J-naker
Jurnal Ketenagakerjaan

Jurnal Ketenagakerjaan
Volume 20 No. 3, 2025
Online ISSN: 2722-8770
Print ISSN: 1907-6096

Climate & Gig Work: Is Heat Wave Reducing Gig Riders' Productivity in Greater Jakarta?

Yohanes Eki Apriliawan

BPS-*Statistics Indonesia*

Email Correspondence: *yohanes.apriliawan@bps.go.id*

Abstract

This study demonstrates that rising surface temperatures significantly reduce gig rider productivity in Greater Jakarta, primarily by decreasing their weekly working hours and monthly income. Using spatial panel analysis with socioeconomic and environmental data from 2021 to 2024, we find that heat impacts are most severe in densely built, low-vegetation areas, while green spaces offer mitigation. Vegetation buffers the negative effects of heat, whereas higher night-time economic intensity exacerbates them. Metropolitan-scale analysis reveals that increases in temperature in one area also depress productivity in neighboring areas, highlighting interconnected climate risks. Further, gig riders are especially vulnerable compared to non-gig informal workers due to their mobility, exposure, and limited protections. These findings directly support policy priorities on human capital, economic transformation, and climate adaptation, emphasizing the urgent need for urban heat-safety standards, cooling infrastructure, and adaptive social protection for gig workers.

Keywords: gig economy, heatwaves, urban heat island, worker productivity, greater Jakarta

DOI: 10.47198/jnaker.v20i3.619 Received: 04-12-2025 Revised: 12-12-2025 Accepted: 26-12-2025

1. Introduction

1.1. Background

Digital technology has transformed the global labor market, including Indonesia. A key aspect is the gig economy, a flexible, platform-based system in which workers and employers connect on demand. In Indonesia, more online workers are now joining transportation and delivery services through platforms like Gojek, Grab, and ShopeeFood. According to Permana et al. (2023), gig workers on Java account for 74% of Indonesia's gig workforce, a proportion higher than the island's 60% share of the national population. Behl et al. (2021) found that transportation-sector gig workers are concentrated in metropolitan cities, a point also noted by

Kumar (2024) and Sutherland et al. (2020). Online motorcycle taxi drivers and couriers are described in these studies as operating with flexible systems, lacking long-term contracts, and relying on digitally facilitated demand. While these arrangements expand employment opportunities for individuals with limited access to formal work, the same studies highlight emerging concerns about welfare, job security, and working conditions (Tobing, 2024).

According to data from the Meteorology, Climatology and Geophysics Agency (BMKG), as quoted by the BPS (2025), the average maximum temperature in the Jakarta area increased from 36.5 degrees Celsius in 2015 to 36.8 degrees Celsius in 2024. According to Ningrum (2018) and Poórová et al. (2020), this temperature increase is mainly due to global climate change and the Urban Heat Island (UHI) effect. They identify dense urban development, limited green spaces, and heat absorption by concrete and asphalt surfaces as key factors contributing to the UHI effect. Graff Zivin & Neidell (2014) report that each one degree Celsius rise in daily temperature can decrease outdoor workforce productivity by one to three percent, particularly in labor-intensive sectors without artificial cooling. Somanathan et al. (2021) found that during heat waves in India, informal workers lost up to 5% of their productive working hours and experienced a significant decline in income due to reduced physical capacity in extreme temperatures.

BPS (2024) reports that around 57.95 percent of Indonesia's workforce remains in the informal sector. Gig workers are growing fastest in this group. Most gig workers are informal and lack formal labor protections or social security (Tobing, 2024). Their flexible but unstable work conditions, and their direct exposure to extreme environmental hazards, make them highly vulnerable to climate and economic risks. At the global level, research led by Burke et al. (2015) found that extreme temperature increases have nonlinear effects on economic production across countries. Heat stress negatively affects work capacity, especially among outdoor workers. However, Ioannou et al. (2022) note that most existing studies focus on agriculture or manufacturing. Little research examines these relationships in the context of the digital economy and platform-based work.

Liu et al. (2021)demonstrated that UHI intensity correlates strongly with settlement density, limited vegetation, and nighttime economic activity. Nightlights indicate this activity. This suggests that spatial, data-driven analyses are crucial for understanding workers' vulnerability to extreme heat in densely populated metropolitan areas like Greater Jakarta. To address this knowledge gap, this study analyzes how Land Surface Temperature (LST) affects gig worker productivity in Greater Jakarta from 2020 to 2024. The analysis uses spatial panel data. LST is measured with MODIS satellite imagery. Productivity data come from the National Labor Force Survey (Sakernas) managed by BPS, and are integrated with environmental indicators, including NDVI, nightlights, and population density.

This research directly supports Indonesia's national development vision and global climate adaptation commitment. In the 2024-2029 Presidential Ideal (Asta Cita), this research contributes to the 2nd, 3rd, 6th, and 8th Ideals. These focus on the digital economy, quality job growth, local economic equity, and sustainable development (Presidential Regulation Number 12, 2025). This research also aligns with the 2025-2045 National Long-Term Development Plan (RPJPN). The plan calls for a green and digital economic transformation for Golden Indonesia 2045. RPJPN requires inclusive, productive, and climate-adaptive economic development. This research provides evidence on climate risks for the digital economy and urban jobs (Law Number 59, 2024).

This study supports the 2025–2045 RPJPN's focus on green, digital transformation for Golden Indonesia 2045 and the 2020–2024 RPJMN's goals on digital economy growth, urban sustainability, and climate resilience (Law Number 59, 2024). Globally, this research helps achieve SDG 8 (Decent Work and Economic Growth) and SDG 13 (Climate Action). It also supports the Paris Agreement and the ILO's Just Transition Framework for a fair transition to a sustainable economy. The framework provides protections for vulnerable workers (ILO, 2015; UN, 2015, 2025).

