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Assessing the Economic Impacts of High-Speed Rail Operation on Surrounding Areas: Evidence from Indonesia

ABSTRAK

Sebagai negara berkembang, Indonesia telah berhasil membangun kereta api cepat pertamanya sebagai bagian dari modernisasi infrastruktur transportasi nasional untuk meningkatkan konektivitas antarwilayah strategis. Namun, bukti empiris mengenai dampak ekonomi kereta api cepat di Indonesia masih relatif terbatas. Penelitian ini bertujuan untuk mengukur dampak kausal beroperasinya kereta api cepat terhadap perekonomian di sekitar stasiun. Penelitian ini penting untuk memberikan evaluasi berbasis bukti mengenai dampak ekonomi beroperasinya kereta api cepat, sehingga dapat mendukung pengambilan kebijakan dalam pengembangan jaringan kereta cepat di masa mendatang. Penelitian ini menggunakan data panel tahun 2018 sampai 2024, dengan menggunakan intensitas cahaya malam sebagai proksi aktivitas ekonomi. Metode yang digunakan adalah Difference-in-Differences (DID). Hasil estimasi menunjukkan beroperasinya stasiun kereta api cepat secara signifikan meningkatkan aktivitas ekonomi lokal. Secara keseluruhan, manfaat ekonomi kereta api cepat terkonsentrasi secara spasial di wilayah paling dekat dengan stasiun, yang mencerminkan adanya efek aglomerasi. Temuan ini mengimplikasikan bahwa pengembangan koridor kereta api cepat ke depan perlu dilakukan secara cermat melalui penentuan lokasi stasiun yang strategis, penguatan konektivitas transportasi pendukung, integrasi dengan perencanaan tata ruang, serta kebijakan proaktif dalam menarik investasi guna memaksimalkan dan mendistribusikan manfaat ekonomi yang lebih luas.
Kata kunci: Kereta api cepat, aktivitas ekonomi, Difference-in-Difference
Klasifikasi JEL: R4, R11, C23

ABSTRACT

As a developing economy, Indonesia has introduced its first high-speed rail (HSR) service as part of broader efforts to modernize its transportation system and improve connectivity across key regions. However, the economic implications of HSR in Indonesia remain relatively underexamined. Accordingly, the analysis estimates the causal impact of HSR operation on economic activity in communities located around HSR stations. The study provides an evidence-based evaluation of the economic impacts associated with the operation of HSR, thereby contributing to policy-making and informing future decisions regarding the future expansion of the HSR network. The analysis draws on panel data covering the period from 2018 to 2024. Nighttime light intensity serves as proxy of local economic activity, while the Difference-in-Differences (DID) framework is used to estimate the causal impact of HSR operation. The estimates show a positive and statistically significant effect of HSR operation on local economic activity. Spatially, the economic benefits are concentrated in areas closest to the stations, reflecting the presence of agglomeration effects. These findings imply that future HSR corridor expansion should be carefully designed through strategic station placement, strengthened feeder transport connectivity, integration with spatial planning, and proactive investment policies to foster a more balanced diffusion of economic gains.
Keywords: High-speed rail, economic activity, Difference-in-Differences
JEL Classification Codes: R4, R11, C23

INTRODUCTION

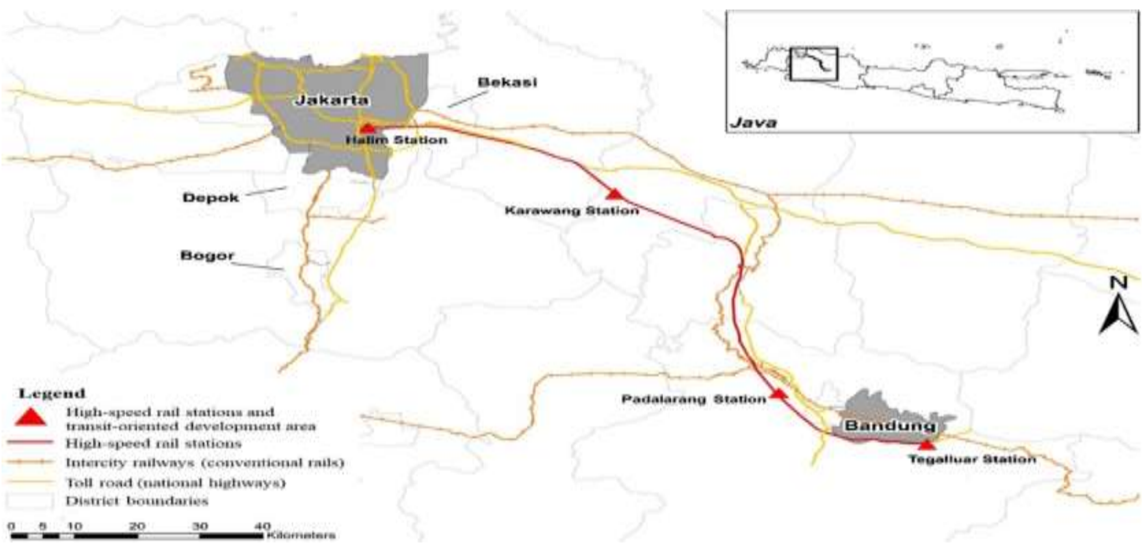
High-speed rail (HSR) has emerged as an important component of modern transportation infrastructure and regional connectivity. Several studies conducted in East Asian and European countries have shown that HSR can enhance intercity accessibility, reduce logistics costs, and create new economic growth centers around HSR stations (Ahlfeldt and Feddersen, 2018; Carbo et al., 2019; Cascetta et al., 2020; Du et al., 2021; Huang et al., 2024; Yoo et al., 2024; Zheng et al., 2025).

While preceding studies emphasize the potential economic benefits of HSR, the broader literature also points to several limitations and risks. HSR projects require substantial capital investment and typically involve lengthy implementation periods, creating considerable financing challenges. In many cases, HSR projects absorb large amounts of public funds and struggle to achieve financial break-even, raising concerns about their long-term economic sustainability in the absence of sufficiently high demand (Wong et al., 2022). Moreover, HSR may exacerbate existing regional disparities, as economic gains tend to concentrate in already developed areas while less developed regions capture fewer benefits (Wang et al., 2025). In addition, both the construction and operation phases may generate negative externalities, including environmental degradation during infrastructure development (Rus, 2021).

Indonesia's HSR experience began with the Jakarta–Bandung High-Speed Rail (KCJB) project, marking the country's entry into high-speed rail transportation. The introduction of HSR forms part of broader efforts to modernize the national transportation infrastructure with the aim of enhancing connectivity between strategic regions. This project, a collaboration between Indonesia and China, represents the first HSR initiative in Southeast Asia (Kemenhub, 2023). The Jakarta–Bandung corridor was selected due to the relatively higher purchasing power of its population compared to other regions (Simorangkir, 2016)

The construction permit for the Jakarta–Bandung high-speed rail was issued in 2016. The project was subsequently designated as a National Strategic Project under Presidential Regulation No. 3 of 2016 on the Acceleration of National Strategic Projects (KCIC, 2025 The construction phase spanned the period from 2017 to 2023, after which the Jakarta–Bandung High-Speed Rail (KCJB) was officially rebranded as *Kereta Cepat Whoosh*. The Whoosh officially commenced operations on 18 October 2023, serving Halim, Padalarang, and Tegalluar stations, while Karawang Station began operations on 24 December 2024. The HSR project is anticipated to contribute to regional economic growth, particularly in the areas surrounding the railway corridor (Bappenas, 2016).

Figure 1: Jakarta–Bandung HSR Route



Source: Mahardika et al. (2022)

From the perspective of accessibility-based agglomeration theory, improvements in transport infrastructure enhance market access and reduce effective distance, thereby strengthening agglomeration benefits and shaping the spatial pattern of economic activity (Credit, 2019). In this context, the presence of an HSR station can stimulate local economic through enhanced connectivity, improved mobility of production factors, agglomeration effects, tourism development, and increased demand for services and commerce in the surrounding areas (Lakshaman, 2011; Diao, 2018; Liu and Zhang, 2018; Guo et al., 2020; Ren et al., 2023; Zhang et al., 2023; Huang et al., 2024; Zheng et al., 2025).

