

The Impact of High-Speed Railway Infrastructure on Regional Economy

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Abstract: This paper explores the impact of China Railway High-speed (CRH) station construction on prefecture-level cities in terms of regional economic and spatial heterogeneity. Based on a generalized Difference-in-Differences (DID) model applied to panel data for 218 cities from 2008 to 2016, the study estimates the causal effects of CRH infrastructure on local GDP. To strengthen robustness by taking into consideration potential selection bias and heterogeneity of treatment effects, the Callaway and Sant'Anna Difference-in-Differences (CSDID) model is employed, utilizing staggered treatment timing and propensity-score re-weighting. A Difference-in-Difference-in-Differences (DDD) model is also used to explore how the distance to regional economic centers influences the economic impact of CRH stations. Results show that there are positive economic impacts of CRH construction, with GDP gains increasing over time. However, these economic gains are not evenly distributed, favoring cities located near regional economic centers. These findings point to the need for targeted regional policy to promote equitable economic development stemmed from high-speed rail construction.

Keywords: transportation economics, spatial economics, economic development

1. Introduction

Transportation infrastructure is essential to local growth and economic growth. Travel networks facilitate labor mobility, market expansion, and industrial agglomeration by enhancing communication, improving availability, and reducing vacation days. High-speed rail (HSR) has emerged as a transformative component of regional economic integration, providing a quicker and more effective alternative to conventional rail and road networks among these investments. HSR's economic impact is still debatable, with different opinions on whether it promotes healthy regional growth or worsens economic disparities between industrial and external areas.

China Railway High-speed (CRH), the nation's largest HSR network, has been a crucial component of China's Medium- and Long-Term Railway Network Plan, designed to integrate local economies by improving intercity connectivity. In contrast to standard road systems, which generally concentrate on freight transportation, CRH generally facilitates customer mobility, which has the potential to affect labor markets, strong productivity, and urbanization patterns. While some experiments suggest that HSR accelerates economic growth by fostering industrial development and industrial clusters, some raise issues that the benefits are concentrated in major metropolitan areas, leaving smaller cities disadvantaged.

This research seeks to provide a comprehensive empirical assessment of the financial impact of CRH place construction on prefecture-level cities in China. A generalized Difference-in-Differences (DID) model is used, which accounts for staggered treatment timing as CRH stations were introduced at various points in time, to estimate the causal effect of HSR infrastructure. However, to address concerns regarding treatment effect heterogeneity and local disparities, the analysis is extended with a Callaway & Sant'Anna Differences (CSDID) model, which improves counterfactual estimation by incorporating propensity score re-weighting and group-time specific ATT estimation. In order to determine whether CRH's economic effects vary depending on a city's distance from its regional center, this study introduces a Difference-in-Difference-in-Differences (DDD) model, which provides deeper insights into spatial heterogeneity in HSR-driven economic development.

This study makes a significant contribution to the literature on transportation economics and local development by using strong empirical data on the CRH's economic results with a panel dataset that spans the years 2008 to 2016. The findings provide important insights for policymakers on optimizing HSR opportunities to promote healthy provincial development and support discussing facilities in economic growth.

The structure of this paper is as follows. The literature on economic development and transportation infrastructure is reviewed in Section 2. Part 3 outlines the data and approach, describes the empirical strategies used in the analysis, and presents the key results. Section 4 discusses key findings, policy implications, and future research directions.

2. Literature Review

Many studies have discussed the topic of transportation economics, and one of the seminal works in this area is [1], which examined the relation between highway growth and vehicle kilometers travelled in the United States. Their findings establish the basic rules of road congestion, which state that increasing street capacity results in equal increases in traffic. Congestion levels remain unchanged. This finding emphasizes the need for careful planning in transportation investments to avoid unintended consequences.