1.2. Problem Statement

Based on the background, this research asks:

1. What is the spatial distribution of gig workers in the Greater Jakarta area during the 2021-2024 period?
2. How does surface temperature (LST) affect the productivity of gig riders, as measured through hours worked and income?
3. How do environmental conditions, such as vegetation (NDVI), population density, and economic activity, affect the relationship between heat and productivity?
4. Are gig riders more susceptible to heat productivity decline than non-gig informal workers?
5. What are the recommendations for climate adaptation policies that can protect gig workers from the risk of extreme heat in urban areas?

1.3. Purpose of Study

This research aims to:

1. Analyzing the relationship between surface temperature (LST) and the productivity of gig riders in the Greater Jakarta area in 2021-2024.
2. Identify environmental and spatial factors that modify the impact of heat on productivity.
3. Comparing the level of vulnerability of gig riders to extreme heat with that of non-gig informal workers.
4. Provide recommendations for urban employment-based climate adaptation policies that support the implementation of the 2025-2045 RPJPN, 2025-2029 RPJMN, and SDGs 8 and 13.

1.4. Benefit of Study

1. Academic benefits:
   Contribute new data on labor economics, climate change, and the digital economy by integrating socio-economic (Sakernas) and remote sensing (ESG, NDVI, nightlights) data. Practical benefits:
2. Practical benefits:
   Give scientific evidence to help governments create climate-adaptive employment policies and motivate digital platforms to protect gig workers.
3. Policy benefits:
   Support national policies in the 2020-2024 RPJMN, the 2025-2045 RPJPN, and global goals in the SDGs and Paris Agreement.

2. Research method

2.1. Theoretical Framework

This research departs from a theoretical framework that connects the physical environment, digital labor market structure, and the city's spatial dynamics. The framework is based on three main dimensions. First, the theory of labor productivity under environmental pressure (heat-productivity nexus). Second, the theory of the gig economy and digital work flexibility. Third, the theory of spatial economics explains how regions interact in economic activities. These three form a conceptual basis to explain how extreme temperatures in urban areas like Greater Jakarta affect gig workers' productivity. This especially applies to those working outdoors, such as online transportation drivers or delivery couriers.

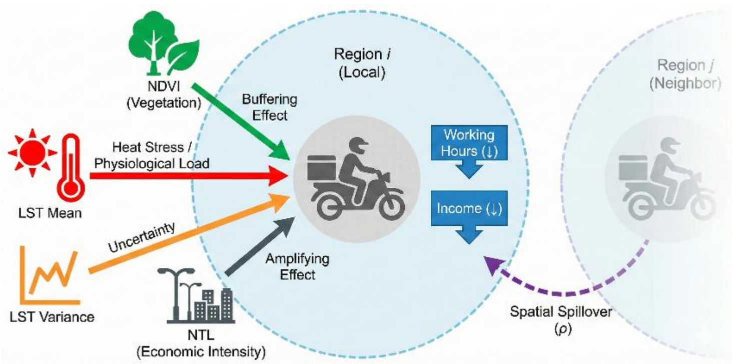

Figure 1. Conceptual Framework of the Climate-Gig Productivity Nexus

In classical labor productivity theory, productivity is a function of human capital, physical capital, and technological efficiency (Solow, 1956). Later, this approach included environmental factors, as research showed that climate conditions affect working capacity. Excessive heat exposure reduces physical and mental capacity through heat stress. Heat stress is physiological stress caused by elevated body temperature that affects metabolism and concentration. For outdoor work, a temperature rise of one degree Celsius above the optimal threshold (26-30 degrees Celsius) can reduce productivity by one to three percent. The reduction depends on the work type and adaptation level. This aligns with the theory of human capital depreciation under environmental stress. It states that exposure to extreme heat temporarily reduces labor capacity, increases rest time, and decreases output per hour worked (Kjellstrom et al., 2014).

In the digital economy, the emergence of a platform-based work system, or gig economy, has changed the traditional structure of the labor market. Gig work is defined as an economic activity mediated by digital platforms, in which the working relationship between workers and employers is temporary, task-based, and flexible in terms of time and location. This flexibility is one of the main attractions for urban workers, especially in developing countries, as it offers the freedom to set one's own hours and the opportunity to earn without the limitations of long-term contracts. However, gig economy theory also emphasizes the vulnerability side, including the lack of social protection, income instability, and direct exposure to market and environmental risks. In the Indonesian context, gig workers such as online motorcycle taxi drivers, food couriers, and digital logistics workers make up the largest share of the platform's workforce, where most work outdoors with long working hours and direct exposure to weather and pollution. Therefore, they are the most sensitive group to urban climate change, especially to increasing temperature extremes and the phenomenon of urban heat islands (De Stefano, 2015; Kässi & Lehdonvirta, 2018).

The relationship between ambient temperature and labor productivity is not only individual but also spatial. In regional and spatial economic theory, especially as explained by, there is an assumption that economic activities in one region are not independent, but rather affect each other between regions through spatial dependency mechanisms and spillover effects. Spatial dependence can arise from labor mobility, transportation network connectivity, or market proximity. In the context of this study, spatial interaction becomes relevant due to the high mobility of gig workers, especially gig riders, which affects their productivity not only by the environmental conditions in their area of residence but also by the heat and density of the surrounding area. For example, rising surface temperatures in Central Jakarta have the potential to affect the workload and income of online drivers operating across regions, such as to Bekasi or Tangerang, so analyses that ignore spatial relationships risk biasing estimates of the effects of climate on productivity (Anselin, 2003; LeSage & Pace, 2009).

The interaction among productivity theory, gig economy theory, and spatial theory provides the conceptual framework for this research. Conceptually, the productivity of labor in the region i in the year $t(Y_{it})$ is influenced by surface temperature conditions (LST_{it}), digital job characteristics ($GigShare_{it}$), and environmental factors such as vegetation and intensity of the nocturnal economy ($NDVI_{it}$ dan NTL_{it}). The interaction between regions is represented by the influence of these variables in the surrounding area, which is spatially appropriate. This relationship can theoretically be inferred in the form of a general function:

$$Productivity_{it} = f(LST_{it}, GigShare_{it}, NDVI_{it}, NTL_{it}, Spillover_{it}) \quad (1)$$

which illustrates that the level of worker productivity in a region results from a complex interaction among environmental factors, the digital economy, and dynamics between urban areas.

