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The Long-Term Nexus of Population Density, Number of Vehicles, and Local Communities' Welfare in Indonesia

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Abstract

One of the main problems found in developing countries is the improvement of welfare. Many policymakers have attempted to determine the aspects that promote community welfare. Several prior findings are still debatable regarding the relationship between population density, number of vehicles, and community welfare. In addition, studies at the subdistrict level are also rare in Indonesia. This study intends to assess the impacts of density and size of the population on the long-run income of local communities in subdistricts in the Tangerang Municipality. We utilized data from 13 subdistricts during the 2014–2022 period. The *FMOLS* panel showed that population density is proven to have significant negative impacts on the welfare of local communities in Tangerang Municipality's subdistricts in the long-term. In addition, an increase in the number of vehicles contributed strongly to the improvement of the local communities' welfare. In this study, information about population density and the number of vehicles owned by the communities can be used by the Tangerang Municipality Government to develop a policy instrument that promotes local community welfare. The findings have implications that the increasing population density should be controlled, and the flow of urbanization should be reduced. The Tangerang Municipality government should manage the high number of vehicles so that problems that arise on the road can be reduced.

Keywords: population density; vehicle; welfare

JEL: I31; J11; O18

1. Introduction

The government has an important role in improving people's welfare and economic growth because the increase in economic growth will encourage the success of economic development, so the standard of living, happiness, and welfare of the people will also increase (Fitriadi et al., 2023; Niu et al., 2021; Seprillina et al., 2021; Sutikno & Suliswanto, 2017). Community welfare is the condition of fulfilling the material, spiritual and social needs of citizens so that they can live a decent life and be able to develop themselves,

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so they can carry out their social functions (Pemerintah Republik Indonesia, 2009). The measure of the level of welfare can be assessed from the ability of an individual or group in its efforts to meet its material and spiritual needs. Material needs are related to income which will later fulfill the needs for clothing, food, shelter and health, while spiritual needs consist of fulfilling education, security and a peaceful life. Increased welfare achieved by individuals or countries can be seen from increased real income, expanded national accounts, quality of life and human development, subjective well-being, and objective happiness (Roberts, 2008).

Previous studies conclude that the indicators of community welfare include the economic, health, and social aspects (Rossouw & Greyling, 2021). From the economic aspect, welfare indicators include the level of per capita income and expenditure (Amri, 2014; Fajar, 2014; Iskandar, 2023; Seprillina et al., 2021). Then, from the health aspect, it is related to the quality of life (Cramer et al., 2004; Feldman et al., 2016; Khusaini et al., 2023; Senlier et al., 2009). The researchers selected a measure of per capita income as a community welfare variable in this study since welfare increases with per capita income and vice versa. Per capita income tends to be studied at the international, regional, intranational, national, provincial, and regency/muncipality levels as a measure of economic development. However, prior investigations utilizing secondary data at the subdistrict level is still lacking.

As an initial illustration, the welfare of the community of Tangerang Municipality as a proxy for per capita income during the period of 2016-2022 shows an upward trend however with a slow growth rate. The highest growth in per capita income (current price) was 20.19% in 2022 and the lowest was -3.42% in 2020. Meanwhile, based on BPS Kota Tangerang (2023), per capita income growth (constant price=2010) was the highest in 2020 (8.19%) and the lowest in 2021 (2.67%). The increase in per capita income does not necessarily represent the actual income of the communities of Tangerang Municipality. However, this condition indicates an increase in the welfare or prosperity of society. Increasing community welfare as proxied by per capita income is determined by various factors, including population density (Ahlfeldt & Pietrostefani, 2019; Amri, 2014; Hasan, 2010; Hummel, 2020; Iskandar, 2023; Mattson, 2021; Rossouw & Greyling, 2021), number and ownership of vehicles (Ma et al., 2019; Tiawan et al., 2020; Ukonze et al., 2020; Yang et al., 2017), availability of road infrastructure (Gertler et al., 2019; Iskandar, 2023; Laborda & Sotelsek, 2019; Moszoro & Soto, 2022), educational infrastructure (Iskandar, 2023; Khusaini et al., 2022), and health facilities (Cook & Twigg, 2020; Djanggo et al., 2020; Mays, 2020). However, the findings of the study on the relationship between population density, number of vehicles, and community welfare are still debate. Previous researchers measured different welfare variables, including different analysis models, research locations, and sample sizes. The current research complements previous research and increases the consistency of the relationship between population density and vehicle ownership on community welfare.

The increase in high population density is one of the main issues and has an impact on boosting community welfare. The ratio of the population to an entire region is referred to as the population density. Population density will rise with a significant increase in the population. Because it is influenced

by the number of population and the size of the area, population density differs between geographical areas. Birth rates, family planning program, and urbanization trends are key factors in rising population density (Amri, 2014; Hasan, 2010; Mattson, 2021). Population density in Tangerang Municipality during 2020-2021 shows an increasing trend, namely an average of 2.96%. The highest increase in population density was in Cipondoh Subdistrict at 8.34% and the lowest was in Tangerang Subdistrict at 0.28%. In the same period, there were two subdistricts that were able to control the increase in population density, namely Jatiuwung and Cibodas Subdistricts at minus 0.02% and 0.56% respectively. Controlling population density by policy makers is expected to be able to reduce various population problems so they have an impact on the welfare of the population in their area. Population distribution policies can avoid population accumulation in certain areas so as not to disrupt work productivity due to limited land availability.

Some scholars have conducted studies on the correlation between population density and community welfare as measured by per capita income. According to Iskandar (2023), per capita income and population density were negatively correlated. Mattson (2021) also investigated the connection between population density and per capita exapenditure which revealed that there was a significant negative connection. Another study, however, discovered that low-density development patterns led to inefficiencies in the cost of offering local public services (Hortas-Rico & Solé-Ollé, 2010). In fact, high population growth results in increased population density, which reduces the economic scale (Tran et al., 2019). In addition, there is a positive connection between population density and aggregate per capita income (Ahlfeldt & Pietrostefani, 2019; Pontes, 2021; Rahman et al., 2020; Rossouw & Greyling, 2021). In addition, previous studies also showed that the population growth determines an economic growth (Busari et al., 2022; Mubarak & SBM, 2020). However, the relationship between population density and welfare is still inconclusive because of the different approaches to measuring welfare variables and analysis.

