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ANALYSIS OF THE IMPACT OF RAILWAY STATION DEVELOPMENT POLICIES ON LOCAL AIR POLLUTION CONCENTRATIONS: PROPESINTY SCORE MATCHING (PSM) ESTIMATES USING IFLS-5 DATA

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Abstract

Railway infrastructure development is often hailed as an environmentally friendly transportation mode; however, the presence of stations may trigger economic activity agglomerations that potentially increase local air pollution. This study aims to evaluate the causal impact of train stations on air pollution levels while controlling for confounding variables such as industrial activity and rainfall intensity. Utilizing data from 534 territorial observations, this research employs Propensity Score Matching (PSM) to address selection bias and establish a balanced counterfactual framework. Baseline estimation results indicate that the presence of train stations does not have a statistically significant effect on air pollution levels (ATE=0.009; p=0.564). These findings remain robust across various sensitivity analyses, including the Average Treatment Effect on the Treated (ATET; p=0.189), heteroscedasticity correction via hetprobit (p=0.769), and k-nearest neighbor matching (n=4; p=0.498). Covariate balance tests demonstrate superior matching quality, with a Mean Bias of 3.5% and a Pseudo R2 of 0.000 post-matching. This study concludes that train stations are environmentally neutral regarding regional air quality, suggesting that emissions from activity clusters around stations may be offset by the efficiency of mass transit.

Keywords: Train Station, Air Pollution, Propensity Score Matching, Regional Econometrics, Transportation Infrastructure.

INTRODUCTION

Background

The availability of adequate transportation facilities is critical for the rapid growth of regional economies. The expansion of railway networks in developing countries is considered a strategic tool for logistical efficiency, accessibility and integration between growth centers (Zheng et al., 2019). However, the development of transportation nodes such as railway stations often presents a dilemma with respect to negative environmental externalities, in particular, the deterioration of air quality.

Theoretically, railway transportation is a lower-emission alternative compared to road-based transport (Lalive et al., 2018). In urban reality, however, stations frequently act as catalysts for the agglomeration of economic activities and an increase in the volume of feeder vehicles in surrounding areas. This dynamic risks creating pollution concentration points (hotspots) along station corridors.

There is a methodological problem of selection bias in the assessment of the environmental impacts of such infrastructure. Railway stations are usually located in areas with some characteristics that are inherently different from those without railway stations, e.g., more advanced stages of industrialization, or certain climatic conditions. Direct comparisons of areas without controlling for these variables will yield inaccurate impact estimates (Rosenbaum & Rubin, 1983).

As a solution, this study applies the Propensity Score Matching (PSM) method to construct a balanced counterfactual condition. Through PSM, areas with railway stations will be matched with control areas that share similar characteristics in terms of industrial activity and rainfall levels. This approach enables researchers to precisely isolate the pure causal effect of station presence on fluctuations in air pollution. This section contains the research background, objectives, contributions (research benefits from theoretical and practical), novelty should be explicitly written, research results and implications (Practical advice based on research results). Contains the background, research objectives and scope of discussion.

Research Problem

Railway infrastructure is anticipated to generate sustainable mobility. Yet, empirical evidence of its air quality implications remains unresolved Train operations are often blamed for high pollution levels near stations, but essential confounders such as industrial density and precipitation patterns are often ignored. This study therefore addresses two major questions:

1. Does proximity to a railway station increase local air pollution concentrations controlling for industrial and climatic confounders?
2. How sensitive are these results to alternative estimation strategies, such as ATET and heteroskedasticity consistent specifications?

Objectives and Benefits

Objectives

1. To empirically analyze the impact of the presence of train stations on air pollution levels in various regions while controlling for confounding variables (covariates) such as industrial activity and rainfall.
2. To apply the Propensity Score Matching (PSM) method to create comparable conditions between regions with train stations (treatment group) and regions without train stations (control group).
3. Ensuring the consistency of research results through various robustness checks, including estimates of the Average Treatment Effect on the Treated (ATET), heteroskedasticity correction, and variations in the number of matches (k-nearest neighbor matching).