However, evidence suggests that the economic effects of HSR are neither guaranteed nor evenly distributed. The impacts depend on factors such as station location, integration with subsequent transportation networks, regional accessibility, and the condition and readiness of the local economy (Garmendia et al., 2012; Long et al., 2018; Deng et al., 2020; Dong et al., 2021; Niu and Zhu, 2025). In the Indonesian context, this issue is particularly relevant as several KCJB stations (such as Tegalluar and Karawang) are situated in suburban areas that are still in the process of development. Moreover, Indonesia's structural characteristics may differ from countries with long-established HSR systems, potentially leading to different economic outcomes. These considerations raise an important question: to what extent can the presence of an HSR station significantly stimulate local economic activity? This study therefore aims to estimate the causal effects of HSR operations on economic activity in areas surrounding the stations, as measured by nighttime light intensity. We also aim to examine how these effects vary with distance from HSR stations. The study uses village/urban ward-level panel data covering the period 2018–2024, encompassing the pre-operation period and the commencement of HSR operations in October 2023. To estimate the causal effect of HSR operation on local economic activity, this study employs a Difference-in-Differences approach, comparing changes in economic activity before and after HSR operation between affected and unaffected villages/urban wards. The treatment group comprises villages/ urban wards located within the areas affected by HSR operation, while the control group consists of villages/urban wards located outside the treatment areas.

The majority of empirical literature (Ahlfeldt and Feddersen, 2018; Carbo et al., 2019; Zheng et al., 2019; Cascetta et al., 2020; Du et al., 2021; Yu, 2021; Huang et al., 2024; Yoo et al., 2024; Zheng et al., 2025) suggests that the operations of HSR networks generally has a positive impact on economy in the regions they connect. Nevertheless, several studies have demonstrated that HSR can have negative or insignificant effects on the economy. Jia and Qin (2017) found that the economic impacts of HSR vary across cities, with some HSR lines having statistically negative effects on economic performance. Yu and Jin (2023) similarly reported that HSR has a significantly negative impact on the output of the service industry, particularly in coastal areas and medium-sized cities located near large metropolitan centres. Qin (2017) also observed that counties traversed by HSR lines experienced declines in GDP and GDP per capita following the expansion, with the strongest effects occurring in the service sector. Research conducted in Japan by Wetwitoo and Kato (2019) at the provincial and county levels further indicated no significant impact on economic productivity in areas surrounding HSR stations.

Most empirical studies on the economic impacts of HSR (Jia and Qin, 2017; Qin et al., 2017; Ahlfeldt and Feddersen, 2018; Long et al., 2018; Carbo et al., 2019; Cascetta et al., 2020; Deng et al., 2020; Guo et al., 2020; Dong et al., 2021; Du et al., 2021; Yu, 2021; Huang et al., 2024; Niu and Zhu, 2025) have focused on the municipal or district level, using these administrative units as the primary unit of analysis. This approach implicitly assumes that the effects of an HSR station do not vary across the entire jurisdiction. However, municipalities and districts often exhibit heterogeneous geospatial characteristics, with varying access networks and land-use patterns (Glaeser and Kohlhase, 2004). Consequently, the economic impacts of HSR are unlikely to be evenly distributed across an entire jurisdiction and may instead be concentrated in specific areas around the station. Several studies reporting insignificant or even negative impacts of HSR suggest that these effects may be highly localised, confined to specific areas surrounding the station, and thus may not be accurately captured when the analysis is conducted at an overly aggregated spatial scale.

To date, empirical evidence on the economic impacts of HSR in Indonesia is relatively limited. Existing studies have predominantly focused on the social and economic aspects of communities surrounding the project, adopting a qualitative approach based on local perceptions (Abiyi, 2024; Azhari, 2024). These studies indicate that HSR has not improved the economic conditions of nearby communities and, in some cases, has reduced public space. Other research has examined station infrastructure evaluations and customer satisfaction with services provided by KCIC (Widyanesti and Rafii, 2024). All of these studies rely on qualitative methods such as case studies or interviewa, and thus have yet to capture a quantitative picture of the economic impacts. One of the few studies employing a quantitative approach is that of Hendra et al. (2023), which utilised input–output analysis to examine the effects of HSR on various economic sectors in Indonesia, finding that HSR makes a substantial contribution to overall national economic growth. Similarly, Pratiwi et al. (2022) applied input–output analysis to assess the economic impacts of HSR in West Java and reported comparable results.

This study makes three principal contributions to the literature on the economic effects of high-speed rail operations. First, it enriches the existing literature by providing empirical evidence from a developing country context, specifically Indonesia, where rigorous evaluations of high-speed rail remain limited. Whereas the majority of previous research has concentrated on East Asian and European economies, this study broadens the geographical focus and enhances understanding of high-speed rail impacts in emerging market settings.

Second, from a methodological perspective, the study adopts a causal inference framework through a difference-in-differences approach, complemented by several robustness analyses such as Propensity Score Matching. In addition, it utilizes a highly disaggregated spatial unit of analysis at the level of villages and urban wards, enabling more precise identification of localized and heterogeneous economic effects that may not be captured in studies employing broader municipal or district level data.

Third, this study provides localized economic evidence that may inform policymakers and relevant stakeholders in evaluating future expansions of HSR corridors in Indonesia. By documenting the spatial concentration and gradient of economic effects at the village/urban ward level, the findings offer insights into how station placement and surrounding land-use planning can influence the distribution of economic benefits.

Although the study focuses on Indonesia, this study may have policy relevance for countries in a similar state of development to Indonesia that plan to expand their transportation infrastructure project to include HSR system. This study also aims to complement previous studies on a similar topic that focuses on countries with relatively mature public transport system, by providing developing countries experiences and perspectives.

The following section will be organized as follows. The next section provides research methodology used for causal estimation. Followed by discussion of the results, including robustness analysis. Lastly, the conclusion will summarize the research findings and their implications.

RESEARCH METHODOLOGY

Data and Scope

The study employs village/urban ward-level (*desa/kelurahan*) panel data covering the period 2018–2024. Given the the limited availability of certain time-varying village/urban ward-level control variables from the Potensi Desa (PODES) dataset, the baseline specification excludes the years 2022 and 2023. In addition, 2023 is excluded because HSR operations commenced only in October of that year, leaving only a limited period of operation that is insufficient to represent a full year of treatment exposure. To address the implications of this data limitation, alternative specifications are estimated over the full 2018–2024 period using a more limited set of control variables. In addition to these temporal limitations, the spatial scope of the analysis is restricted to HSR stations that began operations in October 2023. Karawang Station, which commenced operations on 24 December 2024, is not included in the analysis because the lack of post-treatment observations for 2025. The study utilizes data from multiple sources, including the Central Bureau of Statistics, the Earth Observation Group (EOG) of the National Oceanic and Atmospheric Administration (NOAA), the Ministry of Finance, the Ministry of Investment and Downstreaming, and the Climate Hazards Center.

This study employs nighttime light (NTL) data to proxy economic activity around HSR stations. Compared with conventional measures such as GDP, NTL data offer finer spatial resolution and broader geographic coverage. At present, the smallest administrative level at which GDP data are available is the regency (*kabupaten*) level. In addition to its spatial flexibility, NTL offers several advantages over GDP (Huang et al., 2024). NTL data are not subject to human-induced sampling or non-sampling errors in data collection, making them more objective.

Moreover, NTL is less susceptible to manipulation, unaffected by revisions to statistical methodologies, independent of price levels or interregional inflation, and better able to capture certain informal activities that are not officially recorded. Numerous studies have employed NTL as an economic proxy to examine the impacts of HSR (Long et al., 2018; Zheng et al., 2019; Du et al., 2021; Huang et al., 2024; Niu and Zhu, 2025; etc.).

Nighttime light data are available from two widely used satellite-based sources, DMSP and VIIRS (Gibson et al., 2021). VIIRS offers superior sensor capabilities and higher spatial resolution compared to DMSP. Gibson et al. (2021) conducted a study examining which NTL source serves as a better proxy for economic activity, focusing on Indonesia, China, and South Africa. Their findings indicate that VIIRS data are more accurate than DMSP in predicting GDP. Therefore, this study employs VIIRS data from the National Oceanic and Atmospheric

Administration (NOAA) as the NTL proxy for economic activity.