Community welfare is also determined by the increase in the number of vehicles in an area. The number of vehicles in Tangerang Municipality during 2019-2022 showed negative growth of 0.59%. The highest average growth in the number of vehicles during that period occurred in Cipondoh and Pinang Subdistricts, namely growing by 3.28% and 1.57% respectively. The lowest average growth in the number of vehicles occurred in Jatiuwung and Larangan Subdistricts, namely negative growth of 5.37% and 3.38% respectively. This condition indicates that the reduction in vehicles will reduce the welfare of the people in Tangerang Municipality, because it hampers the mobility of goods and services in the economy. Earlier studies found that the quantity of vehicles will continue to rise significantly in the world (Ma et al., 2019; Ukonze et al., 2020). The well-being of people may be negatively impacted by traffic congestion, road accidents, and other social issues that result from a significant rise in the number of automobiles. Additionally, as the quantity of vehicles rises, pollution rises (Richter et al., 2005; T. Wu, Zhang, et al., 2014; Y. Wu et al., 2011), energy consumption, and unhealthy urban environment (Ma et al., 2019). Given that the level of economic development, resource wealth, and transportation planning varies by region in

Indonesia, it is important to build supporting infrastructure and other services based on accurate vehicle ownership data. On the other hand, prior research revealed that the rapid growth of car manufacturing and sustainable transportation was not only related but also a significant driver of economic development (Burrow et al., 2013; Yang et al., 2017). Therefore, achieving sustainable solutions and encouraging the development of the vehicle industry is still an important direction for long-term economic growth (Burrow et al., 2016).

Proper production and sales planning, based on precise vehicle ownership estimates, are necessary for the growth of a viable motor vehicle industry (Qian & Soopramanien, 2014). According to prior studies, a rise in the number of motor vehicles could promote growth in the economy (Tiawan et al., 2020), which in turn can increase community income. Ukonze et al. (2020) found that per capita income has an effect on the increase in vehicle ownership. Priyambodo (2018) showed that the increase in the number of sedans, jeeps and motorbikes in regencies and municipalities in East Java had an effect on real *GRDP*. Likewise, a study conducted by T. Wu, Zhao, et al. (2014) confirmed that an increase in the number of vehicles was followed by by an increase in *GDP* per capita. On the contrary, research employed by Tiawan et al. (2020) found that there is no direct correlation between the number of vehicles and income because income is more influenced by population.

Despite its relevance to the results of social and economic impacts, to fluctuations in community welfare at regional and national levels in Indonesia, and its importance at the subdistrict level, this debate resulted in two things that motivated this research. First, only a few studies have explored the factors of population density and number of vehicles on local welfare, mainly focusing on analysis at the subdistrict level in Indonesia, especially sub-districts in Tangerang Municipality. Second, the impact of population density and number of vehicles on community income is inconclusive. This study contributes to filling this gap by offering a systematic investigation of the impact of population density and number of vehicles on the welfare of local communities in subdistricts in Tangerang Municipality. Utilizing data from 13 subdistricts in Tangerang Municipality and in 2014–2022, we proposed a Fully Modified Least Square (*FMOLS*) Panel Analysis which was also rarely utilized by previous researchers. The current study aimed to assess the long-term correlation between population density and the number of vehicles with community welfare in Tangerang Municipality. The findings are expected to provide consistent results and input for policies related to community welfare in Tangerang Municipality. Theoretically, this study is useful for developing the literature on development economics. The researchers wish that the findings can be used as a reference for planning economic development, especially in controlling population density and the number of vehicles.

2. Literature review

Bentham's (1748–1832) broad theory of the "Welfare State" encourages the idea that it is the duty of the state to ensure the welfare (happiness) of the majority of its citizens. Bentham referred to the idea of happiness or welfare as 'utility'. He defined good as something that can lead to further happiness in accordance with the utilitarian principle (Baloglou, 2012). On the other hand, unpleasant experiences are undesirable

(Sukmana, 2017). The definition of well-being includes, among other things, the ability to evaluate one's "participation in public decision-making" (Fajardo-Gonzalez et al., 2021). Well-being has been associated with success in the interpersonal, personal, and professional spheres. People who are in good health are more productive at work, learning efficiently, creative, behave socially, and form powerful relationships with others (Diener, 2012; Huppert, 2009; Huppert & So, 2013; Oishi et al., 2007).

The World Bank defines welfare as eradicating the feeling of being poor (Roser & Ortiz-Ospina, 2019). The National Association of Social Worker (*NASW*) stated that the definition of social welfare is as a nation's system of benefits, programs, and services that support people in obtaining the economic, educational, social, and health needs that are essential to their existence (Zastrow, 2010). In the end, the discussion about social welfare focuses on two main points, namely: (1) what individuals receive from their society; and (2) to what extent their needs are met (Godin in Azizy, 2015).

By dividing it by the population, the assessment of national income provides an overview of the level of wealth and prosperity of a nation. The outcome of this is referred as per capita income of a nation's people. The welfare and level of development of a nation can also be evaluated by analyzing per capita income. Since per capita income is one indicator of welfare, the greater the per capita income level, the better off society as a whole is. In simple logic, if per capita income is higher, people's purchasing power, opportunities to obtain nutrition, health, and education will also be improved. However, this can work properly if the increase in per capita income goes along with equal distribution of income (Rahardja & Manurung, 2008). Per capita income is an indicator of economy performance as a whole income. It is calculated by dividing the nation's or region's total income by its entire population (Febriansah & Prapanca, 2019). The prosperity and level of development of a country or region are often measured utilizing per capita income.

The relationship between population density and the welfare of local communities refers to the classical theory (Malthus, 1798; Smith, 1776) that high population growth will increase productivity growth, but if controlled, it will cause decreased welfare and food scarcity. Empirical research was conducted by Amri (2014) on Sumatera Islands in Indonesia. He examined the effect of population density on per capita income using panel regression with the pooled least square method with time series data for the period 2007-2013 and cross-sectional data from 9 provinces in Sumatera. This study found that population density negatively affects per capita income. Hasan (2010) investigated the relationship between population size and per capita income in mainland China in a multivariate vector autoregressive model. This study found evidence of a general stochastic trend between population size and per capita income indicating a long-term relationship between the two variables. Empirical results also showed that there is a negative long-term causal relationship between per capita income and population. The short-run relationship between population growth and per capita income growth varied across model specifications. The neoclassical growth model showed that population growth makes a positive contribution to per capita income growth while the modified endogenous growth model showed a negative relationship between the two variables. In addition, Tran

et al. (2019) used data from the 2015–2016 fiscal year to analyze the expenditure of 68 South Australian local governments in order to determine whether there are economic scales in council expenditure. However, given the relationship between the expenditure of population and population density, it is crucial to ascertain if fluctuations in population density are to blame for the impact of population on expenditure. The results of the study show that the grouping of local governments into subgroups based on population density, the scale of the economy, is mostly evaporated.

By taking into account 347 analyses of the density elasticities of outcomes ranging from salaries, innovation, rents, amenities, public service costs, transport-related and environmental outcomes to health and welfare, Ahlfeldt & Pietrostefani (2019) summarized the economic consequences of density. Of these estimations, more than 100 have never been published. We discovered that density seems to be a convenience with beneficial external welfare consequences. Hummel (2020) investigated how urban density affected American income. It is predicted that income rises as urban density rises based on ideas from the economics of urbanization and social output. Additionally, cross-sectional mediated multiple regression was employed to find that population and housing density have statistically significant indirect impacts on income using a sample of more than 300 United States metropolitan areas.