Benefits

1. **Academic (Theoretical) Benefits**
   This study contributes to the development of regional econometrics, particularly in:
   a. The use of the Propensity Score Matching (PSM) method for analyzing the impact of policies/infrastructure.
   b. Empirical evidence that transportation infrastructure does not always have a significant impact on the environment, thereby enriching the literature on transportation externalities.
2. **Practical Benefits**
   a. For governments and regional planners:
   This provides empirical evidence that the presence of train stations tends to have a neutral impact on air pollution, meaning that rail-based transportation policies can still be considered as a mobility solution without significant concerns about increased pollution.
   b. For the transportation and environmental sectors:
   Serves as a basis for evaluation that increased pollution around stations is likely more influenced by supporting activities (feeder services, economic agglomeration) rather than solely from train operations themselves.

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3. **Methodological Benefits**
   a. Demonstrates the importance of using methods capable of addressing selection bias in observational research.
   b. Provides an example of applying covariate balance tests and robustness checks as robust analytical standards in econometric research.
4. **Policy Benefits**
   a. Provides evidence-based recommendations that the construction of train stations does not automatically worsen air quality.
   b. Serves as a basis for policymakers to focus more on controlling other sources of pollution, such as industry and feeder vehicles around station areas.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

Theoretical Framework

Causal Inference & Public Policy

Causal inference is the primary framework for evaluating policy impacts. In the context of transportation policy, its main objective is to isolate the net effect of government interventions on air quality. Evaluations cannot rely solely on comparisons of average reductions in pollution, as changes in air quality are influenced by various external factors such as meteorological conditions, seasonal fluctuations in economic activity, and changes in public behavior (Imbens & Rubin, 2015). Therefore, addressing this issue requires a methodology capable of demonstrating that changes in the outcome variable are truly caused by the policy (treatment), rather than other factors.

Counterfactual Air Pollution

In this problem, each observation unit whether an individual or a region in the IFLS has two potential outcomes. This is addressed through the Potential Outcomes framework pioneered by Donald Rubin, also known as the Rubin Causal Model (RCM). Within this framework, causality is understood as the comparison between the outcomes that actually occurred and the outcomes that should have occurred but were not observed.

Each observation unit i (an individual or household in the IFLS data) has two potential outcomes related to the status of transportation policy. The variable Di is defined as a treatment assignment indicator, where Di = 1 indicates that the unit is located in an area or under conditions exposed to a specific transportation policy, and Di = 0 indicates conditions without policy exposure. Based on this framework, there are two potential outcome values:

Yi (1): The level of air pollution exposure or respiratory health indicator for individual i when exposed to the transportation policy intervention.

Yi (1): The level of pollution exposure or health condition of the same individual (i) at the same time, assuming the transportation policy had never been implemented (Counterfactual).

$$\Delta i = Yi\ (1) - Yi\ (0)$$

i The causal effect of the transportation policy on individual i is the difference between the two potential outcomes. The unobserved value is referred to as the counterfactual condition. Propensity Score Matching (PSM) is used to construct this counterfactual condition by creating “shadow individuals” or matched controls that have socio-economic, demographic, and geographic characteristics very similar to those of individuals in the treatment group (Morgan & Winship, 2014).

Selection Bias in Transportation

Selection bias may arise because individuals living in areas that implement specific transportation policies such as emission restrictions or mass transit infrastructure development typically have systematically different socioeconomic statuses and environmental characteristics. Residents in city centers may have better access to transportation but are exposed to higher levels of pollution compared to rural residents. Without controlling for socioeconomic and geographic variables, the observed differences in air quality will result in biased impact estimates.

Propensity Score Matching (PSM)

Definition of Propensity Score Matching

Propensity Score Matching (PSM) is a statistical method used to match study participants based on their likelihood (propensity) of being exposed to a specific factor. PSM helps create a comparison group that is equivalent in terms of baseline characteristics, thereby enabling a more accurate comparison between the exposed and unexposed groups. The propensity score ($P(X)$) is defined as the probability that an individual will be exposed to the impact of a transportation policy based on initial characteristics (covariates): $P(X) = Pr(D = 1 \mid X)$, where the variable X includes data from the IFLS such as income level, asset ownership (vehicles), age, and geographic location (urban/rural).

Key Assumptions

Key assumptions for an estimation

1. Conditional Independence Assumption (CIA): It is assumed that, after controlling for variable X, the assignment to treatment is independent (random) of the potential outcome.
2. Common Support (Overlap): There must be an overlap in the distribution of propensity scores between the treatment and control groups to ensure that every individual has a matching counterpart. Both assumptions can be considered valid and suitable for publication if both are met (Caliendo & Kopeinig, 2008).