2.2. Data

This study uses quantitative secondary data from various sources, compiled into regency/municipality spatial panels for the Greater Jakarta area, for the period 2021 to 2024. The main source of data is from Sakernas, organized by BPS. From Sakernas, a number of key variables are used to identify gig workers, including employment status, classification of industrial sectors based on two-digit KBLI, use of the internet in work, employment contract status, and work location. In addition, weekly working hours and monthly income are used to measure labor productivity. When this microdata is processed, normalization and cleanup are performed to eliminate duplicate records.

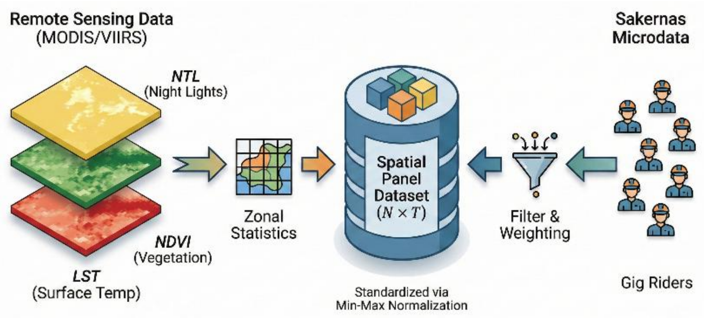

Figure 2. Data Integration Workflow

The operational definition of gig workers in this study follows the criteria: individuals who are self-employed, do not have a permanent employment contract, and use the internet to support work. The gig riders subgroup comprises gig workers in transportation and public sectors, as well as outdoor activities. Non-gig informal workers are individuals with a similar informal employment status who do not use the internet to work and do not work in the digital transportation sector. This approach allows for direct comparisons between groups of workers with relatively homogeneous socioeconomic characteristics who differ in their technology use and environmental exposure.

In addition to socioeconomic data, remote sensing data is used to describe the region's physical environmental conditions. Surface temperature (LST) data were obtained from MODIS imagery with a spatial resolution of 1 km and a temporal resolution of eight days. All satellite images for the 2021-2024 period are processed using zonal statistics at the regency/municipality administrative boundaries of the BPS, resulting in a series of surface temperature values for each region in a given year. These values are then converted to degrees Celsius and averaged to obtain the average annual LST for each regency/municipality, representing the region's baseline heat exposure level.

In addition to the average value, the study also calculated annual temperature variations to describe the degree of instability or temperature fluctuations in a region throughout the year. Variance is used as an indicator of the intensity of daily temperature changes and the frequency of heat-stress variability, which, in theory, affects the productivity of outdoor workers. Variance is calculated by the formula:

$$LST_{var,it} = \frac{1}{n}\sum_{d=1}^{n}\left(LST_{idt} - LST_{mean,it}\right)^2 \tag{2}$$

By being the value of surface temperature on the day of observation in the region in the year, and is the average value of the annual temperature of the region.

In addition to LST, the vegetation index (NDVI) from MODIS is used to describe vegetation density, and the night lighting intensity (NTL) from the VIIRS satellite is used as a proxy for urban economic activity. Other supporting data, such as population density and road network length, are taken from BPS and OpenStreetMap.

The research analysis unit is a regency/municipality in Greater Jakarta, which consists of five areas of DKI Jakarta (Central Jakarta, North Jakarta, West Jakarta, East Jakarta, South Jakarta) and eight surrounding areas (Bogor, Depok, Bekasi, Tangerang, Bogor City, Bekasi City, Tangerang City, and South Tangerang City). This analysis unit was selected because Greater Jakarta is the region with the highest concentration of gig workers in Indonesia and has experienced a significant increase in urban temperatures over the last decade.

2.3. Methodology

The research process follows a systematic analytical framework, progressing from micro-data processing and spatial environmental data integration to spatial panel formation and econometric estimation. The first stage involves the processing and classification of Sakernas microdata. Individual records from 2021 to 2024 are combined, cleaned, and categorized into gig workers, gig riders, and informal non-gig workers, following the criteria described in the previous subchapter. The aggregation process incorporates survey weights to produce estimates representative of the regency/municipality population. The weighted average estimate for weekly working hours and monthly income is calculated using the formula:

$$\hat{Y}_{ig} = \frac{\sum_{j=1}^{n_i} w_{ij} y_{ijg}}{\sum_{j=1}^{n_i} w_{ij}} \tag{3}$$

where $\hat{Y}_{ig}$ is the weighted average estimate of the productivity variable for the worker group in the regency/municipality, and w_{ij} is the individual survey weight. The estimated total worker population for each group is calculated as:

$$\hat{N}_{ig} = \sum_{j=1}^{n_i} w_{ij} \tag{4}$$

To calculate the standard deviation of these estimates, the Taylor linearization method is employed, accounting for the variation between Primary Sampling Units (PSUs) within the strata.

The third stage constructs a regency/municipality spatial panel with a two-dimensional structure (i, t), where i denotes the region and t denotes the year. This structure facilitates both longitudinal analysis (temporal changes) and spatial analysis (inter-regional interactions). Importantly, prior to the econometric estimation, all continuous independent variables (including LST, $NDVI$, and NTL) were standardized using Min-Max Normalization. This transformation ensures convergence in the spatial models and implies that the resulting coefficients represent the effect of a full-range shift (from the minimum to the maximum observed values) of the respective variable, rather than a single-unit change.

The fourth stage employs panel and spatial panel econometric models. The baseline specification is the Fixed Effects (FE) Model:

$$Y_{it} = \alpha_{it} + \lambda_t + \beta_1 LST_{it} + X_{it}\beta + \varepsilon_{it} \tag{5}$$

which controls for time-invariant regional characteristics through α_{it} and temporal shocks through time fixed effects λ_t. To capture inter-regional dependencies, the model is expanded into the Spatial Durbin Model (SDM):

$$Y_{it} = \rho WY_{it} + X_{it}\beta + WX_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where W represents the spatial weight matrix based on geographical proximity (contiguity) between regencies/municipalities. The coefficient ρ captures the spatial lag effects (endogenous interaction), while θ captures the spatial spillover effects of the independent variables (exogenous interaction).