In addition, Bremberg (2020) examined how the population density affected health in four Nordic nations. The findings demonstrated that life expectancy and possible years of life lost are among the health parameters being examined. The difference in life expectancy lost as a result of a 10-fold increase in population density was used to measure the impact of population density. Mortality rates were consistently higher in fewer population-dense cities in Finland, Norway, and Sweden. Rahman et al. (2020) assessed the effects of population density on the economic growth of five South Asian nations by including other variables. A panel cointegration strategy with an extended neoclassical growth model was utilized with data collected between 1990 and 2017. The findings indicate that population density has a positive effect on South Asia's growth in economy. They also found that *CO2* emissions and trade openness also had a significant effect.

Mattson (2021) investigated the correlation between density, land use, and per capita expenditure. It was discovered that there was a negative association between density and per-capita city expenditure. In general, it can be said that a decline in per capita municipal spending across a number of expense categories is correlated with an increase in density in the United States. A composite social wellbeing index was created by Rossouw & Greyling (2021) to analyze variations among 30 African nations. They utilized the Blinder-Oaxaca decomposition and the centralized influence function methods to analyze the variance of social welfare on potential influential factors. Population density is strongly linked to inequality. A recent study conducted by Iskandar (2023) evaluated the impact of road infrastructure and population density variables on per capita income. He concluded that road infrastructure is not a significant factor that determines the increase in community income. Meanwhile, population density is very influential on people's income.

An empirical study on the number of vehicles and welfare was conducted by (e.g. T. Wu et al., 2014). Under low, medium, and high development scenarios, the study proposes a

model for projecting China's vehicle stock and road vehicle energy demand up to the year 2050. The Gross Domestic Product (*GDP*) of China was calculated using a recursive dynamic Computable General Equilibrium (*CGE*) model in order to determine the Gompertz function, which is dependent on *GDP*. The findings indicate that *GDP* per capita plays a significant role in determining the rise of China's car demand. Population expansion has little impact on vehicle demand, and the Gompertz curve is only slightly influenced by the vehicle saturation rate. More firmly, T. Wu, Zhao, et al. (2014) predicted a pattern of increasing the number of vehicles followed by an increase in *GDP* per capita in China. Yang et al. (2017) also investigated the dynamics and variables affecting ownership in Chinese cities. Using a fixed effects model, the study sought to understand the relationships among vehicle ownership, per capita road area, population, average annual per capita income, building area, urban population density, number of taxis, and bus passenger volume. The results show that car ownership is positively connected with average annual per capita income, building area, road area per capita, urban population density, and taxi availability on a national level.

In addition, Priyambodo (2018) tested the effect of density or number of motorized vehicles in districts and cities in East Java on *GRDP*. By utilizing descriptive statistical analysis and regression analysis, the research results show that the increase in the number of sedans, jeeps and motorbikes in districts and cities in East Java has an effect on *GRDP*. Ma et al. (2019) predicted China's provincial vehicle ownership from 2018 to 2050 using the Gompertz model. They found that vehicle ownership would increase over the next 30 years in each province. However, there were differences in how many vehicles each province provides. Other findings concerned each province's pattern of vehicle growth, its economic development stage, and its government policies regarding *GDP* per capita and *GDP* per labor force growth rates. Tiawan et al. (2020) applied the Path Analysis approach to assess the effect of population density, government policies, and the total of vehicles on economic growth from 2000 to 2018 in Jambi Province. The findings demonstrate that Jambi Province's economic growth is directly influenced by the quantity of motor vehicles there. However, the amount of motor vehicles and the population density have a negative effect on the province of Jambi's economic development.

To provide a background for updating the nation's transportation and other economic sector policies, Ukonze et al. (2020) evaluated the increase in car ownership in Nigeria. The increase in vehicle ownership throughout the course of the study's four decades was compared using variance analysis techniques. The findings indicate that the growth in car ownership has undergone significant fluctuation. The peak (highest rate of car ownership) occurred in the fourth decade (2000–2010). Major policy implications for the environment, energy demand, transportation infrastructure, traffic management, and car production result from the astonishing growth in vehicle ownership that this condition involves.

3. Research method

3.1. Method and Data in Empirical Research

In this current study, the author used a type of quantitative research which aims to determine the relationship between independent variables and dependent variables or other

outcomes in a population (Singh, 2007). Quantitative research is characterized by the use of observations that generally include hundreds, thousands, or even hundreds of thousands of observations (Stockemer, 2019). The design of this research is a causal relationship. One form of quantitative method that combines time series and cross-section data is called panel data (Gujarati & Porter, 2009). The researchers examined the long-run effects of population density and vihicles number on community welfare in urban subdistricts utilizing *FMOLS* panel regression (Pedroni, 2001). We also compared the data obtained using *GLS* fixed effect panel data regression to employ consistent findings (Baltagi, 2005). This research data works with secondary data collected through secondary information in the form of records, registers and documents available in official institutions and respective individuals (Singh, 2007). The data required for this study were secondary data in the form of time series data between the period of 2014-2022 and times series data for 13 subdistricts (9 x 13 = 117) in Tangerang Municipality, Indonesia. The data were obtained from the Central Bureau of Statistics for Banten Province, Tangerang Municipality, other relevant agencies.

3.2. Research Variables

Variables refer to properties or attributes of a concept that can be measured in a certain way and the process of turning a concept into a variable is called operationalization (Singh, 2007). In this study, the dependent variable used to measure community welfare was per capita income at the subdistrict level according to constant 2010 prices (Deaton & Deaton, 1980; Fajar, 2014; Iskandar, 2023; Sen, 1980; Seprillina et al., 2021). The independent variable of population density was proxied by the ratio total population per area of the sub-district (Badan Pusat Statistik, 2022; Pontes, 2021; Rahman et al., 2020). The number of vehicles was calculated by the ratio of the number of vehicles per population per region (Ma et al., 2019). We also included some control variables in order to control the impact of population density and vihicles number on community welfare. The control variables included road quality (Gertler et al., 2019; Laborda & Sotelsek, 2019; Moszoro & Soto, 2022), education infrastructure (Iskandar, 2023; Khusaini et al., 2022), and health facilities (Mays, 2020; Sixt & Aßmann, 2020). Then, the data measurement scale of these variables was ratio.