Impact Estimation: ATT (Average Treatment Effect on the Treated) and Pollution Policy Mechanisms

ATT (Average Treatment Effect on the Treated)

In transportation policy evaluation, the most relevant parameter to measure is the Average Treatment Effect on the Treated (ATT). ATT estimates the average difference in outcomes for individuals who are actually exposed to the policy (the treatment group). Mathematically, ATT is defined as: $ATT = E[Y(1) - Y(0) \mid D=1]$, where $E[Y(1) - Y(0) \mid D=1]$ represents the average observed outcome in the group affected by the transportation policy. The main challenge in this estimation is the counterfactual condition, which describes what would have happened to the treatment group had the policy not been implemented.The Propensity Score Matching (PSM) method addresses this by using a control group with matched characteristics as a proxy for the counterfactual value (Caliendo & Kopeinig, 2008).

Policy Mechanisms for Pollution

The mechanisms through which transportation policies impact air quality in this study are explained via two main pathways:

1. Transportation Activity Change Pathway: Policies such as vehicle restrictions (e.g., odd-even restrictions), emissions taxes, or improved access to public transportation aim to alter public mobility behavior. A reduction in private vehicle use will directly reduce the volume of gas emissions.
2. Public Health Channel (IFLS Data): Since the Indonesia Family Life Survey (IFLS) data does not provide technical measurements of air pollutants at each household location, the impact mechanism is validated through respondents' self-reported respiratory health symptoms.

Existing Research

Numerous studies on the impact of public policies on environmental quality and health have been conducted using data from the Indonesia Family Life Survey (IFLS). The use of the Propensity Score Matching (PSM) method has become the standard in this literature to address issues of selection bias and endogeneity. The following are several key studies that underpin the theoretical framework of this research:

1. The Impact of Environmental Regulations in Developing Countries. In their study titled "Environmental Regulations, Air and Water Pollution, and Infant Mortality in Indonesia," Greenstone and Hanna (2014) evaluated clean air policies. Although they employed a broad quasi-experimental approach, this study demonstrated that transportation policies, such as

vehicle emissions testing, have a significant impact on reducing air pollutants in urban areas. This research serves as a crucial foundation for researchers to link macro-level regulations with micro-level health outcomes available in household surveys.
2. Evaluation of Transportation and Emission Policies. Gallego, Montero, and Salas (2013) evaluated vehicle restriction policies in several major cities through the study “The effect of transport policies on car use and air pollution.” They found that the effectiveness of policies depends heavily on public behavioral responses. The use of matching methods in similar studies allows researchers to control for vehicle owner characteristics, thereby isolating the pure impact of the policy on emission reductions from lifestyle factors.
3. Use of IFLS for Environmental Health. Suryadarma, Suryahadi, and Sumarto (2010), through a SMERU Research Institute study titled “The Effects of Environmental Quality on Child Health: Evidence from Indonesia,” utilized IFLS data to examine the relationship between environmental quality and children’s health. They demonstrated that respiratory health indicators in the IFLS, such as coughing and shortness of breath, constitute valid data for measuring exposure to air pollution at the local level. This provides strong justification for using health variables from the IFLS as dependent variables in studies of the impact of transportation policies.
4. Validation of the PSM Method Using IFLS Data: Johar (2009), in his article “The Impact of the Indonesian Health Card Program: A Matching Estimator Approach,” demonstrated the effectiveness of PSM in correcting biases in IFLS data. Johar showed that individuals receiving government assistance often have initial characteristics that are significantly different from those of the control group. This study serves as the primary methodological reference in this research regarding how to perform proper matching using the socio economic variables available in the IFLS module.
5. The Relationship Between Outdoor Air Pollution and Respiratory Diseases. Hidayat and Adiatma (2018) specifically linked exposure to outdoor air pollution with the prevalence of lung diseases in Indonesia. Using a causal framework, the researchers found that residents living near dense transportation infrastructure face a higher risk of respiratory disorders. This study supports the transmission mechanism employed in this research, namely that transportation policies successfully reducing vehicle volume will directly improve respondents’ respiratory health indicators.

RESEARCH METHODS

Type of Research

This study employs a quantitative approach with an explanatory nature, focusing on testing causal relationships. To evaluate the impact of the presence of train stations on air pollution, this study applies the Propensity Score Matching (PSM) method. The selection of the PSM method aims to address the issue of selection bias that frequently arises in observational data, where areas with railway stations tend to have different inherent characteristics compared to areas without stations. Using PSM, this study is able to construct a balanced counterfactual condition, thereby allowing the pure impact of transportation infrastructure to be estimated more accurately.