Additionally, to test the hypothesis that gig workers are more thermally sensitive than other informal workers, an interaction model is estimated:

$$Y_{it} = \alpha_{it} + \lambda_t + \beta_1 LST_{it} + \beta_2 (LST_{it} \times GigShare_{it}) + X_{it}\gamma + \varepsilon_{it} \tag{7}$$

The coefficient β_2 measures the differential sensitivity of productivity to heat in regions with a higher proportion of gig workers.

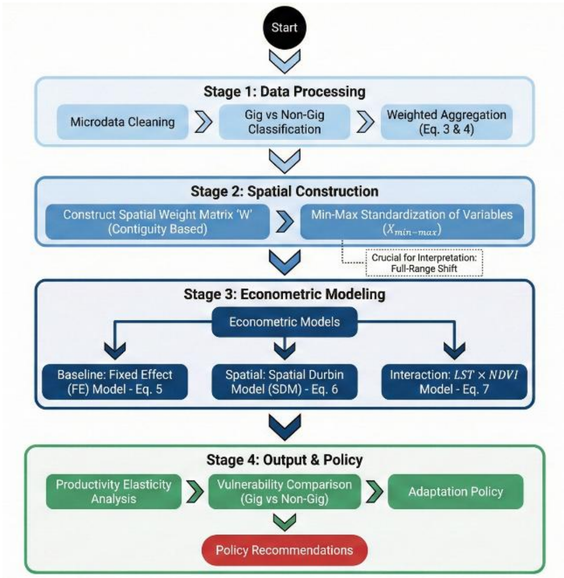

Figure 3. Methodological Flowchart

These integrated stages provide a robust empirical framework to quantify how rising surface temperatures and the urban heat island effect impact labor productivity in Indonesia's metropolitan areas. The findings are intended to contribute to the labor economics and climate change literature while providing an evidence base for formulating adaptive social protection policies.

3. Results and Discussion

3.1. Overview

The Greater Jakarta area is the largest metropolitan area in Indonesia, comprising six administrative cities in DKI Jakarta and eight surrounding districts/buffer cities. This region is known as the center of digital economy activities and the home base for the highest concentration of gig riders in Indonesia. A descriptive analysis of the 2021–2024 panel dataset reveals consistent spatial heterogeneity in surface temperature (LST_{mean}), green space ($NDVI$), night-time light intensity (NTL), and population density, which collectively shape gig workers' vulnerability to extreme heat.

Table 1. Descriptive Statistics

Variable	Mean	Standard Error	Minimum	Median	Maximum
Gig Working Hours	52.3744	4.0215	43.0489	53.2962	58.9448
Gig Monthly Income	2,616,177	522,869	1,329,675	2,651,506	4,097,270

Variable	Mean	Standard Error	Minimum	Median	Maximum
Gig Productivity	199,750	36,736	108,029	201,129	304,743
Informal Non-Gig Productivity	205,910	55,934	127,393	191,126	365,206
LST_{mean}	35.5083	2.5038	29.1815	36.2018	38.3186
LST_{var}	11,478	2,910	6,835	10,919	19,415
NDVI	0.3806	0.1012	0.2325	0.3546	0.6261
NTL	19.3096	9.9474	2.7523	19.3924	48.3487
Population Density	11,349	6,277	1,845	10,933	23,001
Road Density	20.3948	7.5199	5.3262	22.8847	31.2112

The variable LST_{mean} consistently exhibits the highest values in the administrative cities of North Jakarta, Central Jakarta, Tangerang, and Bekasi. These areas represent urbanization pockets characterized by high building density, a lack of green open space, and the dominance of impervious surfaces. The high LST_{mean} in these regions aligns with the Urban Heat Island (UHI) mechanism, where residential density, intensive economic activity, and reduced vegetation cover amplify surface temperatures. In contrast, areas such as Bogor City and Bogor Regency show significantly lower LST_{mean} values, supported by high NDVI and greener regional structures.

The temperature variance (LST_{var}) indicates more volatile temperature dynamics in metropolitan suburbs such as Bekasi Regency, Tangerang Regency, and Bogor Regency. This condition is typical of urban-rural transition zones, which tend to exhibit land-cover heterogeneity, rapid spatial change, and intense development. Analyzing this variance is crucial because daily and seasonal temperature fluctuations are often the primary triggers of heat stress among outdoor workers (Zander et al., 2015).

In terms of productivity, gig riders differ from informal non-gig groups. The cities of Bekasi, Depok, and South Tangerang record high average working hours for gig riders, consistent with the dominant usage patterns of online transportation apps in suburban residential areas. Meanwhile, the highest gig monthly income is found in areas with strong night-time economic activity, such as West Jakarta, South Jakarta, and Tangerang. The high intensity of NTL serves as a proxy for consumption centers that drive demand for transportation and delivery services, thereby potentially increasing the performance hours of gig riders.

Overall, the spatial description suggests that environmental factors, specifically vegetation, urban economic intensity, and surface temperature, form a highly variable risk pattern across cities. Greater Jakarta is not a homogeneous area; the combination of density, spatial structure, and road infrastructure creates complex patterns of vulnerability that necessitate analysis through panel-based empirical models and spatial approaches.

3.2. The Effect of Surface Temperature on Gig Riders' Productivity

Fixed-effects panel estimation serves as the core model to address the first research objective: measuring the impact of heat on gig rider productivity. This model controls for time-invariant regional characteristics (α_i) and annual productivity shocks (λ_t). Crucially, since the independent variables were standardized using Min-Max Normalization, the coefficients for LST_{mean} and LST_{var} should be interpreted as the productivity response to a full-range shift in temperature (from the lowest to the highest observed values in Greater Jakarta), rather than a single-degree change.