Variables

The outcome variable in this study is nighttime light (NTL) intensity, which is used as a proxy for economic activity. The data were obtained from https://eogdata.mines.edu/nighttime_light in GeoTIFF format, containing radiance values for each pixel. Annual NTL data were constructed from the average of monthly cloud-free NTL observations. These data have been pre-processed to remove pixels illuminated by sunlight or moonlight and are expressed in units of nW/cm²/sr (Elvidge et al., 2021). The NTL data used in this study were further masked and filtered by transforming negative pixel values to zero. The NTL value for each village/urban ward represents the average nighttime light intensity within that administrative area, calculated by dividing the total radiance value within the village/urban ward boundaries by the number of pixels in that area.

The variable of interest in this study is the presence of an HSR station in proximity to a village/urban ward. This variable encompasses not only villages/urban wards hosting an HSR station but also those located within a specified radius of the nearest HSR station. The study distinguishes between two observation groups: the treatment group and the control group. The treatment group consists of villages situated within a 0–5 km radius of an HSR station. This radius selection is informed by Zheng et al. (2019), who employed a 4 km radius in defining the treatment group, but also found significant effects at distances of 5 km. This range is considered to capture the area logically within the potential influence of an HSR station. The control group comprises villages located within a 5–20 km radius of an HSR station to ensure geographic proximity between treated and control areas, which may reduce differences in local characteristics and make the parallel trends assumption more plausible. In addition, two time periods are defined: *Post* and *Pre*. *Post* refers to the period during which the HSR became operational and the subsequent year, while *Pre* refers to all other years. The variable of interest is defined as the interaction between the treatment group and *Post*, taking the value of 1 if a village is located within 0–5 km of an HSR station and the year is 2024.

This study incorporates several control variables that are expected to influence economic activity at the village/urban ward level. First, the variable *Covid* which assigned a value of 1 for the years 2020 and 2021, is used to control for the pandemic's impact on economic downturns. Second, the *Village Fund* variable, sourced from the Ministry of Finance, accounts for fiscal transfers that may affect local economic activity. Third, the *Transportation Cost to/from the Regency Capital* variable represents the level of accessibility, which can influence regional economic growth. Fourth, the *Disaster* variable controls for the effects of natural disasters on local economic activity. Fifth, the *Crime* variable reflects the security situation, which may affect community-level economic activities. Sixth, the *Gross Regional Domestic Product (GRDP) per capita* at the municipal/district level serves as a proxy for purchasing power and is included as a seven-year lag to avoid bias as a "bad control," since this variable may itself be influenced by the presence of the HSR project. Control variables three through six are sourced from the Central Bureau of Statistics. Seventh, *Domestic Investment (PMDN)* at the municipal/district level, obtained from the Ministry of Investment and Down streaming, is also included as a seven-year lag to control for the influence of domestic investment on economic activity, following similar considerations as with GRDP per capita.

This study also employs several supplementary variables for robustness checks, particularly in the application of Propensity Score Matching (PSM) as a method for determining the control group. These variables include the administrative status of the village/urban ward, elevation, topography, primary road type, and main economic sector of the village/urban ward. All of these variables are sourced from the Village Potential Statistics (*Potensi Desa*, PODES) dataset published by the Central Bureau of Statistics (Badan Pusat Statistik/BPS). In addition, a rainfall variable derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) provided by the Climate Hazards Center is also included.

The descriptive statistics of the variables are presented in Table 1.

Table 1: Variable and Descriptive Statistics

Variable	Description	Obs	Mean	Std. dev.	Min.	Max.
NTL	Average nighttime light intensity at the village/urban ward level (nW/cm²/sr)	4410	17.861	15.398	0.381	111.831
Covid	Year experiencing the COVID-19 period (1 = Yes, 0 = No)	4410	0.4	0.489	0	1
Distance	Distance from the village/ urban ward to the HSR station (km)	4410	11.642	4.510	0.599	19.917
Cost	Travel cost to/from the regency/city capital from the village/urban ward (thousand Indonesian Rupiah)	4410	30.064	22.191	1	90
Disaster	Number of disaster events experienced by the village/urban ward within one year (incidents)	4410	0.794	1.278	0	6
Crime	Presence of criminal activities in the village/urban ward (1 = Yes, 0 = No)	4410	0.204	0.403	0	1
Village Fund	Village fund received by the village/urban ward (million Indonesian Rupiah)	4410	605.561	631.093	0	2,365.53
GRDP per Capita	GRDP per capita in the regency/city where the village/urban ward is located (million Indonesian Rupiah)	4410	62.204	78.698	10.907	442.813
Domestic Investment	Domestic Capital Formation in the regency/city where the village/urban ward is located (billion Indonesian Rupiah)	4410	2,978.363	4,316.701	0.294	24,388.29
Status	Status of the village/urban ward (1 = Urban/perkotaan, 2 = Rural/pedesaan)	4410	1.028	0.165	1	2
Elevation	Elevation of the village/urban ward location (meters above sea level)	4410	459.859	372.43	0	1323
Topography	Dominant topography of the village/urban ward area (1 = Cliff, 2 = Slope, 3 = Plain, 4 = Valley)	4410	2.749	0.438	2	4
Road	Most prevalent type of road surface in the village/urban ward (1 = Asphalt/Concrete, 2 = Paved, 3 = Dirt, 4 = Others)	4410	1.001	0.033	1	2
Sector	Main source of income for the village/urban ward population (1 = Agriculture, 0 = Non-agriculture)	4410	0.111	0.314	0	1
Rainfall	Average annual rainfall in the village/urban ward (mm/year)	4410	2,306.707	493.681	1,369.8	4,858.7

Empirical Model

To measure the causal impact of high-speed rail operations on economic activity in areas surrounding the stations, this study adopts a Difference-in-Differences approach. This method is selected because it enables the estimation of the causal effect of HSR operation by comparing changes in economic activity before and after HSR operation between treated and control villages/urban wards. The approach is particularly well-suited for evaluating infrastructure policies that are not implemented randomly, as it can isolate the effects of HSR operations from general time trends and time-invariant differences between regions. This method also addresses endogeneity concerns within the model and allows for the estimation of a causal impact of HSR operations on the economies of areas surrounding the stations. The DiD model employed in this study adopts and modifies specifications from previous studies (Long et al., 2018; Zheng et al., 2019; Niu et al., 2021; Zheng et al., 2025). The main specification includes 375 treated villages/urban wards, with 75 treated villages/urban wards associated with each of the five HSR station areas. The empirical model specification is as follows:

$$\boldsymbol{NTL_{it} = \beta_0 + \beta_1 HSR_{it} + \beta_j X_{it} + \gamma_i + \delta_t + \varepsilon_{it}} \quad (1)$$

Because HSR operation commenced simultaneously across all treated observations, the two-way fixed-effects (TWFE) specification in Equation (1) yields a readily interpretable estimate of the average effect of HSR operation (Roth et al., 2023). The NTL_{it} denotes the average nighttime light intensity of village/urban ward i in year t. HSR_{it} is a dummy variable that takes the value of 1 for villages/urban wards located within a maximum distance of 5 km from an HSR station after the commencement of its operation, and 0 otherwise. The coefficient β_1 represents the estimated impact of HSR operations on economic activity in villages/urban wards surrounding the stations. X_{it} is a vector of control variables as described in the variable section. These include: *Covid*, *Village Fund*, transportation cost to/from the regency capital, *Disaster*, *Crime*, per capita GRDP, and domestic investment

(PMDN). These time-varying covariates are included because parallel trends may be more plausible conditional on factors that can influence local economic activity and its underlying trends (Roth et al., 2023). Their inclusion helps account for observable factors that may contribute to differences in outcome trends between the treatment and control groups prior to HSR operation. The coefficient γ_i denotes village/urban ward fixed effects, capturing time-invariant characteristics of each location, while δ_t denotes year fixed effects. Tha last, ε_{it} is the random error term. The baseline specification estimates the effect during the first full year of HSR operation (2024).

In the context of this study, the inclusion of both individual (village/urban ward) fixed effects γ_i and time (year) fixed effects $\delta_t$plays a critical role in ensuring the validity of the estimated causal effect. First, the individual fixed effects account for all unobserved, the time-invariant characteristics specific to each village/urban ward that may influence economic activity. These characteristics may include geographic location, historical infrastructure endowment, cultural factors, or long-standing institutional quality. By holding these factors constant over time, the model eliminates potential bias arising from omitted variables that differ across locations but remain stable throughout the study period. Second, the time fixed effects control for shocks or trends that are common to all villages/urban wards in a given year, such as national macroeconomic fluctuations, policy reforms, inflationary pressures, or external events. This ensures that the estimated treatment effect is not confounded by temporal dynamics affecting all regions simultaneously.