Data Sources

The data used in this study are secondary data comprising a total of 534 regional observations. These data include 91 observations for the treatment group and 443 observations for the control group. This dataset combines indicators of pollution levels, the presence of stations, and other confounding variables such as industrial activity and rainfall.

Research Variables

In this study, the variables used can be divided into three main types, namely:
1. Dependent Variable (X)

The dependent variable in this study is the level of air pollution, which reflects air quality in each region.

2. Independent Variable (Treatment Variable)
   The primary variable of focus in this study is the presence of a train station. This variable is a dummy variable, defined as follows:
   a. A value of 1 indicates a region with a train station
   b. A value of 0 indicates a region without a train station
3. Control Variables (Covariates)
   To reduce bias in the estimates, several control variables are used, namely:
   a. Industry, describing the level of industrial activity in a region
   b. Rainfall, indicating the intensity of rainfall

These control variables are used in the matching process to ensure that the comparison between the treatment and control groups is conducted under relatively similar conditions.

Estimation Model

In this study, an impact analysis to determine the estimation model for the effects of transportation policies on air pollution was conducted using the Propensity Score Matching (PSM) approach to address this issue. The estimation steps were as follows:

1. Propensity Score Estimation: The initial step involves predicting the probability that a region is exposed to a policy using a Logit/Probit regression model. The independent variables used are "rainfall" and "industrialization" levels as control factors.
2. Matching Algorithm: After the scores are obtained, matching between the policy and control groups is performed using the Nearest Neighbor algorithm. This is done to find comparison pairs with the most identical environmental characteristics.
3. Balancing Test: An evaluation is conducted to ensure that, following the matching process, there are no longer any significant differences in the "industrial" and "rainfall" variables between the two groups. This ensures that comparisons of pollution levels are made on an equal footing.
4. ATET Estimation: The final step is to calculate the Average Treatment Effect on the Treated (ATET) to assess the net impact of the policy on air pollution in the policy's target area.

Software

This study uses STATA and R software to ensure the validity and reliability of the results from the data used:

1. STATA: Used as the primary tool for processing IFLS data. The main commands used are "teffects psmatch," "psmatch2," and "pstest"
   a. "teffects psmatch": As the primary command to estimate the policy's impact on the "pollution" variable based on the probability determined by the "industrial" and "rainfall" variables. This command is also used to generate ATT values, which serve as the primary indicator of the success of transportation policies.
   b. "psmatch2": Used for a more in-depth and flexible matching analysis. This command generates comparison tables between the Treated and Control groups under both unmatched and ATET conditions. It automatically provides information on the common support status to ensure sample validity.
   c. "pstest": As a matching procedure to evaluate whether the "industrial" and "rainfall" variables are balanced. Based on the "pstest" table, this command reports the Standardized Bias and Variance Ratio to ensure there are no systematic differences between the policy and control groups.
2. R: Used as a robustness check via the MatchIt package. The use of R aims to verify the consistency of the estimation results obtained from STATA, particularly in the visual inspection of the propensity score distribution. It is used for the visual inspection of the propensity score distribution to ensure the quality of overlap between observation groups in greater detail.

RESULTS AND DISCUSSION

Result

Table 1. Descriptive Statistical Analysis

Variable	Descriptive Statistic			
	Obs	Mean	Std. Error	Std. Dev
Variable Control (0)	443	0,323	0,0060923	0,1282277
Variable Treatment (1)	91	0,334	0,0138805	0,1324118
Difference		-0,011	0,014807	

Source: Processed by the author, 2026

This study used a total of 534 observations, consisting of 443 observations for the control variables and 91 observations for the treatment variables. The train variable is a dummy variable indicating the presence of a railway station in the study area, where a value of 0 represents an area without a railway station (control variable) and a value of 1 represents an area with a railway station (treatment variable).

Based on the results of the descriptive statistical tests above, the mean for the control variable group is 0.323, while for the treatment variable group it is 0.334. This indicates that the mean value in areas with a railway station is slightly higher than in areas without a railway station. The difference in means between the two groups is -0.011, so the Propensity Score Matching (PSM) method is required to control for potential selection bias and ensure a valid comparison between the two groups.