The estimation results reveal that an increase in average surface temperature (LST_{mean}) has a negative impact on gig riders' productivity. These findings align with the global literature, which posits that extreme heat compromises human work capacity by elevating physiological heat load, thereby affecting stamina, motor reactions, and physical endurance1111. For gig riders, this relationship is intensified as their work is performed entirely outdoors, often with minimal protection from direct solar radiation.

Table 2. Fixed Effects Panel Model on Gig Riders' Productivity

Variable	Coefficient		
	Productivity	Hours	Income
LST_{mean}	-0.0775**	-0.6186**	0.0614
LST_{var}	-0.0000	-0.0000	-0.0000
NDVI	-0.0707	-24.0890	-0.5773
NTL	-0.0033	-0.1012	-0.0055
Population Density	0.0008*	-0.0071	0.0007**
Road Density	-0.0316	1.2029	-0.0077
R^2	0.2487	0.0136	0.2242

Note: Coefficients represent the effect of min-max standardized variables. Significance Level: (*) 10%, (**) 5%. Dependent variables for Productivity and Income are in natural logarithms.

The temperature variance coefficient (LST_{var}) also exhibits a negative influence, although the magnitude is small. High year-to-year temperature variability indicates unstable environmental conditions, where extreme heat events and sharper daily fluctuations occur more frequently. The results suggest that not only does high average heat suppress productivity, but thermal instability, which exacerbates physical discomfort, also creates a latent burden on workers, echoing findings by Somanathan et al. (2021) on informal workers in India.

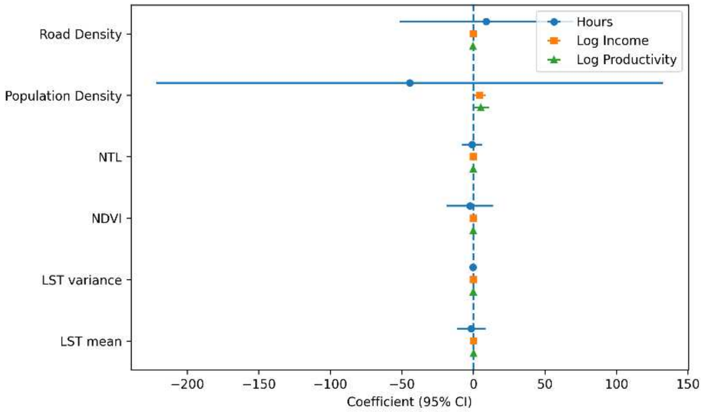

Figure 4. Coefficient Plot of Key Variables

When productivity is decomposed into working hours and income, a nuanced pattern emerges. Gig Working Hours tend to decrease as average temperatures rise (coefficient: -0.6186). This reduction is likely driven not only by heat-induced physical fatigue but also by adaptive behaviors, such as riders deliberately avoiding shifts during peak heat hours to mitigate health risks.

Interestingly, in this baseline model, Gig Monthly Income (coefficient: 0.0614) did not show a statistically significant decline despite the reduction in working hours. This anomaly suggests that while riders reduce their physical labor supply (hours) in response to heat, the impact on total income might be masked by other factors in the basic model, such as dynamic pricing (surge pricing) during difficult weather or riders maximizing high-value orders during cooler hours. However, as shown in the subsequent interaction models, the negative income effect becomes clearer when controlling for environmental modifiers.

Overall, the fixed effects results provide initial evidence that extreme heat acts as a productivity depressant for gig workers. Gig riders in Greater Jakarta are empirically shown to be susceptible to rising urban surface temperatures, primarily through the channel of reduced labor supply (working hours).

3.3. Interaction of Temperature with Vegetation and Economic Intensity

To address the second research objective, identifying environmental factors that mitigate or exacerbate the impact of heat on gig rider productivity, we employed interaction models ($LST \times NDVI$ and $LST \times NTL$). The results reveal two distinct spatial patterns essential for understanding urban climate adaptation.

The interaction between average surface temperature (LST_{mean}) and vegetation density ($NDVI$) yields a positive and statistically significant coefficient. Since the main effect of heat on working hours is negative, this positive interaction indicates that green spaces act as a protective buffer, effectively attenuating the heat-induced productivity loss.

Theoretically, this finding is consistent with urban ecology literature, which posits that vegetation lowers micro-temperatures through shading and evapotranspiration, thereby improving human thermal comfort (Bowler et al., 2010). In the context of gig riders, this is particularly relevant as their labor is performed in open road environments directly exposed to solar radiation. Urban green spaces, tree-lined streets, and canopy corridors function as microclimate refuges, reducing the physiological thermal load on riders' bodies and allowing them to sustain working hours even during hotter periods.

Table 3. Fixed Effects Panel Model with Interaction

Variable	Coefficient		
	Productivity	Hours	Income
LST_{mean}	-0.1683	-13.9300**	0.4280*
LST_{var}	0.0000	0.0016	0.0000
NDVI	-0.6551	1391.7**	26.209*
NTL	0.1352	2.5582	0.1797
Population Density	0.0008	0.0152	0.0010**
Road Density	-0.0926	1.7881	-0.0524
$LST_{mean} \times$ NDVI	0.0221	40.9520**	0.8110*
$LST_{mean} \times$ NTL	-0.0042	-0.0653	-0.0053
$LST_{var} \times$ NDVI	0.0001	-0.0011	0.0000
$LST_{var} \times$ NTL	0.0000	-0.0000	0.0000
R^2	0.2714	0.2326	0.3294

Note: Coefficients represent the effect of min-max standardized variables. Significance Level: (*) 10%, (**) 5%.

In contrast, the interaction between LST_{mean} and NTL consistent negative coefficients, although the statistical significance varies across models. This trend suggests that areas with high economic intensity tend to experience a steeper decline in gig rider productivity as temperatures rise.

This implies that highly dense, concrete-dominated commercial districts are not only hotter but also functionally more stressful for gig workers. The density of activity correlates with congestion, pollution, and mobility friction, which, when combined with high temperatures, accelerates rider fatigue. These findings align with urban economics literature suggesting that economic density generates negative externalities (Duranton & Puga, 2004) creating a "double burden" for outdoor workers in the city center compared to those in greener suburban areas.

