently implemented using Python 3.0 to generate realistic system dynamics. The third stage focuses on policy experimentation, conducted by running simulations under multiple scenarios: a baseline condition without intervention, the implementation of mandatory BPJS and social security schemes, an increase in minimum service tariffs, and the provision of subsidies to platforms or workers. The outcomes of each scenario are then compared to assess variations in worker welfare indicators and national economic growth.

Table 1. Agent Structure and Environment Model

Types of Agents	Attributes	Objective
Worker Agents	Income, Operating costs, Working hours, Welfare,	Maximizing individual utility functions based on the trade-off

Types of Agents	Attributes	Objective
	and BPJS membership status.	between income and work fatigue
Platform Agents	Service rates, Number of active workers, Profit, and Regulatory costs.	Maximizing net profits while considering regulatory compliance costs
Regulator Agent	Level of intervention, BPJS rates, and subsidies	Maximizing the social welfare function by maintaining a balance between economic growth and worker welfare

Source: Processed by Author (2025)

The functions used by each agent are as follows:

Worker utility function:

$$U_i = \alpha \cdot \ln(Y_i - C_i) - \beta \cdot H_i \quad (1)$$

Each worker maximizes the utility determined by net income and the disutility caused by working hours. The parameter α indicates preference for income, while β represents the level of work fatigue.

Worker income function:

$$Y_i = p_t \cdot O_i - C_i - B_{bpjs} \quad (2)$$

Workers' income is derived from the rate per order multiplied by the number of orders, minus operational costs and BPJS contributions.

Platform profit function:

$$\Pi_t = (p_t - w_t) \cdot D_t - B_{reg} \quad (3)$$

The platform maximizes profits by taking the difference between service fees and worker incentives, multiplied by the number of requests, after deducting regulatory costs.

The social function of national welfare:

$$SW_t = \lambda_1 \cdot U_t + \lambda_2 \cdot GDP_t - \lambda_3 \cdot Unemp_t \quad (4)$$

The government seeks to maximize aggregate social welfare based on the average utility of workers, aggregate economic growth, and unemployment rate. Weight λ describes policy priorities.

2.3. Interaction Between Agents, Model Dynamics, and Key Formulas

The interactions among agents in this model follow the principles of adaptive learning and feedback dynamics, whereby each agent dynamically updates its behavior based on outcomes and experiences from previous periods. The relationship between Gig Workers and Platforms is represented through the platform's adjustment mechanisms for service rates and incentives to maintain the number

of active workers at an optimal level, while workers adjust their working hours according to actual income and prevailing market conditions. The interaction between Platforms and the Government is reflected in the implementation of social obligations (τ_t) and the establishment of minimum service tariffs, to which platforms respond by optimizing service pricing and operational cost structures. Meanwhile, the relationship between Workers and the Government operates through subsidy or social compensation mechanisms (σ_t) provided by the government, after which workers decide whether to remain active or exit the system based on their perceived relative welfare level. The model dynamics and key functional formulas applied in this study are presented as follows:

Service Request Function

$$D_t = \alpha - b \cdot p_t \quad (5)$$

Demand for services decreases as rates increase; $\varepsilon < 0$ showing price elasticity.

Aggregate Economic Growth Function:

$$GDP_t = \sum_{i=1}^{N_t} (Y_i - C_i) \quad (6)$$

Aggregate domestic product is the sum of all workers' income and platform profits.

Aggregate Welfare Function

$$Welfare_t = \frac{1}{N_t} \sum_{i=1}^{N_t} U_i \quad (7)$$

National welfare is calculated from the average utility of all active workers in period t .

Gig Unemployment Rate Function

$$Unemp_t = 1 - \frac{N_t^{aktif}}{N_t^{total}} \quad (8)$$

Shows the proportion of workers who are inactive due to high costs or low demand.

The impact of regulations on platforms

$$R_t = \tau_t \cdot (w_t \cdot N_t) - \sigma_t \cdot N_t \quad (9)$$

The impact of the policy is calculated based on BPJS contribution fees, minimum tariff policies, and the amount of government subsidies.