Also, [2] investigated the role of transport costs in shaping urban growth patterns in Sub-Saharan Africa. The research found that cities with better connectivity to ports experienced faster economic growth using nighttime lights as a proxy for economic activity. This highlights the importance of integrating hinterland regions with major trade hubs to unlock their economic potential. Similarly, the World Bank emphasizes that transport costs are a significant barrier to trade and urban development in Sub-Saharan Africa, especially in regions with poor road and rail infrastructure.

[3] extended the analysis by focusing on the impacts of infrastructure projects in India and China. Their analysis revealed that the effects and mechanisms differed while both infrastructure investments promoted regional economic convergence. While China's more unified planning strategy resulted in broader economic gains, road and rail developments in India primarily benefit already-developed areas.

Railway infrastructure has also been a significant focus of academic inquiry. [4] provided a historical perspective by examining the impact of the U.S. railroads on agricultural markets. Their results demonstrated that railroads significantly reduced transport costs, expanded market access, and increased land values. Similarly, [5] analyzed the design and impacts of India Golden Quadrilateral highway network, comparing its outcomes to hypothetical alternative networks that prioritize intermediate cities. This study provided insight into how strategic network design can influence regional development patterns.

Another line of research emphasizes the part of travel in increasing labor mobility and performance. [6] emphasized the crucial role of urban transportation systems in promoting economic agglomeration and improving job opportunities in urban areas. Similarly, [7] examined how Asia's high-speed rail

systems improved economic connectivity, allowing areas to concentrate on their advantages and differences. [8] delved deeper into the position of high-speed rail in China, highlighting its revolutionary impact on prefecture-level cities through increased market access, urbanization, and labor mobility.

The impact of transportation infrastructure on modernization and industry has also received much attention. [9] discussed how import competition affects local labor markets in the United States. Their study focused on how trade and transportation affect economic outcomes, though not directly related to infrastructure. Also, [10] examined the relationship between immigration, railroads, and long-term economic growth in the United States during the Age of Mass Migration.

The impact of transportation infrastructure on modernization and industry has also received much attention. [9] discussed how import competition affects local labor markets in the United States. Their study focused on how trade and transportation affect economic outcomes, though not directly related to infrastructure. Also, [10] examined the relationship between immigration, railroads, and long-term economic growth in the United States during the Age of Mass Migration. More recently, [11] pointed out that China's transportation infrastructure investments can drive economic activity but require careful evaluation to ensure lasting benefits. Complementing this, [12] demonstrates that China's high-speed rail has fostered urban economic growth in connected cities.

These studies collectively highlight the diverse impacts of transportation infrastructure on economic outcomes across different contexts and regions. From reducing transport costs and improving market access to developing urbanization and handling regional inequalities, the current literature underscores the transformative potential of transportation investments. This review provides a foundation for understanding the broader context of infrastructure development and its economic implications, setting the stage for more focused investigations into specific systems such as the China Railway Highspeed, and the heterogeneous effects it might have.

3. Data Analytics

3.1. Data Descriptions

Table 1: Descriptive statistics.

Variable	Definition	Mean	Std. dev.
$GDP_{i,t}$	The Gross Domestic Product of city i in year t , measured in billion RMB.	208.2855	294.0392
$CRH_{i,t}$	A binary indicator representing whether city i has a CRH station at the beginning of year t .		
$Employment_{i,t}$	The total number of employed individuals in city i in year t , measured in thousands of persons.	1171.632	2078.742
$Population_{i,t}$	The total number of registered residents in city i in year t , measured in thousands of persons.	4494.945	3137.955
$Highway_{i,t}$	The total length of highways in city i in year t , measured in kilometers.	12433.84	9623.956
$Distance_i$	The geographical distance between city i and its regional center, measured in kilometers.	366.7447	291.0413
$region_i$	A dummy variable assigning city i to the regional cluster.		

Using data from the CEIC database, this study aims to examine the economic impact of China Railway Highspeed (CRH) station construction on prefecture-level cities in China. The dataset covers

a panel of 218 cities, spanning the years 2008 to 2016. Table 1 presents the descriptive statistics for the variables included in the analysis.