Conclusively, NDVI serves as a mitigating factor that softens the heat penalty, while NTL acts as an amplifying factor that intensifies it. These empirical results provide a robust scientific basis for spatial planning, emphasizing the urgency of integrating strategic green infrastructure along high-traffic gig routes to safeguard the labor force.

3.4. Vulnerability Comparison: Gig Riders vs Non-Gig Informal Workers

The comparative estimation reveals a distinct divergence in climate vulnerability between gig riders and traditional informal workers. When the fixed-effects model is applied to the informal non-gig group, the impact of average surface temperature (LST_{mean}) on productivity metrics is notably different in both magnitude and significance compared to gig riders, confirming the hypothesis that gig riders are the more susceptible subgroup.

Table 4. Fixed Effects Panel Model on Non-Gig Informal Workers Productivity

Variable	Coefficient		
	Productivity	Hours	Income
LST_{mean}	-0.0283	-0.1781	-0.2946*
LST_{var}	-0.0000	-0.0003	0.0000
NDVI	3.9736	1.6607	4.1574
NTL	0.0122	0.7119	0.0328
Population Density	0.0014	-0.0059	0.0013
Road Density	-0.1129	0.6096	-0.1223
R^2	0.2416	0.1299	0.2217

Note: Coefficients represent the effect of min-max standardized variables. Significance Level: (*) 10%, (**) 5%.

A critical distinction emerges from the coefficient comparison. For gig riders (refer to Table 2), heat stress primarily manifests as a significant reduction in working hours (coefficient = -0.6186**), indicating a physical withdrawal from the labor supply. Conversely, for non-gig informal workers (Table 4), the effect on working hours is smaller and statistically insignificant (coefficient = -0.1781), yet the impact on monthly income is negative and significant (coefficient = -0.2946*).

This suggests that while traditional informal workers (e.g., street vendors, construction laborers) tend to stay at their workplace despite the heat (rigid labor supply), their earnings suffer, likely due to reduced customer footfall or lowered work intensity. Gig riders, however, have the flexibility, or the physical necessity, to log off, resulting in direct lost hours.

This heightened vulnerability of gig riders can be attributed to the unique spatial nature of their work. Unlike non-gig workers who may operate in kiosks, shaded workshops, or semi-permanent spots, gig riders are in a state of constant mobility on heat-radiating asphalt. Additionally, algorithm-based incentive systems on digital platforms often pressure riders to operate during peak demand hours (which may coincide with high heat), creating a conflict between health safety and economic necessity. These findings align with recent literature on platform precarity, which highlights how the lack of occupational safety standards exposes gig workers to disproportionate environmental risks (ILO, 2015; Tobing, 2024).

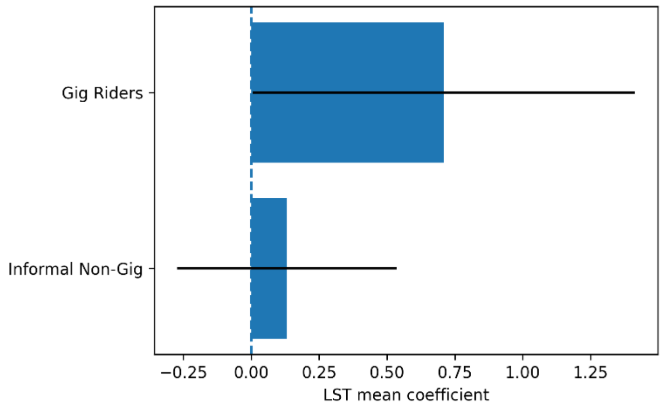

Figure 5. Sensitivity of Productivity to LST Comparison

In conclusion, the results provide empirical evidence that the impact of extreme heat is uneven across the informal economy. Gig riders represent a "hyper-exposed" subgroup within the urban workforce, bearing a heavier physiological and productive burden from climate risks compared to their non-gig counterparts.

3.5. Spillover Temperature and Productivity Between Metropolitan Cities

Using the Spatial Durbin Model (SDM), this study identifies significant spatial spillovers across the Greater Jakarta metropolitan region. The analysis distinguishes between the exogenous spillover effects of environmental factors ($W \times X$) and the endogenous interaction of productivity dynamics (ρ).

The spatial lag coefficients for environmental variables reveal that urban heat transcends administrative boundaries. Specifically, the spatial lag of temperature ($W \times LST_{mean}$) shows a significant negative impact on Gig Monthly Income (coefficient = -0.1007*). This implies that when core metropolitan areas, such as Central and North Jakarta, experience rising temperatures, the economic productivity of riders in neighboring districts (like Bekasi or Tangerang) is also depressed.

These findings align with the concept of "heat propagation" in urban climatology, which posits that metropolitan heat patterns are driven by regional wind flows, contiguous building density, and landscape thermal structures (Santamouris, 2015). The heat burden is not localized; it is a regional phenomenon that drags down rider income across the agglomeration.

Table 5. Spatial Durbin Panel Model on Gig Riders' Productivity

Variable	Coefficient		
	Productivity	Hours	Income
Direct Effects			
LST_{mean}	-0.0726	-0.5953	0.0660
LST_{var}	-0.0000	-0.0003	-0.0000*
NDVI	-0.7004	18.2850	-0.8999
NTL	0.0012	0.2624	0.0061

Variable	Coefficient		
	Productivity	Hours	Income
Population Density	0.0007	-0.0079	0.0005
Road Density	-0.0483	7.0809	0.0625
Spillover Effects			
$W \times LST_{mean}$	-0.1013	1.3066	-0.1007*
$W \times LST_{var}$	-0.0000	0.0006	0.0000
$W \times NDVI$	0.2172	-25.9560	-0.2688
$W \times NTL$	-0.0012	-0.7736	-0.0198**
$W \times Population\ Density$	-0.0000	0.0014	-0.0000
$W \times Road\ Density$	0.0588*	-0.8408	0.0564*
Spatial Autoregression			
ρ	0.0159	-0.6764*	0.1567
R^2	0.3870	0.3293	0.4028

Note: W denotes the spatial weight matrix. Coefficients represent the effect of min-max standardized variables. Significance Level: (*) 10%, (**) 5%.