2.4. Simulation Process

The simulation in this study is executed through a series of algorithms that represent the dynamic interactions among agents and the policy impacts on the gig economy system. The process begins with an initialization stage, where the initial values of all agent attributes such as income, service rates, number of workers, and government policy parameters are defined. The simulation then proceeds iteratively across multiple time periods, during which the government sets policies related to social obligations and subsidies, platforms adjust service rates and worker bonuses, and workers determine their working hours and participation levels based on market conditions and available incentives. Subsequently, the system automatically computes both macro- and micro-level indicators, including aggregate income, platform profit, unemployment rate, and overall welfare. The outcomes from each simulation are then evaluated for the corresponding policy scenarios under examination. The final

stage, policy optimization, involves identifying the combination of parameters that maximizes the social welfare function, thereby yielding the most effective policy configuration for enhancing worker well-being and maintaining national economic stability.

Model validation was conducted using a combination of qualitative face validation and parameter sweep calibration to ensure the internal consistency of emergent outcomes. Furthermore, parameter configurations follow empirical ranges reported in previous platform labor studies, and robustness was assessed through scenario-based sensitivity analysis.

3. Results and Discussion

3.1. Research Results

This study employs an Agent-Based Modeling (ABM) approach to represent the dynamic interactions among three key actors within the gig economy ecosystem: workers (drivers), digital platform companies, and consumers (transportation service users). The simulation is executed under a baseline configuration designed to realistically capture the dynamics of gig work ecosystems. The number of worker agents is set at 50, representing a reasonably representative population for a single operational area of a platform. The simulation runs for 200 time steps, equivalent to 200 days, allowing for the observation of medium-term dynamics and adaptive responses to new policy interventions.

The initial platform fare is set at 10 monetary units per order as a reference point to monitor tariff adjustment mechanisms resulting from changes in demand, workforce size, and profitability levels. The average order probability of 0.8 reflects a high-demand condition typical of mature gig markets. The BPJS contribution for workers varies across 0, 1, and 3 units, representing scenarios of no obligation, light obligation, and full obligation, respectively. Meanwhile, the BPJS cost for platforms is initially set to 0 to assess the direct policy impact on workers before incorporating cost-sharing schemes. Worker income preferences are defined at 0.5, 0.7, and 0.9, capturing variations in work motivation, while price elasticity values of -0.5 , -1.0 , and -1.5 reflect different levels of consumer sensitivity to price changes. The combination of these parameters yields a total of 27 simulation scenarios ($3 \times 3 \times 3$), representing various possible system equilibria under differing policy regimes and market conditions.

In the simulation, the three main agents interact through a dynamic mechanism. First, drivers decide whether to work based on their expected net income after deducting operational costs and BPJS (social security) contributions. The decision to work is determined by comparing the perceived economic benefits (income) with the associated costs. Next, the platform adjusts its pricing according to the level of demand, the number of active drivers, and the net profit earned. When profits are positive and demand is high, the platform increases fares to maximize margins. Conversely, when there is an oversupply of drivers or declining profitability, the platform reduces fares accordingly. Finally, consumers determine their demand levels based on price and waiting time. Higher fares or longer waiting times caused by a shortage of drivers lead to a decrease in demand, consistent with the specified price elasticity.

The interaction among these three agents generates a feedback loop that reflects the dynamics of the digital labor market: workers' welfare depends on regulatory policies, which in turn affect platform profitability and the balance of consumer demand. Table 2 reports a representative subset of five scenarios selected through boundary-case sampling, allowing the analysis to capture the extreme and moderate interaction effects among BPJS fees, income preferences, and demand elasticity without presenting redundant outcomes.

Table 2. Average Simulation Results for Various Policy Scenarios

BPJS Driver Fees	Income Preference	Price Elasticity	Average Income	Platform Benefits	Platform Rates	Consumer Demand
0	0.5	-1.5	11.9	528.52	18.13	43.06
0	0.5	-1.0	15.71	710.07	24.18	43.88
0	0.5	-0.5	18.91	1059.17	28.74	61.68
1	0.7	-1.0	14.89	707.79	24.18	43.88
3	0.9	-0.5	15.90	1059.40	28.74	61.68

Source: Output ABM (2025)

Consistently, an increase in BPJS contribution costs from 0 to 3 units leads to an average decline in workers' income by approximately 18%, as illustrated in Figure 1. For instance, under the scenario with a price elasticity of -1 and an income preference of 0.7 , the average income decreases from about 15.88 to 13.01 . This indicates that social contribution burdens directly reduce workers' welfare when not accompanied by fare adjustments or tax incentives. However, this negative effect is not linear. At a higher income preference level (0.9), the reduction in income is relatively smaller, as workers are more likely to remain active despite rising costs. In other words, individual economic motivation acts as a moderating factor that mitigates the adverse impact of social contribution policies.