3.3. Empirical Model

The empiracl analysis utilized in this study was panel model. It combines cross-sectional data and historical series. Greater information may be structured in panel data, which is one of its benefits (Baltagi, 2005; Wooldridge, 2018). In addition to helping us deal with endogeneity and measurement errors of different variables, panel analysis is a useful technique for dealing with multicollinearity issues. By including time invariant variables, it also enables the accounting for heterogeneity. The resulting panel data set is unbalanced because of the fixed number of observed units (regions) in time, but models can still be estimated using traditional methods using panel data (Baltagi, 2005). According to Greene (2003), the model shown below is the standard panel regression model.

$$y_{it} = \beta_1 X_{it2} + \beta_2 X_{it2} + \cdots + \beta_k X_{itk} + \alpha_1 z_{i1} + \alpha_2 z_{i2}\alpha_3 + \cdots + \alpha_q z_{iq} u_{it} \quad (1)$$

where *i* represents an invidual dimension *i* = 1, …, *n*. A *t* is time dimension *t* = 1, …, *t*. Unit vectors are excluded in the explanatory

variables X_1 to X_k. Individual effects, or variability that can identify people or whole groups from various other factors, are represented by variables z_1 for z_q; however, individual effects are constant across time.

We applied common effect model (*CEM* or Pooled), fixed effect model (*FEM*), and Random Effects Model (*REM*) approaches. We specified the panel empirical model as follow:

$$pic_{it} = \alpha_1 + \alpha_2 lden_{it} + \alpha_3 lnrv_{it} + \alpha_j Z_{it} + u_{it} \quad (2)$$

where pic_{it} = income of the local community in subdistrict *i* period *t*, $lden_{it}$ = population density in subdistrict *i* period *t*, $lnrv_{it}$ = number of vehicles per length of road in subdistrict *i* period *t*, Z_{it} = control variable which includes road quality, health infrastructure, education infrastructure in subdistrict *i* period *t*, α_0 = intercept, α_i = coefficients 1, 2, ..., 4, and u_{it} = error term, *i* = 1, 2, ..., 13, and *t* = 1, 2, ..., 9.

3.4. Classical Assumption Test and Model Selection

The econometric model estimation stages above include classical assumption tests and model selection tests. The classic assumption test is used to verify whether the statistical analysis is met. This test includes assumptions of residual normality, heteroscedasticity, autocorrelation, and multicollinearity. The normality test uses the Jarque-Berra test to ensure that the residual data follows a normal distribution. The hateroscedasticity test to identify the variance of variables at each time and observation unit should be constant. This test uses the Breush-Pagan-Godfrey test (Breusch & Pagan, 1980). Next, the Durbin-Watson test is used to identify whether there is a correlation between observations in the same unit at different times. Whether or not there is a perfect linear relationship between the variables used in the analysis is called multicollinearity using the variance inflation factor (*VIF*) test.

In selecting the model, the researcher first carried out a Chow test to select the Common Effect Model (*CEM*) or Fixed Effect model (*FEM*). The criteria set are if the probability value is <0.05 then the model chosen is the fixed effect model. Next, the author chose between the Fixed Effect and Random Effect (*REM*) models using the Hausman test (1978). Both models are basically potentially valid in estimating panel models with unobserved sub-district heterogeneity. Therefore, the *FEM* or *REM* model can be a valid model to use based on the results of Hausman specification testing. To make the right decision between the *FEM* and *REM* models, the formal Hausman (1978) specification test is estimated with the criterion that if the probability value is < 0.05 then the selected model is the fixed effect model.

3.5. Cross-sectional Dependence

The use of panel data requires checking whether there is cross-sectional dependence (*CD*) in panel variables (Breusch & Pagan, 1980; Pesaran, 2004). The *CD* test uses the correlation coefficient between the time series for each region in the panel (Pesaran, 2007). Therefore, the test to overcome the problem of mutual interaction of variables and the *CD* test uses the equation:

$$CD = \sqrt{\frac{2t}{z(z-1)}} \left(\sum_{i=0}^{z-1} \sum_{j=i+1}^{z-1} \rho_{ij} \right) \quad (3)$$

where *CD* = cross-sectional dependence, *z* = cross-sections data, *t* = time horizon, and ρ_{ij} = cross-sections connection between *i* and *j*. Therefore, the *LM* test for studying *CD* is:

$$y_{it} = \alpha_{it} + \beta_i x_{it} + \varepsilon_{it} \quad (4)$$

The results of the *CD* test test the null and alternative hypothesis statements. The null hypothesis in this test is that there is cross-sectional dependence between variables, while the alternative hypothesis states that there is no cross-sectional dependence. The existence of cross-section dependence between series will provide biased and inconsistent empirical results. The existence of this cross-sectional dependence also guides which generation unit root tests will be used to obtain empirical results.

3.6. Panel Unit Root Test

In addition, the use of the *FMOLS* panel model is to determine the long-term relationship between the variables of population density and the number of vehicles, and the welfare of the Tangerang Municipality community. This model goes through several stages first, considering that this is a dynamic panel model. The first stage is to test the data stationarity, cointegration test, and *FMOLS* model test. Unit root testing aims to ensure that data from a variable is stationary. The most widely utilized testing methods in the literature are namely an Augmented Dickey and Fuller (*ADF*), Phillips and Perron, Maddala and Wu, *LLC*, *IPS*, and Hadri tets (Breitung, 2001; Dickey & Fuller, 1979, 1981; Hadri, 2000; Im et al., 2003; Levin et al., 2002; Phillips & Perron, 1988). The null hypothesis (Ho) indicates that there is a unit root (non-stationary data) and the alternative hypothesis (Ha) indicates that there is no unit root (stationary data). This hypothesis is applied to all types of tests. The equation used to test the unit root is:

$$y_{it} = \rho y_{it-1} + \vartheta X_{it} + \varepsilon_{it} \quad (5)$$

with i = 1, 2, ..., N for each individu in panel, t = 1, 2, ..., T for time period, X_{it} = symbol of the combination of all exogenous variables in the model. ρ_i denotes the autoregression coefficient and ε_{it} is the error term. If $\rho_i > 1$, y_{it} is reflected as having a stationary tendency, whereas if $\rho_i = 1$, then y_{it} will contain a unit root. The study of Im et al. (2003) allows different orders of serial correlation and uses a typical augmented Dickey Fuller (*ADF*) test that averages:

$$\varepsilon_{it} = \sum_{j=1}^{p_i} \rho_{ij}\, \varepsilon_{it-j} + u_{it} \quad (6)$$

If equation (5) is substituted in equation (6), it will be obtained:

$$y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{p_i} \rho_{ij}\, \varepsilon_{it-j} + \vartheta X_{it} + u_{it} \quad (7)$$

where ρ_i shows the number of lags in the *ADF* regression. Statistics, t bar determined by (Im et al., 2003), is the statistical average of individual *ADFs* as shown below:

$$\bar{t}_{NT} = N^{-1} \sum_{i=1}^{N} t_{iT}\,(\rho_i) \quad (8)$$

where t_{iT} (ρ_i) denotes the estimated *ADF*; N is the number of individuals and T is the number of observations. The alternative statistic "t-bar" permits testing the null hypothesis of the existence of a unit root for all individuals.