The dependent variable in the study is Gross Domestic Product (GDP), measured in billion RMB. The average GDP of cities in the sample is 208.29 billion RMB, with a major standard deviation of 294.04 billion RMB, indicating significant variation in economic output across cities. This reflects the different levels of economic development among prefecture-level cities, ranging from major urban centers with strong industrial bases to smaller cities with lower economic activity.

The primary independent variable, CRH, is a binary indicator indicating whether a city has a CRH station in a given year. As a key treatment variable, this variable allows for a comparison between cities with and without CRH stations for an analysis of the economic effects of high-speed rail connectivity. Since CRH stations were introduced at different times across cities, this variable facilitates a generalized difference-in-differences (DID) approach to assess their impact.

Among the control variables, Employment represents the total number of employed individuals in a city, measured in thousands of persons. The mean employment level is 1171.63 thousand, with a standard deviation of 2.08 million, suggesting a great variation in labor market size. Population, which captures the total number of registered residents, also shows substantial dispersion, with an average of 4.49 million people and a standard deviation of 3.14 million.

Highway infrastructure is included as a control variable to control for existing transportation networks. The average length of highways in the sample cities is 12,433.84 kilometers, with a standard deviation of 9,623.96 kilometers. This variation suggests that some cities have extensive road networks that could either complement or substitute for high-speed rail connectivity, potentially shaping the economic impact of CRH station construction.

Additionally, Distance measures the geographical distance between each city and its designated regional center. The ten regional centers (Beijing, Chengdu, Chongqing, Guangzhou, Hangzhou, Shanghai, Shenzhen, Tianjin, Wuhan and Xi'an) were selected based on their economic prominence, identified through GDP and administrative significance. The average distance from a city to its regional center is 366.74 kilometers, with a standard deviation of 291.04 kilometers. This variable is particularly relevant as the benefits of CRH station construction may depend on a city's proximity to its regional hub, influencing factors such as accessibility to economic opportunities and integration into regional markets.

Overall, these descriptive statistics provide insight into the economic and demographic diversity of the sample cities. While the dataset is not inflation-adjusted, the inclusion of year trends in the empirical analysis is expected to account for inflationary trends over time. The subsequent analysis will leverage these variables to estimate the causal effects of CRH station construction on economic growth.

3.2. Data Modeling

3.2.1. The Difference-in-Differences (DID) Model

To evaluate the economic impact of China Railway High-Speed (CRH) station construction on prefecture-level cities, this study uses a generalized Difference-in-Differences (DID) framework. This approach capitalizes on variations in treatment timing, given that CRH stations were built at different points in time across different cities. By comparing GDP trajectories before and after the construction of CRH stations in treated versus untreated cities, the DID model controls for both observed and unobserved, time-invariant city characteristics.

The sample of prefecture-level cities is organized into 10 geographical clusters, each centered around one of the most prosperous and advanced cities. Nearby cities are assigned to the cluster of the central city to which they are geographically closest. Throughout the analyses, standard errors are

clustered at the regional level, reflecting the idea that cities within the same geographical cluster may share correlated shocks and economic conditions.

The city fixed effects account for unobservable characteristics unique to each city, such as historical economic conditions, industrial composition, and geographic advantages. In addition, an interaction term between year and regional cluster dummies accounts for region-specific time trends, ensuring that heterogeneous macroeconomic shocks across different geographical regions do not bias the estimation.

The regression specification for the DID model is:

$$Y_{i,t} = \beta_0 + \beta_1 CRH_{i,t} + \beta_2 Employment_{i,t} + \beta_3 Population_{i,t} + \beta_4 Highway_{i,t} + \gamma_t \times region_i + \alpha_i + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ is the GDP of city i at time t . The term $CRH_{i,t}$ is a binary indicator equal to 1 if city i has a CRH station in year t . Employment ($Employment_{i,t}$) and population ($Population_{i,t}$) serve as control variables. Highway ($Highway_{i,t}$) measures the total length of highways in city i . γ_t represents year, and $region_i$ represents the region. Their interaction accounts for region-specific shocks in a given year. The term α_i denotes a city fixed effect, capturing time-invariant characteristics unique to each city. Finally, $\varepsilon_{i,t}$ is the error term, with standard errors clustered by the ten geographical clusters.