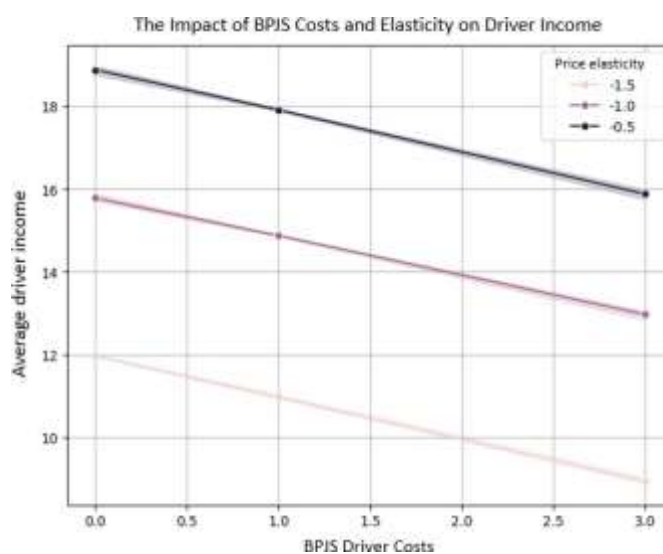


Figure 1. The Impact of BPJS Costs and Elasticity on Driver Income

Source: Output ABM (2025)

An increase in income preference from 0.5 to 0.9 enhances the stability of the active workforce and drives higher aggregate income output, as illustrated in Figure 2. A higher preference indicates that a larger proportion of workers choose to remain active despite fluctuations in fares or additional costs. However, its effect on average income is not always significant, as beyond a certain point, an expanding workforce generates competitive pressure that reduces the number of orders per individual. This finding suggests that individual welfare is not solely determined by work motivation but also by the aggregate balance between labor demand and supply.

The simulation results further reveal that price elasticity exerts the strongest influence on market stability and platform profitability. Under a price elasticity of -0.5 , consumers are relatively insensitive to price increases, allowing the platform fare to rise to 28.74 while maintaining high demand (approximately 61.68 units). Consequently, platform profits exceed 1,050 units. Conversely, when elasticity is -1.5 , demand becomes highly sensitive to price, where even minor fare increases lead to a sharp decline in both demand and revenue. This condition represents a competitive market in which workers' social protection must be supported through fiscal incentives rather than fare adjustments.

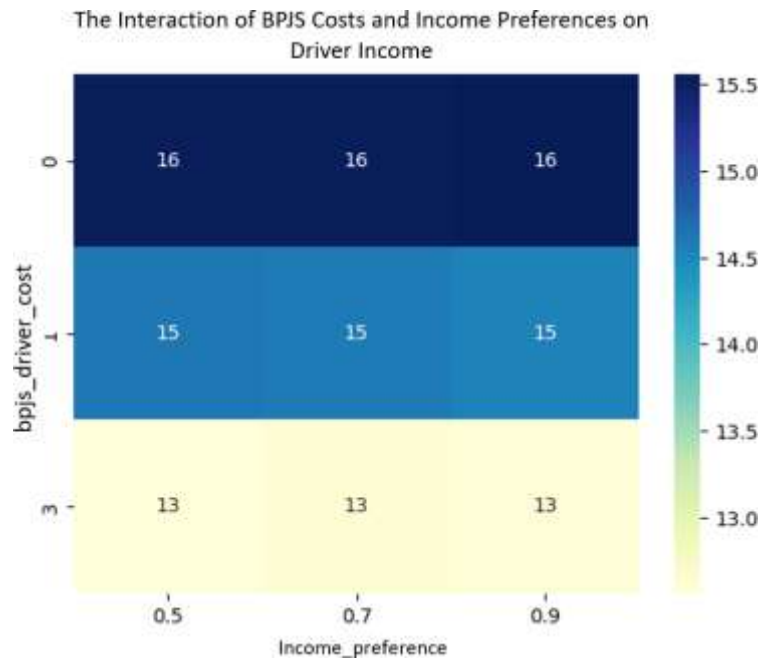


Figure 2. The Interaction of BPJS Costs and Income Preferences on Driver Income
Source: Output ABM (2025)