In the Difference-in-Differences framework, the parallel trends assumption (PTA) serves as the fundamental premise ensuring the validity of causal inference (Roth et al., 2023; Baker et al., 2026). This assumption posits that, in the absence of treatment, the average differences or trends between the treatment group and the control group would remain constant over time (Huntington-Klein, 2021; Roth et al., 2023). In other words, the pretreatment differences in outcomes between the two groups can be regarded as the baseline for predicting the post-treatment outcomes of the treated group had the intervention not occurred. The importance of the PTA lies in its ability to capture common temporal influences that affect both groups similarly, thereby allowing post-treatment differences to be attributed credibly and validly to the treatment itself. In short, the PTA constitutes a necessary condition for addressing endogeneity in the DiD model, and the model will yield valid causal estimates only if this condition holds.

This study employs three distinct approaches to assess the validity of the parallel trends assumption in the model. The first approach is the most common and intuitive method, which involves comparing the average outcome trends of the treatment and control groups prior to the intervention (Huntington-Klein, 2021). If both groups exhibit similar trend patterns before the treatment, the PTA is considered plausible, as this suggests that post-treatment differences in outcomes are more likely attributable to the intervention itself rather than to pre-existing differences in trends. However, this approach may involve a degree of subjectivity in assessing whether the trends are sufficiently similar. To address this limitation, two additional methods are employed: the trend test and the event study approach. These provide more formal and quantitative means of evaluating whether the PTA holds in this context.

The second approach is the trend test. This method applies a linear trend model to formally examine whether the PTA holds, by extending the baseline Difference-in-Differences specification with two additional variables (Gavilanes, 2023; StataCorp, 2023). The model used for this test is specified as follows:

$$\boldsymbol{NTL_{it} = \beta_0 + \beta_1 HSR_{it} + \beta_j X_{it} + \gamma_i + \delta_t + \zeta_1 \omega_i d_{t,0} t + \zeta_2 \omega_i d_{t,1} t + \varepsilon_{it}} \quad \text{..........(2)}$$

Where $d_{t,0} = 1(d_t = 0)$ denotes the pretreatment period, and $d_{t,1} = 1(d_t = 1)$ denotes the post-treatment period. Furthermore, ω_i takes the value of 1 if the village/urban wards belongs to the treatment group, and 0 otherwise.

In this model specification, the coefficient ζ_1 represents the difference in slope between the treatment and control groups during the pretreatment period, while ζ_2 captures the difference in slope between the two groups during the posttreatment period. If ζ_1 is statistically indistinguishable from zero, this indicates that the linear trends of the outcome variable between the treatment and control groups were parallel during the pre-intervention period, thereby satisfying the parallel trends assumption. Accordingly, the null hypothesis in this test states that the linear trends between the treatment and control groups prior to treatment are parallel.

The third approach employs an event study framework. This method enables an explicit examination of the parallel trends assumption within the DiD model by estimating the dynamic effects of treatment over time. By comparing outcomes across multiple periods before and after the intervention, the event study provides a way to assess whether there is evidence of differential trends prior to treatment (Roth et al., 2023). Coefficients for the pretreatment periods that are statistically insignificant and close to zero would support the plausibility of the PTA (Niu et al., 2021). The event study model applied in this study is specified as follows.

$$\boldsymbol{NTL_{it} = \beta_0 + \sum_{k=m}^{q} \beta_k HSR_{it}^{k} + \beta_j X_{it} + \gamma_i + \delta_t + \varepsilon_{it}} \quad \text{..(3)}$$

Where k denotes the difference between year t and the intervention period, taking values from m to q. The lower bound, m, corresponds to the earliest pre-intervention period, whereas q denotes the latest post-intervention period. The PTA test is conducted by examining the coefficients β_k during the pretreatment periods, i.e., when k takes negative values. Since the intervention year is identical for all treated units (as the station openings occurred simultaneously), k can be replaced with t itself, allowing the event study to be analyzed directly by calendar year rather than by the notation of periods relative to the intervention.

RESULT AND DISCUSSION

Baseline Results

Table 2 presents the impact of the High-Speed Rail operations on economic activity at the village/ward level, measured by nighttime light intensity. Standard errors are clustered at the village/urban ward level to account for within-unit dependence in the error term. The regression results show a positive and statistically significant effect of HSR operation on economic activity in areas surrounding the stations. Column 1 shows the model without control variables, revealing that the operations of the HSR significantly raises nighttime light intensity by 0.911 nW/cm²/sr. The coefficient decreases after including village-level controls (Column 2) and district-level controls (Column 3), suggesting that collectively, the control variables exhibit a positive bias, meaning the estimate in Column 1 is likely an overestimate. The model with a full set of controls, shown in Column 3, reports a coefficient of 0.854, indicating a significant increase in nighttime light intensity by 0.854 nW/cm²/sr due to HSR operations. This result demonstrates that the HSR operations successfully enhances economic activity around the stations. The average nighttime light intensity for villages/wards within a 5 km radius of the station is 19.253 nW/cm²/sr, implying that the HSR operations has increased economic activity in these areas by approximately 4.4 percent.

Table 2: Regression Results of the Main Model

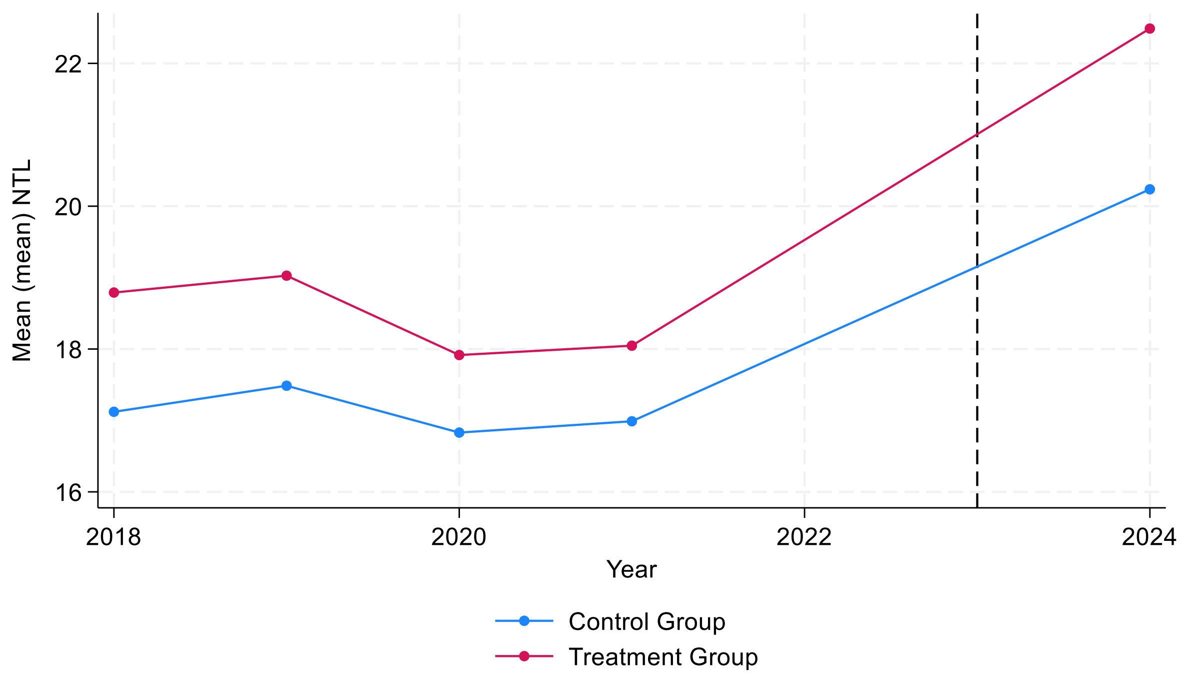
Variable	NTL		
	(1)	(2)	(3)
HSR	0,911***	0,888***	0,854**
	(0,342)	(0,333)	(0,339)
Village/urban ward -level control variables	No	Yes	Yes
Regency-level control variables	No	No	Yes
Village/urban ward fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Robust se	Yes	Yes	Yes
Observation	4410	4410	4410

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

Parallel Trend Test Results

As previously explained in the methodology section, we employ three approaches to examine the plausibility of the parallel trends assumption. The first approach involves comparing the average outcome trends between the treatment group and the control group prior to the intervention, as illustrated in Figure 2. The figure demonstrates parallel movement of the data between the treatment and control groups.