3.2.2. The Difference-in-Differences-in-Differences (DDD) Model

Difference-in-Differences-in-Differences (DDD) framework extends the conventional DID approach by addressing a critical limitation: the assumption of treatment effect homogeneity across spatial and contextual dimensions. While DID estimates the average effect of CRH station construction by comparing treated and untreated cities over time, it implicitly assumes that the economic impact of high-speed rail is uniform regardless of a city's geographical location. This assumption may misrepresent reality, as infrastructure investments often generate heterogeneous effects shaped by geographic, economic, or institutional factors. For example, cities closer to regional economic centers may benefit disproportionately from improved connectivity due to preexisting advantages, labor market integration, or spillovers from adjacent urban centers. On the other hand, peripheral cities might experience mitigated or delayed effects due to weaker economic linkages or infrastructure saturation. The DDD framework explicitly tests this spatial variation by incorporating distance from the regional center as a moderating factor. By interacting CRH treatment with a city's distance from its regional hub, the DDD model captures how geographic positioning mediates infrastructure's economic impact.

The regression specification formalizes this relationship:

$$Y_{i,t} = \beta_0 + \beta_1 CRH_{i,t} + \beta_2 CRH_{i,t} \times Distance_i + \beta_3 Employment_{i,t} + \beta_4 Population_{i,t} + \beta_5 Highway_{i,t} + \gamma_t \times region_{i,t} + \alpha_i + \varepsilon_{i,t} \quad (2)$$

In this equation, $Distance_i$ is the geographic distance of city i from its region's central city, while the interaction ($CRH_{i,t} \times Distance_i$) captures whether the effect of CRH on GDP varies with proximity to the cluster center. Other variables follow the definitions used in the DID model, with standard errors remaining clustered by geographical cluster to account for any within-cluster correlation over time. This DDD specification thus provides a more detailed assessment of whether infrastructure investments confer differential benefits based on each city's position within its regional cluster.

Methodologically, the DDD framework advances policy evaluation in two ways. First, it acknowledges that infrastructure investments operate within spatial and institutional contexts, where

unobserved factors (e.g., historical underinvestment in peripheries, latent demand near hubs) might bias average treatment effects. Second, it places emphasis on where and for whom CRH stations matter most, offering nuanced insights for infrastructure planning. Even if spatial heterogeneity proves statistically insignificant, the DDD model enhances causal inference by ensuring estimates account for infrastructure’s real-world impact.

3.3. Results and Analysis

3.3.1. Results of the DID Model

Table 2: DID results.

Variable	Coefficient	Std. Err.	t	p-value	95% Conf. Interval
CRH	17.70	6.20	2.86	0.019	[3.68, 31.73]
Employment	0.25	0.034	7.38	0.000	[0.18, 0.33]
Population	0.071	0.038	1.88	0.093	[-0.01, 0.16]
Highway	0.007	0.004	1.56	0.153	[-0.003, 0.017]

The results of the DID model are presented in Table 2 above.

Employment is a strong and significant predictor of GDP among the control variables, demonstrating how important labor supply is to economic growth. Population has a marginally significant effect, suggesting that while urban scale contributes to economic development, it may require complementary factors such as industrial expansion or infrastructure investment to maximize its impact. However, the relation between GDP and highway network is not statistically significant. This finding suggests that while highways facilitate regional transportation, their economic impact may be overshadowed by the transformative effects of CRH, which efficiently shorten long-distance travel time.

The DID model results indicate that CRH station construction is associated with a statistically significant increase in GDP. This finding suggests that high-speed rail connection improves economic activity by promoting greater flexibility, enabling market access, and attracting investment. The scale of the impact suggests that the construction of CRH stations contributes significantly to regional development, especially for cities integrated into the road network.