The platform exhibits adaptive behavior through the adjust fare function. When profits increase and demand remains high, fares are raised by 2–3% per iteration; conversely, when demand declines, fares are reduced by the same proportion. Over the long-run simulation (200 iterations), this mechanism generates a dynamic equilibrium with fare levels ranging between 18 and 28 units, depending on market conditions. This adaptive adjustment implies that overly rigid policy interventions such as imposing a high minimum fare may reduce system efficiency and distort equilibrium. In contrast, incentive-based adaptive policies are more compatible with the inherently dynamic nature of the gig economy market.

Ordinary Least Squares (OLS) regression analysis was employed to identify the sensitivity of key variables to workers' average income. The estimated regression model, as presented in Table 3, is specified as follows:

Table 3. Sensitivity Analysis

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Constant	22.502	0.243	92.594	0.000
BPJS Employee Fees	-0.985	0.038	-26.037	0.000
Income Preference	-0.013	0.289	-0.045	0.964
Price Elasticity	6.938	0.116	60.023	0.000
R ² = 0.995 Adj. R ² = 0.994 F-statistic = 1427 (p < 0.001)				
N = 27 Durbin-Watson = 2.93				

Source: Output ABM (2025)

The estimation results indicate that the coefficient (β_1) is negative and statistically significant, implying that each one-unit increase in BPJS contribution costs reduces workers' income by approximately 0.9 units. The coefficient (β_2) is negative but relatively small, suggesting that the influence of work motivation on income is limited under saturated market conditions. Meanwhile, the coefficient (β_3) is positive, indicating that lower price sensitivity (i.e., more inelastic demand) leads to higher income levels for workers. The model explains approximately 99.5% of the variation in average income, demonstrating that the combination of these three factors provides a robust representation of welfare dynamics within the gig economy sector.

3.2. Discussion

The simulation results reveal a complex and dynamic interaction among workers, platforms, and regulators within the gig economy ecosystem. An increase in BPJS (social security) contributions was found to reduce workers' average income by 0.9 units for every one-unit increase in cost, reflecting an income compression effect that occurs when social burdens are not offset by adequate tariff adjustments or subsidies. The feedback loop mechanism indicates that the decline in workers' utility leads some to reduce their working hours, thereby lowering service capacity and increasing consumer waiting times. Platforms, in turn, respond through an adaptation mechanism by adjusting prices and incentives; however, the new equilibrium that emerges remains characterized by lower income levels. Price elasticity plays a critical role: in inelastic markets, platforms can raise prices without losing demand, whereas in elastic markets, even a small price increase significantly decreases orders. Furthermore, individual income preferences also influence system stability, although their effect is not statistically significant. Overall, workers' welfare emerges from the non-linear interaction between public policy, microeconomic behavior, and the adaptive responses of digital platforms.

The results of the Agent-Based Model simulation demonstrate both convergence and notable divergence from previous findings on the gig economy. Broadly, these findings reinforce Meijerink &

Keegan, (2019) argument emphasizing the necessity of social regulation that aligns with the flexibility inherent in digital labor. The simulation confirms that gig workers' welfare depends not only on economic incentives but also on the adaptability of policies to workers' behavior and market dynamics. The implementation of rigid social policies such as mandatory BPJS contributions without considering income fluctuations reduces workers' utility and underscores the need to balance protection with flexibility. Contrary to Tan et al., (2020), the results indicate that in Indonesia, macro-level factors such as tariff structures and social costs exert greater influence than platform algorithmic control. Furthermore, the findings are consistent with Asfahani et al., (2023) regarding career sustainability and extend the perspectives of Silva & Moreira, (2022) and Muldoon & Sun, (2024) by illustrating that equilibrium within the gig system is endogenously shaped through the interaction of social policies, market elasticity, and agent behavior within a complex adaptive systems framework.