Figure 2: Mean Outcome of the Treatment and Control Groups

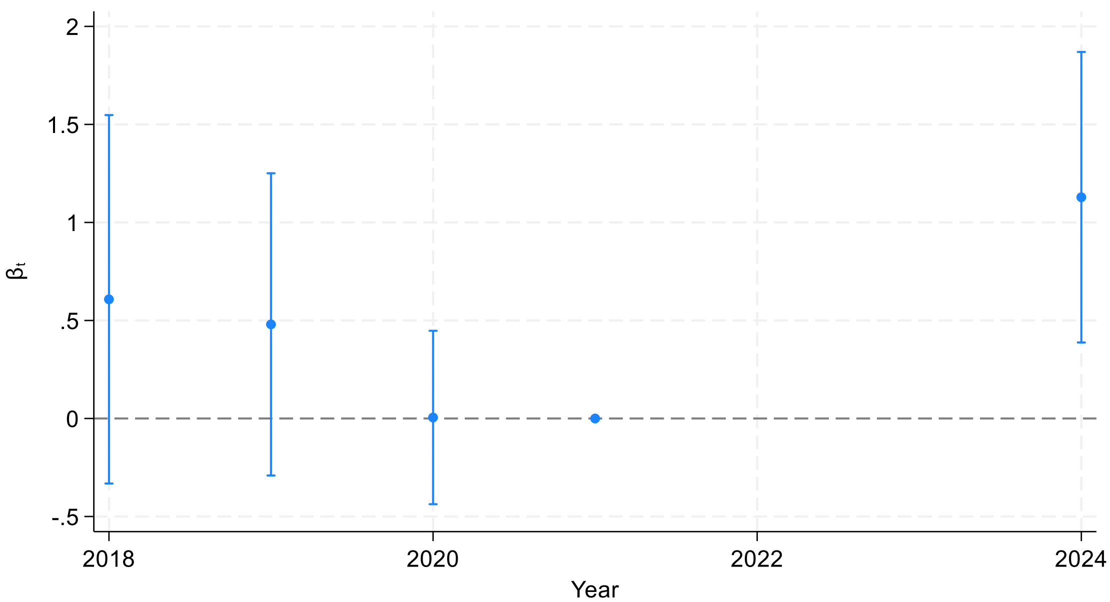


Source: Processed data output (STATA 19)

Although Figure 2 indicates parallel trends, a more formal statistical test is necessary to confirm this. The second test employs the trend test as specified in Equation 2. The results show a p-value of 0.1751, so we fail to reject the null hypothesis. This implies there is insufficient evidence to suggest that the groups followed different trends prior to the intervention. Therefore, based on this test, the parallel trends assumption is satisfied.

The third test utilizes an event study approach as outlined in Equation 3. The event study results are presented in Figure 3, illustrating the dynamic treatment effects over time, including both pre- and post-treatment periods. During the pre-treatment period, the coefficients are not significantly different from zero. This supports the parallel trends assumption, which posits that the trends between the treatment and control groups do not differ systematically prior to the intervention. The results are in line with those obtained from the two preceding parallel trends tests. Furthermore, the absence of significant pre-intervention effects suggests no anticipation effects, suggesting that units did not systematically adjust their behavior before the intervention.

Figure 3: Event-Study Analysis of the Main Model



Source: Processed data output (STATA 19)

To further examine the possibility of anticipatory effects, we conduct a Granger-type causality test by augmenting the DiD specification with interactions between the treatment-group indicator and a set of pre-intervention time indicators. This specification allows us to identify whether the treatment effect emerges prior to the actual intervention. The results provide no evidence of anticipatory treatment effects.

Sensitivity of HSR Impact Based on Distance

To deepen the understanding of the main findings, additional analyses are conducted by varying the definition of the treatment group. In the initial estimation, the treatment radius was set at 0–5 km from the HSR station. However, this distance cutoff may influence the magnitude of the estimated effect, especially if the economic impact of the HSR changes gradually with distance or if the effects extend beyond the initial radius. Therefore, alternative tests were performed by defining the treatment group using different distance thresholds, specifically at 0–3 km, 0–4 km, 0–6 km, and 0–7 km. This approach provides a more detailed spatial profile of the HSR's impact on economic activity and helps identify the distance at which the effect is strongest. The estimation results are presented in Table 3, columns (1), (2), (4), and (5). Parallel trend tests were also conducted for all models. The results indicate that almost all models with alternative distance specifications satisfy the parallel trend assumption, except for the regression results reported in column 4. This finding suggests that, specifically for the regression with the 0–6 km treatment distance, the estimation results remain overestimated. Nevertheless, the results obtained from other distance alternatives can still be considered reliable and valid for interpretation.

The estimation results indicate that the impact of the HSR on nighttime light intensity is relatively influenced by the distance from the station. When the treatment radius is narrowed to 0–3 km, the estimated effect reaches 1.781 and is statistically significant, indicating a very strong increase in economic activity in the immediate vicinity of the station. For treatment group radii of 0–4 km, 0–5 km, and 0–6 km, the coefficient values are similar, around 0.85, and remain statistically significant. This suggests that the effect is relatively consistent within the radius of 0–4 km to 0–6 km. However, at the 0–7 km radius, the effect sharply decreases to 0.619, though it remains significant, implying that the impact begins to diminish around the 7 km area. The relatively large decline at the 0–7 km radius may be due to the impact becoming statistically insignificant around this distance, but still supported by the strong effect within the 0–5 km radius, which causes the 0–7 km radius to appear significant overall.

Table 3: HSR Impact on Economy Based on Distance

Variable	NTL					
	(1)	(2)	(3)	(4)	(5)	(6)
	T : 0-3 Km C : 3-20 Km	T : 0-4 Km C : 4-20 Km	T : 0-5 Km C : 5-20 Km	T : 0-6 Km C : 6-20 Km	T : 0-7 Km C : 7-20 Km	T : 6-8 Km C : 8-20 Km
HSR	1,781**	0,861**	0,854**	0,857***	0,619***	0,176
	(0,798)	(0,441)	(0 ,339)	(0,258)	(0,219)	(0,243)
Village-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Regency-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Village/urban ward fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Robust se	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4410	4410	4410	4410	4410	3855
PTA test:						
Mean outcome	Ok	Ok	Ok	Ok	Ok	Ok
Trend test	Ok	Ok	Ok	No	Ok	Ok
Event study	Ok	Ok	Ok	No	Ok	Ok

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

This is further evidenced by the regression using the treatment defined at the 6–8 km radius, presented in column (6), where the coefficient is no longer statistically significant despite having a positive sign. In addition to validating the main findings that the HSR boosts economic activity, all regression results in Table 3 are consistent with the theory of local agglomeration effects, where optimal access to the station promotes trade, services, and consumption.

Robustness Check

Removing the "Donut" Area

The DiD framework also relies on the Stable Unit Treatment Value Assumption (SUTVA). In this context, SUTVA requires that the treatment received by treatment group does not alter the outcomes of control group through spillover effects. This study adopts the approach used by Doerr et al. (2020), which excludes observations located in contiguous areas between the treatment and control groups. These excluded areas are referred to as the "donut" regions. The removal of the donut area is justified because regions directly adjacent to the outer boundary of the treatment group may still experience spillover effects from the HSR operations. This is also supported by previous findings showing that the HSR impact coefficient is significant when the treatment group is defined within 0–6 km or 0–7 km, but becomes insignificant when limited to 6–8 km. Such patterns indicate that areas within 5–7 km from the station still benefit from the HSR, albeit with diminishing intensity. Therefore, we modify the model by excluding observations located between 5–7 km from the HSR station. The treatment group consists of villages/subdistricts within a 0–5 km radius of the HSR station, while the control group comprises villages/subdistricts located 7–20 km away from the station. Furthermore, we examine the consistency of the effect based on distance by varying the treatment radius as done previously. All robustness test results for this treatment specification are presented in Table 4.