3.3.2. Counterfactual Analysis and CSDID

A fundamental challenge in evaluating the economic impact of CRH station construction is establishing a valid counterfactual—what would have happened in the absence of CRH? Since infrastructure investments are not randomly assigned, selection bias is a major concern. Traditional Difference-in-Differences (DID) models assume that treated and untreated units follow parallel trends, a crucial assumption that may not always hold in large-scale infrastructure projects where regional economic dynamics vary. Furthermore, standard DID models often fail to account for staggered treatment timing, which occurs when different cities receive CRH stations at different times. If not properly addressed, this can introduce bias by using already-treated units as part of the control group.

This study uses the Callaway & Sant’Anna Difference-in-Differences (CSDID) framework in [13] to address these concerns, which refines counterfactual estimation by adopting a more flexible and robust approach. Unlike conventional DID models, CSDID implements propensity score re-weighting, ensuring that only comparable untreated cities contribute to the counterfactual. By assigning weights to control observations based on their similarity to treated cities, CSDID prevents unfavorable “difference” by previously treated units and allows for more precise estimations of treatment effects. Instead of assuming a single, uniform effect, CSDID estimates group-time specific

average treatment effects on the treated (ATTs). This enables a clearer distinction between different treatment groups, capturing heterogeneous treatment effects across periods. Another key advantage of CSDID is its ability to measure dynamic treatment effects, illustrating how the economic benefits of CRH change over time rather than assuming a one-time and constant impact. This is especially important for infrastructure projects, where economic benefits may take years to be fully realized.

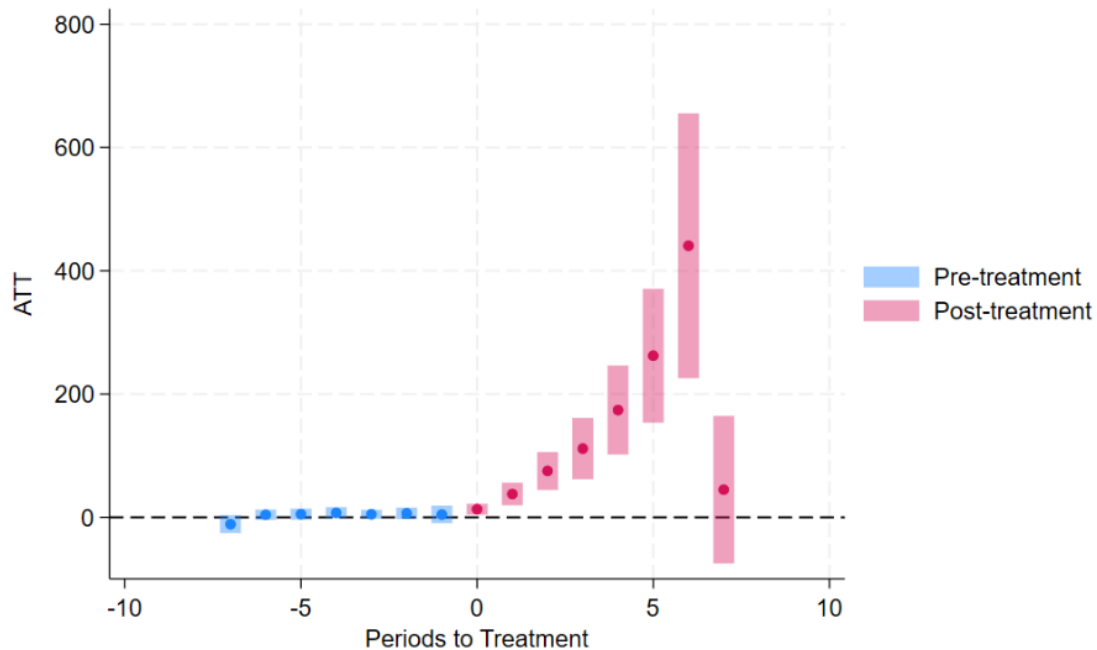


Figure 1: Average treatment effect on the treated (ATT) at different time periods.