The simulation results indicate that system dynamics can be explained through microeconomic mechanisms shaped by agents' adaptive behavior and reciprocal interactions among actors. The decline in workers' income following the increase in BPJS (social security) contributions is not solely attributed to the additional financial burden, but also to rational agent responses that reduce working hours when net utility decreases. Within the framework of bounded rationality, workers balance the benefits of income with the social costs they bear; thus, higher contributions shift the equilibrium point and prompt some workers to lower their work intensity. This micro-level response generates macro-level effects in the form of declining aggregate productivity and stagnation in digital economic growth. Moreover, price elasticity functions as a market-stabilizing mechanism. In inelastic markets, price increases do not significantly reduce demand, thereby creating a self-adjusting equilibrium. However, in elastic conditions, even a small price increase can destabilize the system, leading to a fragile equilibrium. Therefore, the design of socio-economic policies in the gig sector must consider the adaptive interactions among agent behavior, pricing mechanisms, and demand dynamics.

Furthermore, the simulation highlights strategic implications for formulating social protection policies for gig workers, particularly in reformulating BPJS contribution mechanisms to be more adaptive to the dynamics of the digital labor market. The implementation of a fixed contribution scheme has been shown to generate socio-economic distortions by neglecting income fluctuations and unstable working hours, thereby reducing net utility and lowering active labor participation. Conversely, policies involving proportional subsidies and flexible service tariffs are more effective in maintaining equilibrium between workers' welfare and platform sustainability. A proportional contribution mechanism enables automatic adjustments to income changes, creating an automatic stabilizer that responds to market fluctuations. Additionally, flexible pricing policies at the platform level promote business efficiency while preserving competitiveness and worker compensation. Thus, the optimal policy framework for the gig sector is a hybrid policy mix that integrates proportional social protection, adaptive pricing regulation, and fiscal incentives to ensure the sustainability of an inclusive and equitable digital ecosystem.

This study has several limitations that should be taken into account when interpreting its results and generalizing the findings. Since all outcomes were derived using the Agent-Based Modeling (ABM) approach, the interpretation of results remains experimental in nature and does not directly

reflect empirical conditions. The model represents agent behavior based on controlled assumptions to test policy sensitivity rather than to depict real-world situations. Therefore, the findings of this study should be understood as a policy experiment that offers conceptual insights and potential policy directions, rather than as predictive empirical estimates. Moreover, the model employed remains linear and homogeneous, and thus does not fully capture variations in worker behavior across regions and digital platforms. Furthermore, future research should develop a more realistic approach by integrating heterogeneous agents and nonlinear interactions, as well as combining micro-level empirical data for calibration and external validation. Through such methodological refinement, the resulting policy model will become more applicable and valuable for strengthening the digital labor ecosystem in Indonesia.

4. Conclusion and Recommendations

This study provides new insights into the welfare dynamics of gig workers under social protection policies by employing an Agent-Based Modeling (ABM) approach. The simulation results show that increases in BPJS (social security) contribution rates reduce workers' net income, as agents rationally adjust their working hours when utility decreases. Price elasticity functions as a balancing mechanism that enables platforms to sustain demand through adaptive fare adjustments, indicating that welfare outcomes in gig markets are shaped more by macro-policy design than micro-behaviors alone. Accordingly, a hybrid policy mix that combines proportional contributions, flexible service pricing, and targeted fiscal incentives for platforms offers a more sustainable balance between business competitiveness and social equity.

Despite its valuable findings, this study has several limitations. The model operates under homogeneous assumptions that do not fully capture heterogeneity across regions, platforms, or worker characteristics, thus limiting external generalization. Future research should incorporate heterogeneous agents, nonlinear interaction structures, and empirical calibration using transactional microdata or worker-level surveys to enhance model accuracy and policy relevance. Through these refinements, simulation-based policy models can more realistically support evidence-based decision-making in Indonesia's evolving digital labor ecosystem.

References

- Alauddin, F. D. A., Aman, A., Ghazali, M. F., & Daud, S. (2024). The influence of digital platforms on gig workers: A systematic literature review. *Heliyon*, 11. <https://doi.org/10.1016/j.heliyon.2024.e41491>
- Anwar, M. A., Schäfer, S., & Golušin, S. (2023). Work futures: globalization, planetary markets, and uneven developments in the gig economy. *Globalizations*, 21, 571–589. <https://doi.org/10.1080/14747731.2023.2236876>
- Arif, Novianto, Anindya, Dessi, & Wulansari. (2024). *Kemitraan Semu dalam Ekonomi Gig di Indonesia : Analisis Terhadap Kondisi Pekerja Berstatus Mitra*. January.
- Asfahani, A., Alsobahi, G., & Dahlan, D. A. (2023). Navigating the Saudi Gig Economy: The Role of Human Resource Practices in Enhancing Job Satisfaction and Career Sustainability.