Based on Table 4, the results consistently show a positive and significant effect, indicating that the main findings presented in Table 1 are fairly robust. However, changing the control group definition from 5–20 km to 7–20 km yields slightly larger estimated coefficients. This reinforces the notion that areas within 5–7 km from the station likely still receive some positive spillover effects from the HSR, and including these areas in the previous control group caused a downward bias in the estimates. By excluding the affected area from the control group, the contrast between the treatment and control groups becomes sharper, resulting in higher estimated effects. Naturally, this adjustment also accounts for the parallel trends tests. The increase in coefficients after removing the donut area is observed not only for the 0–5 km radius treatment but also for regressions using 0–3 km and 0–4 km treatment definitions.

Table 4: HSR Impact on Economy Based on Distance without "Donut" Area

Variable	NTL					
	(1)	(2)	(3)	(4)	(5)	(6)
	T : 0-3 Km C : 7-20 Km	T : 0-3 Km C : 7-20 Km	T : 0-4 Km C : 7-20 Km	T : 0-4 Km C : 7-20 Km	T : 0-5 Km C : 7-20 Km	T : 0-5 Km C : 7-20 Km
HSR	1,948**	1,882**	0,991**	0,971**	0,946***	0,927***
	(0,809)	(0,785)	(0,448)	(0,439)	(0,345)	(0,339)
Village/ urban ward -level control variables	No	Yes	No	Yes	No	Yes
Regency-level control variables	No	Yes	No	Yes	No	Yes
Village/ urban ward fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Robust se	Yes	Yes	Yes	Yes	Yes	Yes
Observation	3770	3770	3910	3910	4025	4025
PTA test:						
Mean outcome	Ok	Ok	Ok	Ok	Ok	Ok
Trend test	Ok	Ok	Ok	Ok	Ok	Ok
Event study	Ok	Ok	Ok	Ok	Ok	Ok

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

PSM-DID

As a second robustness check, we combine Propensity Score Matching (PSM) with DiD. Due to heterogeneity across villages and urban wards, completely eliminating selection bias remains challenging, even with the DiD estimation that limits observations within a 20 km radius. Therefore, we implement PSM before estimating the DiD model to obtain a control group that is comparable to the treatment group in terms of observed characteristics, rather than restricting observations to a maximum of 20 km from the station. This approach helps to further reduce potential selection bias. Similar methods have been employed by Long et al. (2018) and Zheng et al. (2025).

There is no consensus on which variables should be used for matching. Most studies use pre-policy control variables as matching covariates (Long et al., 2018; Yang et al., 2021; Zheng et al., 2025). Conversely, Niu and Zhu (2025) argue that time-invariant variables are more appropriate for PSM because these variables remain consistent over time. Considering these differing views, the variables used in the PSM procedure in this study include control variables as well as supporting variables such as rainfall and various time-invariant characteristics of villages and urban wards, including administrative status, elevation, topography, primary road type, and the primary economic subsector of the village/urban ward. The propensity scores are estimated using a logistic regression model, specified as follows (Niu and Zhu; 2025).

$$\boldsymbol{P_i = Logit\ (treat_i = \lambda) = \beta_0 + \beta_j X_i + \varepsilon_i} \quad \text{...(4)}$$

Where P_i represents the propensity score of the village/urban ward, indicating the probability of being included in the treatment group. The $treat_i$ is a dummy variable that equals 1 if the village/urban ward is within a 5 km radius of the HSR station, and 0 otherwise. X_i denotes the set of covariates used for matching, as described previously. Subsequently, the estimated propensity scores were employed for matching, yielding the control group observations based on the PSM procedure. Thereafter, the DiD regression was re-estimated using equation (1).

PSM was conducted using baseline characteristics observed in 2021, prior to HSR operation. The matching procedure employed 10-nearest-neighbor matching with replacement and imposed a common-support restriction. Because all treated observations are classified as urban, the variable Status perfectly predicts treatment status for rural village/urban ward (Status=2). Consequently, 48,189 rural observations were excluded during the propensity-score estimation, leaving 29,364 observations for the matching procedure. The results of the covariate balance of 29,364 villages/urban wards before and after propensity score matching are presented in Table 5.

Table 5: Covariate Balance Before and After Propensity Score Matching

Variable	Unmatched/ Matched	Mean		Standardized Bias (%)	Bias Reduction (%)	t test	
		Treated	Control			t	p-value
Cost	U	273.83	801.31	-12.8		-0.88	0.378
	M	273.83	526.94	-6.1	52.0	-0.62	0.539
Disaster	U	1.629	0.817	41.9		4.21	0.000
	M	1.629	2.088	-23.7	43.4	-1.07	0.284
Crime	U	0.209	0.197	2.9		0.27	0.788
	M	0.209	0.209	0.0	100.0	-0.00	1.00
Village fund	U	620.66	801.24	-30.4		-3.36	0.001
	M	620.66	724.7	-17.5	42.4	-1.01	0.313
GDRP per capita	U	56.939	28.831	76.5		8.31	0.000
	M	56.939	49.635	19.9	74.0	1.10	0.272
Domestic investment	U	4,842.5	1,055.6	69.3		14.46	0.000
	M	4,842.5	4,153.1	12.6	81.8	0.62	0.533
Rainfall	U	2,550.5	2,967.2	-74.0		-4.85	0.000
	M	2,550.5	2,571.4	-3.7	95.0	-0.42	0.679
Status	U	1	1				
	M	1	1			0	1
Elevation	U	424.91	164.63	84.7		8.97	0.000
	M	424.91	470.64	-14.9	82.4	-0.76	0.448
Topography	U	2.888	2.791	25.3		2.11	0.035
	M	2.888	2.866	5.8	77.2	0.39	0.694
Road	U	1.012	1.027	-9.3		-0.68	0.499
	M	1.012	1.011	0.8	91.8	0.06	0.950
Sector	U	0.061	0.483	-107.5		-7.60	0.00
	M	0.061	0.032	7.5	93.0	0.89	0.376

Source: Processed data output (STATA 19)

All treated villages/urban wards in main model were within the common-support region, indicating sufficient overlap in the estimated propensity scores. From the initial sample of 77,553 villages/urban wards, 608 were retained as matched observations, while the remaining 48,189 observations were excluded during the propensity-score estimation and remaining 28,756 observations were not matched. The balance diagnostics indicate a substantial improvement in covariate balance following matching. The mean absolute standardized bias declined from 56.1% before matching to 11.4% after matching, while the median bias decreased from 55.6% to 10.1%.

Table 6: HSR Impact on Economy using PSM-DID

Variable	NTL		
	(1)	(2)	(3)
	T : 0-3 Km	T : 0-4 Km	T : 0-5 Km
HSR	1,685**	0,938**	0,887***
	(0,821)	(0,431)	(0,323)
Village/ urban ward -level control variables	Yes	Yes	Yes
Regency-level control variables	Yes	Yes	Yes
Village/ urban ward fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes
PTA test:			
Mean outcome	Ok	Ok	Ok
Trend test	Ok	Ok	Ok
Event study	Ok	Ok	Ok

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

In addition none of the covariates exhibited a statistically significant difference in means between treated and matched control villages. These results indicate that the matching procedure substantially improves the comparability of the two groups, although some residual imbalance remains. The 608 matched observations were subsequently used in the DID estimation, resulting in 3,040 villages/urban ward observations over the five-year study period.

Table 6 presents the estimation results using the PSM-DID approach. The results indicate statistically significant positive coefficients that are close in magnitude to the main findings, demonstrating the robustness of the primary model. Specifically, when the control group is selected via the PSM method from all villages/urban wards across Indonesia, the estimated effect remains consistently significant and comparable. For instance, in the treatment group defined within a 0–5 km radius, the coefficient from the main model (Tables 2 and 3) is 0.854, while the donut model (Table 4) yields a coefficient of 0.927. The PSM-DID model produces a coefficient of 0.887. This relatively small variation reinforces confidence that the main estimates are stable across different methods of defining the treatment group. Furthermore, the results of the parallel trend tests across all models in Table 6 provide no evidence against the parallel trends assumption, supporting the interpretation of the estimates as causal effects. Therefore, the application of PSM-DID not only validates the robustness of the main model in estimating the effect of HSR but also mitigates potential selection bias stemming from baseline differences across regions.

Falsification/ Placebo Test

In addition to the previous two robustness checks, this study also conducts a placebo test by shifting the actual intervention year (2023) to earlier periods, specifically 2021, 2020, and 2019. This test is conducted to assess whether the estimated effects are truly caused by the high-speed rail operations, rather than by pre-existing trends or other concurrent factors. Moreover, the placebo test helps reinforce the validity of the parallel trend assumption. In this test, the treatment variable is artificially reassigned as if the intervention occurred in each of these years, and the DiD regression is rerun for each scenario. A statistically insignificant interaction term in the placebo specification would provide support for the main model's findings and indicates no differential trends prior to the actual intervention.