3.7. Panel Contegration Test

Panel cointegration testing are used in the process, both of which are modified to produce a framework for panel data analysis. The researchers took an *OLS* estimation with panel cointegration. It is a Fully Modified Ordinary Least Square (*FMOLS*) (see Kao, 1999). Phillips & Hansen (1990) proposed the *FMOLS* estimator. Similar to the panel unit root test, the panel cointegration test aims to produce greater reliability outcomes in the test for the presence of cointegration than those attained with the individual tests. When the variable is stationary, the cointegration test is

used. Pedroni (1996, 2001, 2004) introduces a panel cointegration method based on residuals by considering heterogeneity of specific effects, slope coefficients, and individual linear trends across countries. Usually, the cointegration vector may differ among panel members. Pedroni (2004) proposes seven statistical possibilities for testing the null hypothesis without cointegration. This test contains two types of cointegration tests; in-dimensional and group cointegration test.

The panel regression residual value is in the form of a fixed effect which contains the potential for a cointegrated variable relationship, so the Kao test (Kao, 1999) is used to identify it through the *ADF* test. The starting point of the Kao (1999) panel cointegration test is expressed as follows:

$$Y_{it} = X'_{it} + Z'_{it}\gamma + \varepsilon_{it} \quad (9)$$

where Y_{it} and X'_{it} are integrated *I*(1), and suggested to conduct *DF* and *ADF* tests to identifiy the stationary of error $\hat{e}_{it}$ from cointegration model *I*(1) for *ρ*-panel and *ρ*-group statistics as follows:

$$\hat{e}_{it} = \rho e_{it-1} + \varepsilon_{it} \quad (10)$$

where *i* denotes region and *t* times, $\hat{e}_{it}$ is the estimated regression error, while $\hat{e}_{it}$ is error term.

3.8. *FMOLS* Panel Model

The estimation of the cointegration panel regression is usually carried out using two *OLS*-based estimator methods, one of which is *FMOLS*. Utilizing the same cointegration part, the standard combined *OLS* panel estimator is expressed by:

$$\hat{\beta}_{NT} = (\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_t)^2)^2 \sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2 (x_{it} - \bar{y}_i) \quad (11)$$

Pedroni (1996, 2001) have recommended using *FMOLS* in panel cointegration analysis. The "Pooled" *FMOLS* estimator, which is an adjustment to the conventional *OLS*.

$$\hat{\beta}_{FM} = \left(\sum_{i=1}^{N}\hat{L}_{22i}^{-1}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right)^{-1} \sum_{i=1}^{N}\hat{L}_{11i}^{-1}\hat{L}_{22i}^{-1}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2 (y_{it}^{*} - \hat{\delta}_i) \quad (12)$$

where $y_{it}^{*} = (y_{it} - \bar{y}_i) - \left(\frac{L_{21i}}{L_{22i}}\right)\Delta x_{it} + \left(\frac{L_{21i} - L_{22i}}{L_{22i}}\right)\beta(x_{it} - \bar{x}_i)$ and $\hat{\delta}_i \equiv \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^{0} - \left(\frac{L_{21i}}{L_{22i}}\right)(\hat{\Gamma}_{22i} + \hat{\Omega}_{22i}^{0})$.

The problem of heterogeneity with individual mean differences and variations in individual responses to short-term disturbances of cointegration equilibrium is the primary driver behind the dynamically cointegrated panel estimate. The proposed *FMOLS* addresses these two difficulties by accounting for the serial correlation characteristics of error processes that differ across individual panel members and by incorporating individual-specific regression intercept (Pedroni, 2001).

4. Results and discussion

4.1. Statistical summary

The researcher presents a statistical summary of data which includes the mean and standard deviation value of the variables. The mean sub-district per capita income is 19.126. This means that the average per capita income of subdistricts in Tangerang Municipality is *IDR* 75,239,645.37 per year (see Table 1). The average population density during the study period was 12,784 people per km^2. The average number of vehicles is 7,779 units per resident per district. Meanwhile, the average length of subdistrict roads with good quality is 10.02 km in Tangerang Municipality. The average number of students per secondary school is 298 per school per subdistrict and the average health infrastructure per resident

is 1,643 people per sabdistrict in Tangerang Municipality. In addition, we present a statistical summary of the research variable data in the following table:

4.2. Panel Unit Root Test Results

This study also utilized a balanced panel data set to assess the relation between variables with the *FMOLS* panel approach. Before conducting data analysis with this model, unit roots and cointegration tests were first carried out. In the testing phase of the unit root panel, the first step was to identify the presence of "cross-sectional dependence" in the panel data. The four tests' results certainly demonstrate a fairly strong to highly significant cross-sectional dependence (sig. 0.01, 0.05, and 0.1). It also suggests that the second-generation panel unit root test should offer inferences that are more reliable. In the table below, all of the test results are displayed:

The unit root test results including *LLC*, *IPS*, Augmented *ADF*, *PP*, and Breitung tests are presented in Table 3. The findings revealed that local community welfare (*lnw*), population density (*lnden*), vehicle volume (*lnrv*), district road quality (*road*), infrastructure for education (*lneduc*), and infrastructure for health (*lnhealth*) were stationary at the first difference with 1% and 10%. The findings demonstrate that the unit panel roots are present in all six of the study's variables.

Table 1. Statistical Summary

Variables, n = 117	Mean	Std. Dev.	Max	Min
lnw	19.126	0.144	18.589	17.584
lnden	9.401	0.337	10.027	8.779
lnrv	8.909	0.329	9.475	8.221
road	0.002	0.0008	0.004	0.0007
lneduc	5.633	0.356	6.660	4.814
lnhealth	7.387	0.192	7.955	6.701

Table 2. Crossectional Dependence Test Results

Vraibles, *df*=117	Breush-Pagan *LM*	Pesaran scaled *LM*	Bias-corrected scaled *LM*	Pesaran *CD*
lnw	416.339***	27.089***	26.276***	19.795***
lnden	394.133***	25.311***	24.498***	17.741***
lnrv	467.345***	31.171***	30.360***	21.038***
road	702.000***	49.960***	49.147***	26.495***
lneduc	336.486***	20.695***	19.883***	16.489***
lnhealth	200.718***	9.825***	9.013***	1.0483

Notes: H0: no cross-section dependence. Level of significance *p < 0.1, **p < 0.05, ***p < 0.01