The spatial autoregressive coefficient (ρ) is statistically significant for Gig Working Hours (coefficient = -0.6764*). This indicates that the labor supply of gig workers in a specific district is not isolated but is negatively influenced by the working hours in neighboring districts. This can be explained by the highly integrated nature of the Greater Jakarta labor market. Gig riders are mobile agents who cross city borders daily, chasing algorithm-driven demand (surge pricing) and incentives. The significant ρ suggests a competitive spatial displacement or a balancing mechanism: as riders gravitate towards high-demand centers, working hours in origin or neighboring areas may adjust accordingly. Thus, productivity in the gig economy must be interpreted as a fluid, cross-border dynamic rather than a static local attribute.

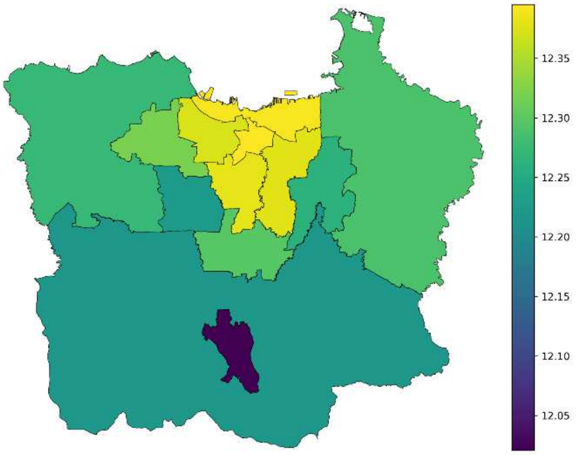

Figure 6. Gig Rider's Productivity Spatial Spillover Map

Overall, the Spatial Durbin Model confirms that analyzing the gig economy requires accounting for spatial dependencies. The results reinforce that climate adaptation and labor protection policies cannot be fragmented; they must be designed at the metropolitan scale to address the transboundary risks of heat and the fluid mobility of the digital workforce.

3.6. Integration of Research Findings with the National Development Agenda

The empirical findings regarding the impact of surface temperature on gig riders' productivity in Greater Jakarta carry strategic implications directly relevant to the National Medium-Term Development Plan (RPJMN 2025–2029) and the Long-Term Development Plan (RPJPN 2025–2045). As Indonesia pursues the "Golden Indonesia 2045" vision, the government emphasizes economic transformation, human capital quality, and climate resilience—three pillars that strongly intersect with the vulnerability of the gig workforce.

The Asta Cita (Eight National Priorities) underscores the importance of improving the quality of life through health and adaptive social protection. Our study reveals that gig riders, who fall under the transportation and warehousing sector but lack formal protections, experience significant income and working-hour losses due to heat stress. This fills a critical evidence gap: while the government aims to boost the Human Capital Index, a large segment of the urban workforce is being physically degraded by climate change. Therefore, achieving "Social Resilience" (as mandated by the RPJPN Law No. 59/2024) requires acknowledging that climate risks are now labor market risks.

The RPJMN designates Jabodetabek as a key engine for economic transformation. Given our finding that gig riders are vital for urban logistics and consumption mobility, their heat-induced productivity loss poses a systemic risk to the efficiency of the metropolitan economy (e.g., higher logistics costs and delivery delays). Importantly, our regression results show that vegetation (NDVI) significantly buffers this productivity loss. This provides empirical justification for the RPJMN's agenda on "Climate-Adaptive Cities," specifically proving that green infrastructure is not merely aesthetic but an economic necessity to sustain outdoor labor productivity.

By integrating these evidence-based strategies, the government can ensure that the digital economy continues to drive growth without compromising the health and productivity of its workforce, aligning with Indonesia's transformation path toward 2045.

4. Conclusions and Recommendations

4.1. Policy Recommendations

Translating the empirical findings into actionable strategies requires a multi-stakeholder approach aligned with the RPJPN 2025–2045. Based on the significant correlations found between heat stress (LST), vegetation$NDVI$), and gig productivity, we propose the following evidence-based recommendations:

1. Adaptive Social Protection (Based on Income Vulnerability):
   - *Evidence*: Our model confirms that heat waves significantly reduce gig riders' working hours and income, with gig workers showing higher vulnerability than non-gig informal workers.

- *Policy Recommendation*: The Ministry of Manpower should pilot "Heat-Wave Cash Transfers" (adaptive social protection) that trigger automatically when the Heat Index exceeds critical thresholds, preventing transient poverty among platform workers.

2. Green Corridors for Gig Mobility (Based on NDVI Buffer Effect):
   - *Evidence*: The positive interaction coefficient ($LST \times NDVI$) proves that vegetation mitigates the productivity penalty of heat.
   - *Policy Recommendation*: Urban planning in Greater Jakarta must prioritize "Cooling Corridors", planting canopy trees along high-traffic routes used by gig riders, rather than just focusing on centralized parks. This supports the "Green Economy" transition mandated by the RPJPN.
3. Metropolitan-Scale Heat Governance (Based on Spatial Spillovers):
   - *Evidence*: The significant spatial lag coefficient (ρ) indicates that heat risks and productivity losses are transboundary, spilling over from Jakarta to satellite cities like Bekasi and Depok.
   - *Policy Recommendation*: Climate adaptation strategies must be integrated at the Jabodetabekjur metropolitan level (not fragmented by municipality), coordinating heat-safety standards and cooling infrastructure across administrative borders.
4. Occupational Safety Standards for Platform Workers (Based on Vulnerability Comparison):
   - *Evidence*: Gig riders are empirically proven to be more vulnerable to heat than non-gig informal workers due to their inability to avoid exposure.
   - *Policy Recommendation*: The government must regulate digital platforms to implement Occupational Safety and Health (OSH) protocols for heat stress, such as mandatory rest breaks during peak heat hours and the provision of "Shelter Points" (water stations and cooling areas) as part of the platform's partnership responsibility.