Table 2. Propensity Score Matching (PSM) estimation

Variable	Descriptive Statistic			
	Coeff	Std. Error	p-value	Conf. Interval
ATE train (1 vs 0)	0,0094139	0,01632	0,564	-0,0225727 – 0,0414006

Source: Processed by the author, 2026

Based on the estimation results, the ATE coefficient was obtained at 0,0094139 with a Std. Error of 0,01632, indicating that after the matching process, the mean in the treatment group was 0,0094139 higher than that in the control group. The p-value is 0,564 (p > 0,05) indicating that the difference between the two groups is not statistically significant, as evidenced by the confidence interval ranging from -0,0225727 to 0,0414006.

Table 3. Matching Quality Test (Balancing Test)

Variable	Descriptive Statistic				
	Coeff	Std. Error	p-value	Prob > chi^2	Pseudo R^2
Industrial	-0,0511447	0,3272925	0,876	0,8769	0,0005
Rainfall	-0,0001083	0,0002184	0,620	0,8769	0,0005

Source: Processed by the author, 2026

Based on the estimation results, the Prob > Chi^2 value is 0,8769 (p > 0,05), indicating that overall, the model used is not statistically significant. The Pseudo R^2 value is 0,0005, indicating that the covariate variables are barely able to distinguish the control group from the treatment group after the matching process. This means that the smaller the Pseudo R^2 value, the more successful the matching process is considered to be. The coefficient values are -0,0511447 for the industrial variable and -0,0001083 for the rainfall variable. Both variables have negative coefficient values, indicating that as the values of industrial and rainfall increase, the likelihood of a region being included in the treatment group actually decreases. The p-value for the industrial variable is 0,876 and for the rainfall variable is 0,620 (p > 0,05), indicating that neither is statistically significant.

Table 4. ATT Estimation Results

Variable	Descriptive Statistic				
	Treated	Controls	Difference	Std. Error	T-Stat
Unamatched	0,334575762	0,322940195	0,011635567	0,14840652	0,78
ATT	0,334575762	0,321899434	0,012676328	0,020933967	0,61

Source: Processed by the author, 2026

Based on the estimation results following the matching process, the ATT value for the treatment group is 0.334575762, while for the control group it is 0.321899434. The difference in ATT between the two groups is 0.012676328, indicating a significant difference in values between the two groups after matching. Meanwhile, the standard error is 0.020933967, indicating that the estimated difference after matching still exhibits significant variation. The T-stat value is 0.61, indicating that there is no significant difference between the two groups. This difference in values before and after matching occurs because the matching process adjusts for the characteristics between the treatment and control variable groups, resulting in a more controlled comparison.

Table 5. Covariate Balance Test

Variable	Descriptive Statistic					
	% Bias	p-value	V(T)/V(C)	Mean Bias	Pseudo R^2	B and R
Industrial	-5,3 (matched)	0,734	1,01	3,5	0,000	5,2 and 0,96
Rainfall	1,7 (matched)	0.0,0908	0,92	3,5	0,000	5,2 and 0,96

Source: Processed by the author, 2026

Based on the results of the covariate balance test, the percentage bias after matching for the industrial variable was -5,3% and for the rainfall variable was 1,7%. Both values are below 10% (0,1) and close to zero, indicating that the control and treatment variables are balanced. Furthermore, the p-value for the industrial variable is 0,734 and for the rainfall variable is 0,908 ($p > 0,05$), indicating that after matching, there is no significant difference between the control and treatment variables. The variance ratio V(T)/V(C) for the industrial variable is 1,01 and for the rainfall variable is 0,92, both fall within the range of 0,5 to 2,0, indicating that the data distribution between the treatment and control groups is relatively equivalent after matching, so there is no significant difference in variance.

Overall, the mean bias value of 3,5 indicates that the level of difference between the control and treatment variables is low. Additionally, the Pseudo R^2 value of 0,000 indicates that after matching, the differences in characteristics between the two groups have become smaller. The B value of 5,2 (B < 25%) and the R value of 0,96 (0,5 < 0,96 < 2) indicate that after the matching process, the data met the criteria for balance.