Table 3. The Root Panel Unit Test Results

Variables	Test types	Level		First difference	
		Intercept	Intercept and trend	Intercept	Intercept and trend
lnw	*LLC*	-5.485***	-8.311***	-17.971***	-17.874***
	IPS	-1.662**	-0.809	-7.581***	-2.800***
	ADF	38.744*	40.395**	106.623***	78.889***
	PP	60.503***	62.034***	136.483***	146.356****
	Breitung	-	-2.300**	-	-6.782***
lnden	*LLC*	-9.818***	-10.535***	-12.040***	-12.1918***
	IPS	-4.132***	-1.711**	-5.1835***	-1.03783
	ADF	67.281***	55.681***	82.692***	45.3512**
	PP	73.731***	136.229***	160.101***	88.1814***
	Breitung	-	-1.810**	-	-1.76720**
lnrv	*LLC*	-5.550***	-5.410***	-10.678***	-10.742***
	IPS	-2.158**	0.527	-3.910***	-0.981
	ADF	43.498**	17.050	67.493***	44.896**
	PP	62.802***	23.312	92.920***	89.509***
	Breitung	-	-0.629	-	-5.878***
road	*LLC*	21.616	44.353	-24.376***	-47.346***
	IPS	9.138	3.941	-12.858***	-8.774***
	ADF	0.037	0.026	159.097***	165.569***
	PP	0.016	14.383	147.679***	239.469***
	Breitung	-	19.953	-	2.122
lneduc	*LLC*	-10.802***	-9.039***	-7.488***	-8.763***
	IPS	-3.751***	-0.141	-2.027**	-0.190
	ADF	62.343***	29.606	44.310**	30.157
	PP	62.601***	51.344***	66.810***	48.291***
	Breitung	-	-0.160	-	-2.754***
lnhealth	*LLC*	-13.280***	-9.841***	-13.339***	- 12.141***
	IPS	-5.633***	-1.139	-5.838***	-1.536*
	ADF	83.569***	45.803***	91.488***	56.468***
	PP	108.781***	106.557***	181.823***	134.087***
	Breitung	-	-3.846***	-	-5.093***

Note: Level of significance *p < 0.1, **p < 0.05, ***p < 0.01

4.3. Panel Conintegrating Test Results

After testing the unit root of the panel, the panel cointegration tests with 7 types of Pedroni cointegration panel tests were conducted. In this test, the researcher set up a deterministic trend and intercepts only. This study found that local community welfare (*lnw*), population density (*lnden*), number of vehicles (*lnrv*), quality of district roads (*road*), education infrastructure (*lneduc*), and health infrastructure (*lnhealth*) were a stationary at the first difference. Additionally, the researchers tested the panel cointegration to explore the long-term relationship between population density, number of vehicles, and control variables with local community welfare. In this research, two different panel cointegration tests—the Pedroni test (Kao, 1999; Pedroni, 2001, 2004)—were applied. Pedroni's test findings are shown in Table 4, and they reveal that out of the seven statistics, four are significant at the 1% level. This result clearly shows the explanatory variable has a long-term relationship with local community welfare.

Table 5 below presents the Kao residual cointegration test which produces an *ADF* statistic of -3.009 with a *ADF* probability value = 0.001 < 0.05 (see Table 5). It stated that there is cointegration. We interpreted that there is balance relationship between the independent variables and the welfare of the community in the long-term. After passing the panel cointegration test, we continue the data analysis.

Table 4. Cointegration Test Results

H_0: common *AR* coefs. (within-dimension)				
	Stat.	Sig.	Weighted	
			Stat.	Sig.
Panel *v*-stat.	-2.673	0.996	-2.925	0.998
Panel *rho*-stat.	3.016	0.999	3.592	0.999
Panel *PP*-stat.	-15.604	0.000	-9.756	0.000
Panel *ADF*-stat.	-8.501	0.000	-4.811	0.000
H_a: individual *AR* coefs. (between-dimension)				
	Stat.		Sig.	
Group rho-stat.	5.168		1.000	
Group *PP*-stat.	-16.024		0.000	
Group *ADF*-stat.	-6.184		0.000	

Table 5. The Results of Residual Kao Cointegration Test

	t-stat.	Sig.
ADF	-3.009	0.001
Residual variance	0.018	
HAC	0.006	

4.4. Classic Assumptions and Selection Model Results

Before conducting data analysis using the *FMOLS* panel model, the researcher first conducted a regular panel test. The test of the classical assumptions has been carried out by testing the residual normality assumption with the Jarque-Berra value = 0.127 and the probability value = 0.938 > 0.05. A *VIF* value of 1.200-7.368 10 was generated from the multicollinearity test, indicating that the model was free of multicollinearity issues. The Breush-Pagan-Godfrey probability value was 0.089 < 0.05. It means that the model was homoscedastic. Meanwhile, the Durbin-Watson value is 2.111, when compared with the criteria for the Durbin-Watson (*DW*) value, namely the *DW* value between 1 - 3 (Field, 2009), and then there is no problem with autocorrelation conservatively.

Researchers applied Chow, Hausman and Lagrange Multiplier tests to select the best model. The Chow test shows that the Cross-section Chi-square statistical value is 44.789 and the probability value is 0.000 < 0.05. This can be stated that between the common effect model and the fixed effect model chosen is the fixed effect model. Meanwhile, the Hausman test results obtained a Chi-Square Cross-section statistical value of 43.296 and a probability value of 0.000 < 0.05. These results can be stated that the selected model is a fixed effect model.

4.5. Static Panel Regression Results

The estimation results using the fixed effect method indicate that for every decrease in population density and an increase in the number of vehicles by 1%, the welfare of local people in Tangerang Municipality subdistricts will increase by 0.33% and 0.67%. Meanwhile, the control variables for quality of road length, education infrastructure, and health facilities did not significantly improve the welfare of local communities in Tangerang Municipality subdistricts (see Table 6).

4.6. Fully Modified Ordinary Least Square (FMOLS) Panel Results

Furthermore, to identify the consistency of the association between population density, number of vehicles, and local community welfare in Tangerang Municipality subdistricts, the researchers used the *FMOLS* panel model estimation with the Pooled approach. It is also intended to identify long-term relationships between the variables used. Previously, the researcher had found variable stationarity and its long-term co-integration in estimating the long-term impact of population density, number of vehicles, and the control variable on the welfare of local communities. The results of the *FMOLS* panel estimation show that a decrease in population density and an increase in the number of vehicles by 1% cause an increase in the welfare of local people by 0.30% and 0.55% respectively in Tangerang Municipality subdistricts (see Table 7). In addition, in the long term, the control variables quality of roads, educational infrastructure, and health facilities consistently do not lead to a rise in people's welfare.