- Sustainability*. <https://doi.org/10.3390/su152316406>
- Axtell, R., & Farmer, J. (2025). Agent-Based Modeling in Economics and Finance: Past, Present, and Future. *Journal of Economic Literature*. <https://doi.org/10.1257/jel.20221319>
- Ayu, R. (2024). Role of Gig Economy Participation in Shaping Worker Economic Security in Indonesia. *International Journal of Sociology*. <https://doi.org/10.47604/ijs.2830>
- Bertani, F., Ponta, L., Raberto, M., Teglio, A., & Cincotti, S. (2020). The complexity of the intangible digital economy: an agent-based model. *Journal of Business Research*. <https://doi.org/10.1016/j.jbusres.2020.03.041>
- Bucos, T. (2023). The GIG Economy – Result of the Labour Market Platformization. *Economica*. <https://doi.org/10.53486/econ.2023.124.025>
- Chen, B., Liu, T., & Wang, Y. (2020). Volatile Fragility: New Employment Forms and Disrupted Employment Protection in the New Economy. *International Journal of Environmental Research and Public Health*, 17. <https://doi.org/10.3390/ijerph17051531>
- Choudary, S. P. (2022). Labor Market in the Digital Economy – Prospects for Regulation. *World Economy and International Relations*. <https://doi.org/10.20542/0131-2227-2022-66-10-102-111>
- Douven, I. (2024). Social Learning in Neural Agent-Based Models. *Philosophy of Science*, 92, 141–161. <https://doi.org/10.1017/psa.2024.33>
- Gill, A., Lalith, M., Poledna, S., Hori, M., Fujita, K., & Ichimura, T. (2021). High-Performance Computing Implementations of Agent-Based Economic Models for Realizing 1:1 Scale Simulations of Large Economies. *IEEE Transactions on Parallel and Distributed Systems*, 32, 2101–2114. <https://doi.org/10.1109/tpds.2021.3060462>
- Guo, J.-C., Tang, Q., & Jin, G. (2021). Labor protection and the efficiency of human capital investment. *Economic Analysis and Policy*, 69, 195–207. <https://doi.org/10.1016/j.eap.2020.12.006>
- Hickson, J. (2023). Freedom, domination and the gig economy. *New Political Economy*, 29, 321–336. <https://doi.org/10.1080/13563467.2023.2254712>
- Indonesiana.id. (2025). *Superposisi Pekerja Gig: Terjebak antara Status “Mitra” dan Realitas “Buruh.”* Indonesiana.Id. <https://www.indonesiana.id/read/187293/superposisi-pekerja-gig-terjebak-antara-status-mitra-dan-realitas-buruh>
- Jin, D., & Liu-Lastres, B. (2024). Critical reflection on the impact of the gig economy on the hospitality workforce. *International Journal of Contemporary Hospitality Management*. <https://doi.org/10.1108/ijchm-08-2023-1297>
- Jung, J., Miller, J., & Page, S. (2025). Agent-based modeling for psychological research on social phenomena. *The American Psychologist*. <https://doi.org/10.1037/amp0001530>
- Koutsimpogiorgos, N., Slageren, J., Herrmann, A., & Frenken, K. (2020). Conceptualizing the Gig Economy and Its Regulatory Problems. *Policy & Internet*. <https://doi.org/10.31235/osf.io/jmqyt>
- Kvart, S., Cuervo, I., Gunn, V., Lewchuk, W., Bosmans, K., Davis, L., Escrig-Piñol, A., Östergren, P., Padrosa, E., Vives, A., Zaupa, A., Ahonen, E., Álvarez-López, V., Bolívar, M., Díaz, I., Gutiérrez-Zamora, M., Ivarsson, L., Juliá, M., Muntaner, C., ... Baron, S. (2025). Labour and social protection gaps impacting the health and well-being of workers in non-standard employment: An international comparative study. *PLOS One*, 20. <https://doi.org/10.1371/journal.pone.0320248>
- Lata, L., Burdon, J., & Reddel, T. (2022). New tech, old exploitation: Gig economy, algorithmic control and migrant labour. *Sociology Compass*. <https://doi.org/10.1111/soc4.13028>
- Malik, R., Visvizi, A., & Skrzek-Lubasinska, M. (2021). The Gig Economy: Current Issues, the