Table 6. Average Treatment Effect on the Treated (ATET)

Pollution	Descriptive Statistic			
	Coeff	Std. Error	p-value	Conf. Interval
Train (1 vs 0)	0,0274454	0,0208762	0,189	-0,0134711 – 0,0683619

Source: Processed by the author, 2026

Based on the estimation results, an ATET value of 0.0274454 was obtained, indicating that the treatment group had a pollution level approximately 0.0274454 higher than the control group after the matching process. The standard error of 0.0208762 reflects the level of uncertainty in this estimate. The p-value of 0.189 ($p > 0.05$) indicates that there is no statistically significant difference, as evidenced by the confidence interval ranging from -0.0134711 to 0.0683619.

Table 7. HETPROBIT

Pollution	Descriptive Statistic			
	Coeff	Std. Error	p-value	Conf. Interval
Train (1 vs 0)	0,0037515	0,0012758	0,769	-0,0212538 - 0,0287568

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Source: Processed by the author, 2026

The results of the heteroskedastic probit estimation show that the ATE coefficient is 0.0037515, indicating that the treatment group has a pollution level that is 0.0037515 higher than that of the control group. The standard error of 0.0012758 reflects the uncertainty of this estimate. The p-value of approximately 0.769 indicates that there is no statistically significant difference, as evidenced by the confidence interval ranging from -0.0212538 to 0.0287568.

Table 8. K-Nearest Neighbors

Pollution	**Descriptive Statistic**			
	Coeff	**Std. Error**	**p-value**	**Conf. Interval**
Train (1 vs 0)	0,0101482	0,0149836	0,498	-0,019219 - 0,0395155

Source: Processed by the author, 2026

Based on the estimation results, an ATE coefficient of 0.0101482 was obtained, indicating that the treatment group had a pollution value 0.0101482 higher than that of the control group. The standard error of 0.0149836 reflects the level of uncertainty in this estimation. The p-value of

0.498 indicates that this difference is not statistically significant, as evidenced by the confidence interval ranging from -0.019219 to 0.0395155.

Discussion

Analysis of the Impact of the Station on Pollution

Based on the Propensity Score Matching (PSM) estimation results, the presence of a train station is positively associated with pollution levels. This is evident from the Average Treatment Effect (ATE) coefficient value of 0.0094139, which indicates that areas with train stations tend to have pollution levels 0.009 higher compared to areas without stations after the matching process. Additionally, in estimating the Average Treatment Effect on the Treated (ATET), a larger coefficient of 0.0274454 was obtained, indicating that in areas with train stations, pollution levels tend to be higher than under the hypothetical condition in which the area did not have a station.

However, all the estimation results indicate that the generated influence is not statistically significant. This is indicated by the p-value of the ATE estimate being 0.564 and the ATET estimate being 0.189, both of which are greater than the 5 percent significance level (0.05). Additionally, the 95% confidence interval for each model also includes the value zero, such as the ATE estimate which ranges from -0.0225727 to 0.0414006. This condition indicates that statistically, there is not enough strong evidence to state that the presence of train stations truly affects the level of pollution.

These findings are also consistent with the initial analysis at the pre-matching stage, where the average pollution level in areas with train stations was 0.334, slightly higher than in areas without stations at 0.323, with a difference of -0.0116. However, the results of the statistical test indicate that the difference is not significant, thus reinforcing the conclusion that overall, the presence of train stations does not have a significant impact on pollution levels in the context of the data used.

Analysis of Insignificant Causes

The lack of a significant influence between the presence of a train station and pollution levels may be caused by several interrelated factors. First, air pollution in a region is likely more influenced by other sectors that have a greater contribution, especially the industrial sector. In the model used, the industrial variable was indeed included as a covariate, but the estimation results showed that this variable is not statistically significant, with a p-value of 0.876. This may indicate that the variation in pollution levels between regions is not fully explained by the variables used in the model, suggesting that other, more dominant factors may not have been accommodated in the analysis.

Second, the presence of train stations does not directly cause changes in the transportation behavior of the community. Although theoretically, mass transportation such as trains can reduce the use of private vehicles, in practice, the community still relies on motor vehicles for daily mobility

(Shirley & Gecan, 2022). This causes the emission levels from the road transport sector to remain high and not experience significant reductions despite the presence of alternative transportation in the form of trains.

Third, the characteristics of the train transportation mode itself also need to be considered. If the railroad system used has a high level of efficiency or employs relatively more environmentally friendly technology, then its contribution to the increase in pollution becomes very small (Nurokhman et al., 2025). This can explain why the obtained coefficient values are relatively small, such as the ATE estimate of 0.0094139 and the even smaller hetprobit model value of 0.0037515. In addition, the limitations of variables in the model can also affect the estimation results. Other variables that could potentially affect pollution levels, such as population density, the number of motor vehicles, the level of urbanization, and economic activity, are not included in the model, which could lead to bias due to unobserved variables. This also explains why the pseudo R^2 value in the model is very small, at 0.0005 before matching and approaching 0.000 after matching, indicating that the model's ability to explain data variation is relatively low.