Table 6. Panel Test Results

Variables, n=117	CEM	FEM	REM
lnden	-0.374*** (0.089)	-0.333** (0.129)	-0.374*** (0.078)
lnrv	0.494*** (0.096)	0.675*** (0.116)	0.494*** (0.084)
road	29.080 (19.498)	-54.516 (35.621)	29.080 * (17.049)
lneduc	-0.123*** (0.036)	-0.151*** (0.048)	-0.122*** (0.031)
lnhealth	0.053 (0.069)	-0.074 (0.074)	0.053 (0.061)
constant	17.476*** (0.690)	16.771*** (1.853)	17.475*** (0.603)
R^2	0.2735	0.5046	0.2736
Adjusted R^2	0.2409	0.4196	0.2409
F-stat	8.361	5.932	8.361
Prob.(F-stat)	0.000	0.000	0.000
Chow test		0.000	
Hausman			0.000

Note: level of significance *p < 0.1, ** p < 0.05, *** p < 0.01

Table 7. *FMOLS* Panel Regression Results

Variables, n=117	Pooled	Pooled (weighted)	Grouped
lnden	-0.308** (0.142)	0.546*** (0.161)	0.375 (0.365)
lnrv	0.553*** (0.132)	0.687*** (0.112)	0.648 * (0.188)
road	-48.816 (35.486)	-54.790*** (0.091)	-15.131 (28.292)
lneduc	-0.168*** (0.054)	-0.229** (0.091)	-0.148 * (0.086)
lnhealth	-0.108 (0.084)	-0.375*** (0.091)	-0.421 (0.351)
R^2	0.3975	-0.0736	-25295.97
Adjusted R^2	0.2785	-0.2857	-30296.54
Long-run variance	0.008	0.003	0.003

Note: Level of significance * p < 0.1, **p < 0.05, ***p < 0.01

In addition, we also validate the *FMOLS* panel model using the Wald Coefficient Restriction test. The criteria of the Wald test are p-value (α) < 0.05 for each explanatory variable, and consistency for the analysis model. The results of the model validation are presented in the following table:

Table 8. Validation of the *FMOLS* Panel Model with a Wald Test

Variables	Wald test: t-statistic		
	Pooled	Pooled (Weighted)	Grouped
C(1)=0, lden	-2.174**	3.334***	1.026
C(2)=0, lnrv	4.181***	4.697***	3.451***
C(3)=0, road	-1.376	-683.292***	-0.534
C(4)=0, lneduc	-3.131***	-2.586**	1.724*
C(5)=0, lnhealth	-1.287	-3.952***	-1.200

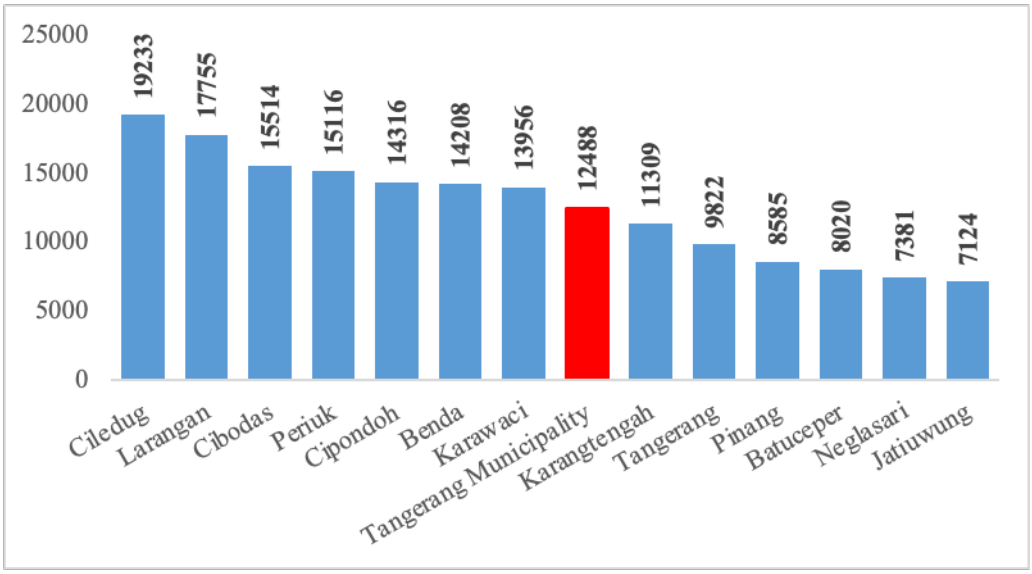
Note: Level of significance * p < 0.1, **p < 0.05, ***p < 0.01

Table 8 shows that the results of the estimated *FMOLS* panel model (pooled weight) have been validated using the Wald Coefficient Restriction Test with a value of each α < 0.05. The results obtained on the Wald Test are consistent with the findings in the estimated *FMOLS* panel model. It means that the variables of population density and number of vehicles have a long-term impact on the welfare of local communities in subdistricts in Tangerang Municipality.

4.7. Discussion

The study findings indicate that decreasing population density significantly increases the income of local communities. Population density in a region is correlated with the growth of population, leading to an increased labor force that can drive faster economic growth. However, population growth that is not balanced with an even distribution of population, resulting in increased density in certain areas. It also can lead to a several issues that impede development, such as unemployment, homelessness, poverty, environmental harm, and so on. Therefore, effectively managing population growth can encourage quick local economic growth and be able to raise people's incomes. The findings of this study, which show that a decrease in population density over time increases local communities' welfare in Tangerang Municipality subdistricts, provide evidence for this condition.

The Tangerang Municipality Government is focusing on population control in several sub-districts that appear to have high levels of density, including Ciledug, Larangan, Cibodas, and Periuk Subdistricts, namely 19,233 people per km^2, 17,555 people per km^2, 15,514 people per km^2, and 15,166 people per km^2, respectively [see Figure 1] (BPS Kota Tangerang, 2023). Therefore, the government should determine appropriate steps to reduce population density in Tangerang Municipality. Government policies regarding population take the form of optimizing population administration, urbanization, and cooperation between levels of government, especially sub-districts with high density levels. Optimizing population administration includes socializing



Sumber: BPS Kota Tangerang (2023)

Figure 1. Tangerang Municipality Population Density by District in 2022

the importance of population documents for every resident, improving population service infrastructure, encouraging increased public awareness about birth certificates which has started to increase. Efforts to control population density are also directed at one source of population growth, namely urbanization. The local government carries out regular population inspections of new arrivals to its territory and sets strict criteria for urban residents. In addition, all levels of government in Tangerang Municipality and other institutions such as hospitals, health centers and other health service units also record birth and death certificates properly as an effort to control the population.

The findings of this research strengthen the classical theory (Smith, 1776) which states that population growth will encourage economic growth when it comes to community involvement in economic development. A larger population will increase markets, leading to more economic specialization. Because specialization will increase worker productivity and encourage technical progress, the division of labor and the process of specialization will accelerate economic growth. Population growth accompanied by relatively strong investment growth allows relatively high investment support for both immigration and birth rates. However, if the population is too large it will also result in high population density so that the increase will reduce the level of economic activity because the productivity of each resident has become negative. Community prosperity will decline again. The economy will reach a very low level of prosperity. If this state is achieved, the economy is said to have reached a state of non-development (Stationary State). Therefore, population control will be very good in maintaining its welfare. Malthus (1798) argued that it was not surprising that people thus chose to reduce (or "check") population growth in an effort to maintain food scarcity.