- Debate, and the New Avenues of Research. *Sustainability*, 13, 5023. <https://doi.org/10.3390/su13095023>
- Mehta, B. (2020). Changing Nature of Work and the Gig Economy: Theory and Debate. *FIIB Business Review*, 12, 227–237. <https://doi.org/10.1177/2319714520968294>
- Meijerink, J., & Keegan, A. (2019). Conceptualizing human resource management in the gig economy. *Journal of Managerial Psychology*. <https://doi.org/10.1108/JMP-07-2018-0277>
- Montgomery, T., & Baglioni, S. (2020). Defining the gig economy: platform capitalism and the reinvention of precarious work. *International Journal of Sociology and Social Policy*. <https://doi.org/10.1108/ijssp-08-2020-0400>
- Muldoon, J., & Sun, P. (2024). The Global Gig Economy: How Transport Platform Companies Adapt to Regulatory Challenges—A Comparative Analysis of Six Countries. *Industrial Law Journal*. <https://doi.org/10.1093/indlaw/dwae010>
- Ostoj, I. (2021). The Logic of Gig Economy (Origins and Growth Prospects). *Studies in Logic, Grammar and Rhetoric*, 66, 451–462. <https://doi.org/10.2478/slgr-2021-0025>
- Raimi, L. (2025). Contributions of the shadow economy and gig economy to entrepreneurship and business development in emerging economies: a systematic review. *International Journal of Sociology and Social Policy*. <https://doi.org/10.1108/ijssp-12-2024-0638>
- Reissl, S. (2022). Fiscal multipliers, expectations and learning in a macroeconomic agent-based model. *Economic Inquiry*. <https://doi.org/10.1111/ecin.13084>
- Silva, B., & Moreira, A. (2022). Entrepreneurship and the gig economy: A bibliometric analysis. *Cuadernos de Gestión*. <https://doi.org/10.5295/cdg.211580am>
- Srihita, R. H., Goli, G., M, R., & Gobinath, R. (2025). “Transformative dynamics of the gig economy: Technological impacts, worker well-being and global research trends.” *International Journal of Engineering Business Management*. <https://doi.org/10.1177/18479790241310362>
- Tan, Z. M., Aggarwal, N., Cowls, J., Morley, J., Taddeo, M., & Floridi, L. (2020). The Ethical Debate about the Gig Economy: A Review and Critical Analysis. *Information Policy & Ethics EJournal*. <https://doi.org/10.2139/ssrn.3669216>
- Tieleman, S. (2021). Towards a Validation Methodology for Macroeconomic Agent-Based Models. *Computational Economics*, 60, 1507–1527. <https://doi.org/10.1007/s10614-021-10191-w>
- Van Doorn, N., Ferrari, F., & Graham, M. (2020). Migration and Migrant Labour in the Gig Economy: An Intervention. *Work, Employment & Society*, 37, 1099–1111. <https://doi.org/10.1177/09500170221096581>
- Vu, A. N., & Nguyen, D. L. (2024). The gig economy: The precariat in a climate precarious world. *World Development Perspectives*, 34, 100596. <https://doi.org/https://doi.org/10.1016/j.wdp.2024.100596>
- Webster, N. A., & Zhang, Q. (2025). Strategic silences for normative work: Inclusions and exclusions of migrant labour in policy foregrounding of the Swedish gig economy. *Geoforum*, 158, 104157. <https://doi.org/https://doi.org/10.1016/j.geoforum.2024.104157>
- White, D. (2023). Adaptive functions in an agent-based model of an economic system. *Adaptive Behavior*, 31, 21–34. <https://doi.org/10.1177/10597123221095644>
- Yasih, D. W. P. (2022). Normalizing and Resisting the New Precarity: A Case Study of the Indonesian Gig Economy. *Critical Sociology*, 49, 847–863. <https://doi.org/10.1177/08969205221087130>
- Zehra, A., & Urooj, A. (2022). A Bibliometric Analysis of the Developments and Research Frontiers of Agent-Based Modelling in Economics. *Economies*. <https://doi.org/10.3390/economies10070171>