Policy Implications

Based on research findings that show no significant impact between the presence of train stations and pollution levels, it can be concluded that the construction of train transport infrastructure alone is not sufficient to effectively reduce pollution levels. Therefore, a more comprehensive and integrated policy approach is needed.

First, the government needs to improve the integration of transportation modes, especially in the effort to transition the mobility patterns of the community. Without easy access to and from train stations, people tend to continue using private vehicles, making the potential for emission reduction less optimal. Second, pollution control policies need to be focused on sectors that have a greater contribution, such as the industrial sector. Considering that the differences in pollution levels between regions cannot be significantly explained by the presence of train stations, controlling industrial emissions thru stricter regulations and the implementation of environmentally friendly technologies becomes very important.

Third, policies are needed to encourage changes in public behavior, such as restricting the use of private vehicles, increasing the cost of using motor vehicles, or providing incentives for public transport users. Without policy interventions that encourage behavioral changes, the existence of transportation infrastructure will not have a significant impact on reducing pollution. Therefore, efforts to reduce pollution levels cannot solely rely on the development of transportation infrastructure but must be supported by integrated policies that simultaneously target various sources of emissions.

CONCLUSION

Based on the results of the analysis using the Propensity Score Matching (PSM) method on 534 regional observations, this study concludes that the presence of a train station does not have a statistically significant effect on air pollution levels. The estimated Average Treatment Effect (ATE) shows a very small positive coefficient, approximately 0.009, with a p-value of 0.564; thus, there is insufficient evidence to conclude that there is a difference in pollution levels between areas with and without railway stations. These results are supported by the Average Treatment Effect on the Treated (ATET) estimates and various robustness tests, including heteroscedasticity corrections via the hetprobit model and the k-nearest neighbor approach, which consistently indicate the insignificance of this effect.

The quality of the fitting process in the PSM method proved to be excellent, as evidenced by a Mean Bias of 3.5%, a Pseudo R^2 approaching zero, and a variance ratio within an acceptable range. This indicates that the characteristics between the treatment and control groups were balanced, so the resulting impact estimates can be considered reliable. Substantively, these findings suggest that train stations are neutral with regard to air quality, where the potential increase in emissions due to the agglomeration of economic activity around stations is likely offset by the environmental benefits of rail-based mass transit

Furthermore, the lack of statistical significance in the study's results also suggests that variations in air pollution levels are more heavily influenced by other factors not fully accounted for in the model, such as population density, the number of motor vehicles, the level of urbanization, and other economic activities. Thus, railway infrastructure development cannot be considered the sole determinant of changes in air quality, but rather as part of a broader and integrated transportation system within the dynamics of regional development.

Based on the research findings, several recommendations can be made for policy development and future research. First, for the government and regional planners, the construction of railway stations can continue as part of a sustainable transportation strategy, as it has been shown not to have a significant negative impact on air quality. However, to maximize environmental benefits, better transportation integration is needed, such as the provision of environmentally friendly feeder transportation systems and improved accessibility to stations to reduce the public's reliance on private vehicles.

Second, air pollution control policies should be more focused on sectors with higher emission contributions, particularly the industrial and road transport sectors. The implementation of stricter emission regulations, the use of cleaner production technologies, and the provision of incentives for the use of low-emission vehicles can serve as strategic steps toward improving air quality comprehensively.

Third, for future researchers, it is recommended to include additional variables that may influence air pollution levels, such as population density, the number of motor vehicles, the level of urbanization, energy consumption, and other meteorological conditions. The use of data with a longer time span or alternative econometric methods, such as Difference-in-Differences (DiD) or Instrumental Variables (IV), can also provide a more comprehensive understanding of the causal impact of transportation infrastructure on the environment.

Finally, increased public awareness and behavioral changes regarding the use of public transportation must continue to be encouraged through educational campaigns, the provision of incentives, and policies restricting private vehicles. Integrated efforts between infrastructure development, environmental regulations, and changes in public behavior are expected to create a transportation system that is not only efficient but also sustainable and environmentally friendly.

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