Table 7: Placebo Test Results

Variable	NTL		
	(1)	(2)	(3)
	Year of Intervention: 2021	Year of Intervention: 2020	Year of Intervention: 2019
HSR	-0,130	-0,144	-0,116
	(0,274)	(0,281)	(0,252)
Village/urban ward -level control variables	Yes	Yes	Yes
Regency-level control variables	Yes	Yes	Yes
Village/ urban ward fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Robust se	Yes	Yes	Yes
Observation	3880	3880	3880
PTA test:			
Mean outcome	Ok	Ok	Ok
Trend test	Ok	Ok	Ok
Event study	Ok	Ok	Ok

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

Table 7 presents the estimation results from the placebo test. The results indicate that when the intervention year is artificially altered, the coefficients obtained are statistically insignificant across all model specifications. This lack of significance suggests that there is no consistent pattern of increase or decrease in nighttime light intensity for the treatment group compared to the control group prior to the commencement of the HSR operations. Therefore, this placebo test reinforces the conclusion that the positive effects found in the main analysis are indeed causal impacts of the HSR operation, rather than results of time trends or other unobserved external factors.

Standard Error Considerations

In the main specification, standard errors are clustered at the village/urban ward level. To allow for correlation in errors across villages/urban wards within the same regency due to shared regional shocks, policies, and economic conditions, we also estimate the model with standard errors clustered at the regency level. We also examine two-way clustering by village/urban ward and regency;

however, because village/urban wards are nested within regencies, this specification produces results equivalent to clustering at the regency level. Given the relatively small number of regency clusters, we further employ the wild cluster bootstrap procedure to obtain inference that is more reliable under a limited number of clusters (MacKinnon and Webb, 2018). The robustness results across these alternative approaches are reported in Table 8. The estimated effect remains positive and statistically significant across all alternative standard error specifications, indicating that the main finding is robust to different approaches to statistical inference.

Table 8: Alternative Standard Error Specifications

Variable	NTL		
	(1)	(2)	(3)
HSR	0,854**	0,854**	0,854**
	(0,339)	(0,353)	
p-value	0,012	0,030	0,040
Village/urban ward -level control variables	Yes	Yes	Yes
Regency-level control variables	Yes	Yes	Yes
Village/urban ward fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Village/Urban Ward Clustered SE	Yes		
Regency Clustered SE		Yes	Yes
Wild Cluster Bootstrap SE			Yes
Observation	4410	4410	4410

Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

Estimation Using All Sample

This study also conducts estimations using the all data spanning from 2018 to 2024 (7 years), without including village-level control variables derived from Podes, as these data are unavailable for the full period. Consequently, several control variables such as transportation costs to/from the district capital, disasters, and crime rates are excluded from the model to maintain a continuous study period.

Table 9: Estimations Using the All Sample

Variable	NTL		
	(1)	(2)	(3)
HSR	0,784***	0,803***	0,780***
	(0,279)	(0,282)	(0,282)
Village/urban ward - level control variables	No	Yes	Yes
Regency-level control variables	No	No	Yes
Village/ urban ward fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes
Observation	6671	6671	6671
PTA test:			
Mean outcome	Ok	Ok	Ok
Trend test	Ok	Ok	Ok
Event study	Ok	Ok	Ok

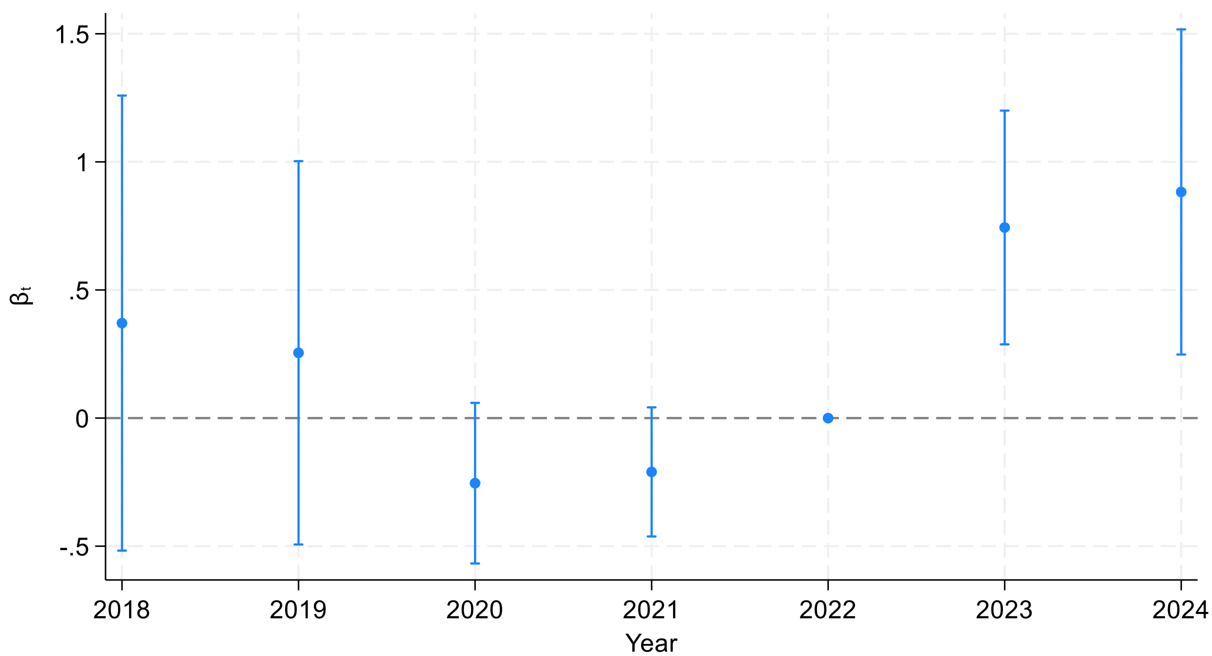
Source: Processed data output (STATA 19)
*p<0,1 **p<0,05 ***p<0,01

Table 9 reports the estimates obtained using the full study period for the treatment group defined within a 0–5 km radius of the HSR station. Based on column (3), the coefficient obtained is 0.780. This figure is slightly lower than the main model estimate of 0.854, but the difference is relatively small and the value remains close to the primary result. With positive and significant coefficient, these results provide additional evidence of the robustness of the main findings. This slight difference can be further explained by the event study analysis from this model. The estimation results remain consistent with the main findings, and it confirm the robustness of the primary model.

Figure 4 illustrates the event study from the full-period model presented in Table 9, column 3. It is evident that none of the coefficients before the HSR operation (pre-treatment period) are statistically significant, indicating that the parallel trends assumption is satisfied. Meanwhile, the coefficients in the post-treatment period reflect the impact of HSR operations in specific years. Overall, the cumulative effect is recorded at 0.780, although the contribution varies by year. The effect in 2023 is estimated at 0.743, which is lower compared to 2024, where it reaches 0.882.

This difference is reasonable considering that the HSR began operations at the end of 2023, so the measured annual effect for that year is relatively small. Conversely, in 2024, the HSR operated for the entire year, resulting in a larger impact. Therefore, the 2024 estimate more closely approximates the coefficient value in the main model, which largely captures the full effect of HSR operations. This also explains why the aggregate coefficient over the full period (0.780) is slightly lower, as it includes the partial impact from the year 2023.

Figure 4: Event-Study Analysis of All Sample



Source: Processed data output (STATA 19)

Based on the various specifications employed in this study, the evidence provides strong support that the HSR has contributed to an increase in local economic activities as reflected by night time light intensity. NTL provides a useful proxy for local economic activity, offering an objective measure that can capture spatial variations down to the smallest administrative units. However, while NTL is highly effective in capturing overall economic dynamics, it remains limited in explaining the specific type of these activities, such as whether the observed growth is concentrated in certain subsectors or which groups of individuals benefit the most from the presence of HSR.

Discussion

The empirical findings indicate that the operation of the HSR generates a statistically significant positive effect on local economic activity, as proxied by nighttime light intensity. This positive impact is consistent with previous studies documenting the growth-enhancing effects of HSR (Ahlfeldt and Feddersen, 2018; Carbo et al., 2019; Zheng et al., 2019; Cascetta et al., 2020; Du et al., 2021; Yu, 2021; Huang et al., 2024; Yoo et al., 2024; Zheng et al., 2025).