The current study confirms earlier findings that reducing population density can increase people's income (Iskandar, 2023). Likewise, Mattson (2021) also specifically concluded that density has a negative correlation with per capita expenditure. In other words, the lower the cost of living, residents can reduce their consumption expenditures along with increasing population density in an area. The findings of this study also strengthen previous studies by Hasan (2010) which found population density has a significant effect on *GDP* per capita in the long term. Even Gielen et al. (2019) show the findings of a Spanish municipal research revealed a negative correlation between per capita spending and population density. The findings of this study are at contrast with earlier findings that suggested a positive relation between population density and per capita income (Pontes, 2021). Other researchers have also found that population density has a positive association with per capita income (Rahman et al., 2020; Rossouw & Greyling, 2021). Other studies that are not confirmed by the research findings state that community welfare is determined positively and indirectly by the population density of a city (Ahlfeldt & Pietrostefani, 2019; Hummel, 2020).

Meanwhile, a rise in the number of vehicles in one region indicates an improvement in the welfare of local people. The findings of this study demonstrate that over time, a higher vehicle density directly affects the average per capita income. However, an increase in the number of vehicles must be accompanied by a decrease in traffic jams so that the mobility of people to work, and the delivery of raw materials, semi-finished products, or final goods are better. Besides, road users are also comfortable driving without having to be under psychological pressure which causes stress, which in turn can increase their income from economic activity. The increase in the number of vehicles in Tangerang Municipality should be accompanied by other policies so as not to cause externalities such as increased air pollution which is dangerous for human life and traffic jams. Therefore, optimization of emission tests for vehicles in Tangerang Municipality subdistricts must continue to be improved. In addition, the application of odd-even vehicle numbers will be implemented immediately, especially at certain times, for example morning and evening. This policy is focused on Cipondoh, Pinang and Karangtengah Subdistricts because the number of vehicle increases was higher during 2018-2022 among the 13 subdistricts in Tangerang Municipality. Given that traffic jams on highways can result in wasted time, fuel inefficiency, reduced income, and discomfort for road users (Kawulur et al., 2020). On the other side, the significant increase in vehicle ownership has major policy ramifications for the environment, energy demand, transportation infrastructure, traffic management, and car manufacture (Ukonze et al., 2020).

The increase in the number of vehicles in Tangerang Municipality subdistricts should be accompanied by other policies so as not to cause externalities such as increased air pollution which is dangerous for human life and traffic jams. Therefore, optimization of emission tests for vehicles in Tangerang Municipality must continue to be improved. Apart from that, the application of odd-even vehicle numbers will be implemented immediately, especially at certain times, for example morning and evening. This policy is focused on Cipondoh, Pinang and Karangtengah subdistricts because the number of vehicle increases was higher

during 2018-2022 among the 13 subdistricts in Tangerang Municipality.

The findings of this study are in line with earlier studies, which discovered that an increase in the number of vehicles can raise per capita income (Ma et al., 2019; Yang et al., 2017) and the effect of the two variables is significantly positive even though it is not optimal (Sakir & Mustari, 2022). Other research also confirms that a rise in the number of vehicles can encourage economic growth in an area (Priyambodo, 2018; Tiawan et al., 2020) so that it can increase people's income. However, T. Wu et al. (2014) found the opposite relationship that the growth in China's vehicle demand is mainly determined by *GDP* per capita. Therefore, government intervention in the economy is urgently needed (Penchev & Özgür, 2019) because the Tangerang Municipality Government should be able to manage the high number of vehicles, both two-wheeled and four-wheeled. Given the increasing number of vehicles, of course, the problems that arise on the road are also getting bigger, including congestion, accidents, theft, traffic violations, and so on. This means that an increase in the number of vehicles can have an impact on improving economic activities and become an instrument in promoting welfare, but on the other hand, it can cause disaster for individuals and others.

The study's weaknesses in terms of variable measurement and research conclusions were acknowledged by the researcher. This study's limitation is that the subdistrict Gross Regional Domestic Product (*GRDP*) in Tangerang Municipality, which was calculated by dividing the subdistrict's total population by the working population aged 15 and over, was utilized as a proxy for the subdistrict's per capita income variable. People over 65 are still included in the population's calculations even when they are no longer employed if they are included in the population of people who are at least 15 years old and are employed. It is challenging for the researchers to employ alternative dynamic panel models because they are using time series data. Therefore, future research requires the addition of longer time series data so that it can compare the variance of the analysis and the strength consistency of the relationship between the main variables used. Future researchers can also utilize population density measurements by including indicators of pure land use in addition to the area of the subdistrict.

5. Conclusions

We investigated the impact of population density and numbers on local community welfare in the long term in Tangerang Municipality for the period 2014-2022 and 13 subdistricts. By using the *FMOLS* panel model, the researchers conclude that population density has a significant negative effect on peoples's income in the long-term in Tangerang Municipality's subdistricts. It means that the lower the population density will increase the local welfare of the community in the long-term. Another variable that has a significant contribution to increasing per capita income is the number of vehicles. The number of vehicles can be used as a policy instrument for the Tangerang Municipality Government to increase community welfare. Meanwhile, control variables such as road quality, educational infrastructure, and health facilities have no impact on increasing the welfare of local communities in the long term. The findings of this research have confirmed previous findings and can be used as a reference by other regions that have the same regional characteristics, while for regions with different characteristics it is necessary

to retest with different data for cases in Indonesia.

The research findings have implications that the increasing population density caused by natural population growth and urbanization flows is an important instrument for the local government to drive local economic development for subdistricts in Tangerang Municipality. In addition, it is hoped that the administrative service policies of each subdistrict government in Tangerang Municipality will be more optimal and cooperation between governments is expected to be further improved. The results of the study have demonstrated that having a population with rising levels of production, education, and skill can be advantageous for Tangerang Municipality's development. For this reason, the government should continue to control population density and distribute it evenly. Besides, the government of Tangerang Municipality should also manage the high number of vehicles so that the problems that arise on the road are decreasing, including establishing road traffic discipline and awareness movements, and checking documents periodically, incidentally, and continuously by the relevant Regional Apparatus Organizations (Indonesian, *OPD*).

Referring to research limitations, the calculation of local economic output (*GRDP*) is only based on formal labor. Future researchers should complete and improve the quality of their research by including the economic output of informal actors in a region. Apart from that, adding other explanatory variables that have not been accommodated in this research. As an alternative model for analyzing community welfare, future researchers can utilize other dynamic panel models to strengthen the findings of this research and add new analytical variants.

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