4.2. Conclusion

Overall, this study makes a significant contribution to understanding the relationship among climate change, urban environmental conditions, and labor productivity in Indonesia's gig economy. By using a spatial panel and integrating socioeconomic and remote sensing data, the study highlights the vulnerability of gig workers, particularly gig riders, to extreme heat. These findings not only enrich the academic literature on labor economics and urban climate but also have direct relevance for national policy formulation towards green and digital economic transformation as mandated in the RPJMN and RPJPN. By strengthening urban governance, implementing adaptive social protection, and restructuring urban infrastructure to be more climate-resilient, the productivity and well-being of gig workers can be improved, in line with Indonesia's vision of an inclusive, adaptive, and sustainable Indonesia.

References

Anselin, L. (2003). *A Companion to Theoretical Econometrics* (B. H. Baltagi, Ed.). Wiley. https://doi.org/10.1002/9780470996249

Behl, A., Sheorey, P., Jain, K., Chavan, M., Jajodia, I., & Zhang, Z. (Justin). (2021). Gamifying the gig: transitioning the dark side to bright side of online engagement. *Australasian Journal of Information Systems*, *25*. https://doi.org/10.3127/ajis.v25i0.2979

Bowler, D. E., Buyung-Ali, L., Knight, T. M., & Pullin, A. S. (2010). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning*, *97*(3), 147–155. https://doi.org/10.1016/j.landurbplan.2010.05.006

BPS. (2024). *Persentase Tenaga Kerja Formal Menurut Provinsi (Persen), 2024*. https://www.bps.go.id/id/statistics-table/2/MTE2OCMy/persentase-tenaga-kerja-formal-menurut-provinsi--persen-.html

BPS. (2025). *Provinsi DKI Jakarta Dalam Angka 2025*. BPS.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

De Stefano, V. (2015). The Rise of the "Just-in-Time Workforce": On-Demand Work, Crowd Work and Labour Protection in the "Gig-Economy." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2682602

Duranton, G., & Puga, D. (2004). *Chapter 48 Micro-foundations of urban agglomeration economies* (pp. 2063–2117). https://doi.org/10.1016/S1574-0080(04)80005-1

Graff Zivin, J., & Neidell, M. (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics*, *32*(1), 1–26. https://doi.org/10.1086/671766

ILO. (2015). *Guidelines for a just transition towards environmentally sustainable economies and societies for all*. ILO.

Ioannou, L. G., Foster, J., Morris, N. B., Piil, J. F., Havenith, G., Mekjavic, I. B., Kenny, G. P., Nybo, L., & Flouris, A. D. (2022). Occupational heat strain in outdoor workers: A comprehensive review and meta-analysis. *Temperature*, *9*(1), 67–102. https://doi.org/10.1080/23328940.2022.2030634

Kässi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological Forecasting and Social Change*, *137*, 241–248. https://doi.org/10.1016/j.techfore.2018.07.056

Kjellstrom, T., Lemke, B., Hyatt, O., & Otto, M. (2014). Climate change and occupational health: A South African perspective. *South African Medical Journal*, *104*(8), 586–587. https://doi.org/10.7196/SAMJ.8646

Kumar, R. A. (2024). Precarious Prosperity: The Gig Economy's Role in Employment Growth and Wage Inequality. *International Journal of Advanced Research in Commerce, Management & Social Science*, *07*(04(I)), 331–341. https://doi.org/10.62823/IJARCMSS/7.4(I).7184

Law Number 59 (2024).

LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Chapman and Hall/CRC. https://doi.org/10.1201/9781420064254

Liu, W., Meng, Q., Allam, M., Zhang, L., Hu, D., & Menenti, M. (2021). Driving Factors of Land Surface Temperature in Urban Agglomerations: A Case Study in the Pearl River Delta, China. *Remote Sensing*, *13*(15), 2858. https://doi.org/10.3390/rs13152858

Ningrum, W. (2018). Urban Heat Island towards Urban Climate. *IOP Conference Series: Earth and Environmental Science*, *118*, 012048. https://doi.org/10.1088/1755-1315/118/1/012048

Permana, M. Y., Izzati, N. R., & Askar, M. W. (2023). Measuring the Gig Economy in Indonesia: Typology, Characteristics, and Distribution. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4349942

Poórová, Z., Li, H., Trakal, L., & Vranayová, Z. (2020). Urban Heat Island Scenarios – A Case study in Technical University, Košice. *IOP Conference Series: Materials Science and Engineering*, *960*(4), 042062. https://doi.org/10.1088/1757-899X/960/4/042062

Presidential Regulation Number 12 (2025).

Santamouris, M. (2015). Analyzing the heat island magnitude and characteristics in one hundred Asian and Australian cities and regions. *Science of The Total Environment*, *512–513*, 582–598. https://doi.org/10.1016/j.scitotenv.2015.01.060

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, *70*(1), 65. https://doi.org/10.2307/1884513

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827. https://doi.org/10.1086/713733

Sutherland, W., Jarrahi, M. H., Dunn, M., & Nelson, S. B. (2020). Work Precarity and Gig Literacies in Online Freelancing. *Work, Employment and Society*, *34*(3), 457–475. https://doi.org/10.1177/0950017019886511

Tobing, H. (2024). The Gig Economy Dilemma: Exploring Alternatives to Create Decent Work for Online Motorcycle Taxi Drivers in Indonesia. *Jurnal Ketenagakerjaan*, *19*(2), 168–183. https://doi.org/10.47198/jnaker.v19i2.340

UN. (2015). *The Paris Agreement*. https://www.un.org/en/climatechange/paris-agreement

UN. (2025). *SDG Indicators: Metadata repository*. https://unstats.un.org/sdgs/metadata/

Zander, K. K., Botzen, W. J. W., Oppermann, E., Kjellstrom, T., & Garnett, S. T. (2015). Heat stress causes substantial labour productivity loss in Australia. *Nature Climate Change*, *5*(7), 647–651. https://doi.org/10.1038/nclimate2623