In interpreting this finding, it is important to consider what the observed increase in nighttime light represents. In the context of transport infrastructure, increases in nighttime light may reflect greater illumination from stations, supporting facilities, roads, commercial buildings, newly established businesses, and other built-up areas accompanying local economic development and activity. The emergence and expansion of businesses around HSR stations, together with increased activity in commercial and built-up areas, may increase nighttime lighting through greater use of buildings, roads, and supporting infrastructure. Thus, increases in lighting from roads, buildings, and other facilities should be understood not merely as physical changes in the built environment, but also as manifestations of increased local economic activity and development.

The temporal pattern of the estimated effect provides further insight into the economic response to HSR operation. Notably, the effect emerges immediately following the commencement of operations, suggesting that the economic response does not require a prolonged adjustment period. This immediate response aligns with the findings of Dong et al. (2021), Niu et al. (2021), and Zheng et al. (2025), who report that improvements in transport accessibility can be rapidly capitalized into local economic activity.

Beyond the temporal dimension, the findings also reveal a spatial gradient in the magnitude of the impact. The positive effect is strongest in villages and urban wards located closer to HSR stations and gradually diminishes as distance increases. This pattern indicates that the benefits of improved accessibility are highly localized and concentrated within the station catchment area. The presence of a distance-decay effect is consistent with agglomeration mechanisms, whereby superior access to the station stimulates more intensive trade, service provision, and consumption activities in nearby areas. These results underscore the critical role of spatial proximity in shaping the distribution of economic benefits arising from large-scale transport infrastructure development.

The observed spatial concentration of effects may also reflect differences in the characteristics of individual station areas. Although this study estimates the average effect of HSR operation across stations, the underlying economic mechanisms may vary depending on the characteristics of individual station areas. Stations located in highly urbanized areas may primarily enhance metropolitan accessibility and business connectivity, whereas those situated in developing suburban areas may stimulate residential and commercial development, the expansion of micro and small enterprises, and mixed-use land development. Similarly, stations serving industrial areas may generate economic benefits through improved logistics efficiency and greater labor mobility. These differences suggest that the estimated average effect should be interpreted as an aggregate effect across station areas with distinct economic and spatial characteristics, rather than as evidence of a uniform mechanism operating across all stations.

Several mechanisms may explain how improved accessibility translates into higher local economic activity. The operation of HSR can enhance regional connectivity and accessibility by reducing travel time and transportation costs between cities. Improved accessibility facilitates the movement of workers, capital, and goods, potentially increasing commuting and labor mobility across regions. As accessibility improves, areas surrounding HSR stations may become more attractive for residential, commercial, and business activities, potentially facilitating transit-oriented development around HSR stations and generating and reinforcing investment in the surrounding areas. These changes can further promote economic agglomeration, as firms and businesses tend to benefit from locations that provide better access to markets, labor, and economic networks. The resulting concentration of activities around stations may intensify land use and contribute to higher levels of local economic activity reflected in nighttime light intensity.

Improved connectivity may also increase the flow of visitors and consumers between major cities, creating opportunities for trade, services, and tourism in areas surrounding HSR stations. The Whoosh service itself may further contribute to this process as a new transportation experience and a distinctive feature of Indonesia's emerging HSR network. These changes can stimulate demand for commercial activities and supporting services, while improved accessibility may also increase incentives for property and land development around station areas. Taken together, greater mobility, agglomeration, tourism, and supporting investment provide plausible channels through which HSR operation can contribute to the observed increase in local economic activity.

A potential concern is that the increase in economic activity around HSR stations may partly reflect the relocation of existing economic activity from nearby areas rather than the creation of new activity. If such displacement were substantial, the estimated effect could be overstated when nearby areas are used as the control group. However, the descriptive trends in nighttime light intensity show that NTL increased over time in both the treatment and control groups, rather than increasing in the treatment group while declining in the control group. Moreover, the robustness analysis using PSM-DID employs comparable villages drawn from a broader geographic area across Indonesia rather than from the areas immediately surrounding HSR stations. The persistence of positive and statistically significant estimates under this alternative specification indicate that displacement of economic activity from nearby control areas to the treatment areas is unlikely to be a major driver of the main findings.

These interpretations should be considered alongside the limitations of using NTL as a measure of local economic activity. Although NTL provides a useful proxy for local economic activity and provides an objective measure that can capture spatial variations down to the smallest administrative units, it also has important limitations. NTL cannot explain the specific nature of these activities, such as whether the observed growth is concentrated in certain subsectors or which groups of individuals benefit the most from the presence of HSR. Although provincial and regency level GDP data provide useful macroeconomic context as additional indicator, the availability of GDP only at the regency level and the relatively small number of high-speed rail stations limit the statistical power and granularity of causal inference at the local level. In addition, NTL may not fully capture changes in asset values, such as increases in land and property prices around HSR stations, which may represent an important indirect economic benefit of large-scale transport infrastructure projects.

Another limitation is that the study cannot establish with certainty whether the increase in economic activity around HSR stations represents newly generated activity or the relocation of existing activities from more distant regions outside the study area. The analysis focuses on economic changes within and around the station areas and does not track the origin or relocation of individual firms, investments, or economic activities across regions. Addressing this issue would require longitudinal establishment- or firm-level data that can identify changes in the location of economic activities over time.

CONCLUSION

The results of this study indicate that the operations of a High-Speed Rail station significantly stimulates economic activity in its surrounding areas, as evidenced by an increase in night-time light intensity. The main estimation, using a treatment radius of 0–5 km, shows that the HSR increases night-time light intensity by 0.854 nW/cm²/sr, corresponding to approximately a 4.4% increase relative to the average NTL of villages/urban ward within that radius. Parallel trends tests conducted through visual comparison, trend test, and event study analysis, confirm that there were no significant pre-treatment trend differences, thereby supporting a causal interpretation of the findings. These results are demonstrated to be robust through several robustness tests.

The distance variation analysis reveals that the HSR effect is strongest in areas closest to the station, particularly within a 0–3 km radius, with an estimated coefficient of 1.781. The impact diminishes beyond 6 km and becomes statistically insignificant within the 6–8 km radius, demonstrating a spatial gradient consistent with agglomeration effects.

Although NTL provides a useful proxy for local economic activity and provides an objective measure that can capture spatial variations down to the smallest administrative units, it also has important limitations. Future research should therefore combine night time light with additional "high resolution" proxies. Micro-level economic data that could potentially be utilized to complement night time light analysis are available from the Economic Census, which covers detailed business activities before and after the operations of the HSR. However, since the Economic Census is conducted only once every ten years, researchers will need to wait at least until the implementation of the 2026 round before these data can be incorporated into empirical analysis.

Future research could extend the analysis to additional HSR stations as new stations become operational or as more data become available. The inclusion of stations with different operation dates would introduce variation in treatment timing and allow future studies to examine heterogeneous effects across different exposure periods. Such variation should be addressed using appropriate DiD estimators that account for treatment-timing heterogeneity (Callaway and Sant'Anna, 2021).

The findings of this study carry several important policy implications for the government. First, while the evidence suggests that HSR can enhance economic activity in surrounding regions as measured by night-time light, future plans to develop new HSR corridors in strategic areas should still be approached with careful consideration. In particular, locating stations in areas outside the existing city center, yet still easily accessible and in close proximity to it, has the potential to foster the emergence of new economic hubs and promote a more balanced distribution of economic activity within the regency or municipality. Nevertheless, policymakers are advised to complement evidence from night-time light with other socioeconomic indicators before formulating comprehensive development strategies. Second, transportation connectivity to and from the stations should be strengthened, particularly for areas beyond the 3 km radius, to facilitate a more equitable diffusion of economic benefits. Third, the government is advised to proactively amplify the economic impact of HSR by attracting investment around the stations. Given that the greatest benefits concentrate in the immediate vicinity, intensive outreach to domestic and international investors about the business potential in these areas is warranted. Efforts can be focused on sectors such as trade, services, tourism, logistics, and real estate that are closely linked to rapid transit access. In doing so, areas surrounding the stations can evolve into sustainable new economic centers, reinforcing the positive effects of the HSR and ensuring that its benefits extend broadly throughout society.

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