The CSDID results validate the strength of our counterfactual approach. Figure 1 plots ATT at different time periods before and after CRH construction. The close-to-zero pre-treatment effects visually confirm that the control group follows a trend paralleling that of the treated group in the pre-treatment period, proving that the CRH construction has led to significant economic growth in cities under treatment. Statistical tests of pre-treatment differences (Table 3) further support this. The pre-treatment ATT estimate (3.16, $p = 0.341$) is statistically insignificant, indicating that treated and control cities exhibited similar economic trends prior to CRH station construction. This strengthens our assumption that any observed post-treatment differences in GDP are attributable to CRH, rather than existing growth disparities.

The post-treatment ATT estimates reveal gradual and sustained economic growth, peaking at 440.62 ($p < 0.001$) in Tp6, with the average treatment effect being 144.91 ($p < 0.001$). This suggests that the economic benefits of CRH accumulate over time, as cities become more and more integrated into the high-speed rail network. The initial effect is relatively modest (Tp0 = 13.08, $p = 0.004$), likely reflecting the time required for businesses, labor markets, and investment activity to adjust to the new transportation infrastructure.

The increase in the ATT coefficients over time is one crucial finding. The significant gains in Tp3-Tp6 align with expectations that high-speed rails foster economic development through various channels, including reduced transportation costs, enhanced labor mobility, and improved market access. This pattern suggests that CRH promotes long-term economic transformation.

The insignificance of Tp7 ($p = 0.463$) can be primarily attributed to data limitations rather than a real decline in economic benefits. Since fewer cities have seven years of post-treatment data, standard

errors increase, and statistical power is reduced. This does not mean that CRH's impact diminishes but rather that more extended post-treatment data is needed to accurately assess long-run effects.

By leveraging CSDID's staggered treatment framework, this study provides a more precise and credible estimation of the economic impact of CRH, addressing key concerns about selection bias and treatment effect heterogeneity.

Table 3: CSDID results.

	Coefficient	Std. Err.	z	P> z	95% Conf. Interval	
Pre_avg	3.1573	3.314008	0.95	0.341	-3.338036	9.652636
Post_avg	144.9131	33.86335	4.28	0.000	78.54212	211.284
Tm7	-11.10862	7.443167	-1.49	0.136	-25.69696	3.479715
Tm6	4.222796	4.277683	0.99	0.324	-4.161308	12.6069
Tm5	5.22652	4.572638	1.14	0.253	-3.735686	14.18873
Tm4	7.40249	4.645022	1.59	0.111	-1.701586	16.50657
Tm3	5.139057	3.630865	1.42	0.157	-1.977308	12.25542
Tm2	6.562537	4.694478	1.40	0.162	-2.638472	15.76355
Tm1	4.656325	7.262027	0.64	0.521	-9.576987	18.88964
Tp0	13.08207	4.485079	2.92	0.004	4.291473	21.87266
Tp1	37.84854	9.343575	4.05	0.000	19.53546	56.16161
Tp2	75.22833	15.67456	4.80	0.000	44.50675	105.9499
Tp3	111.4836	25.29673	4.41	0.000	61.90288	161.0642
Tp4	174.0267	36.83957	4.72	0.000	101.8225	246.231
Tp5	262.1811	55.41738	4.73	0.000	153.565	370.7971
Tp6	440.6242	109.5843	4.02	0.000	225.843	655.4055
Tp7	44.83004	61.06391	0.73	0.463	-74.85303	164.5131

3.3.3. Results of the DDD Model

Table 4: DDD results.

Variable	Coefficient	Std. Err.	t	p-value	95% Conf. Interval
CRH	45.01	14.88	3.03	0.014	[11.36, 78.67]
CRH x Distance	-0.066	0.029	-2.28	0.049	[-0.13, -0.0004]
Employment	0.24	0.03	7.08	0.000	[0.17, 0.32]
Population	0.083	0.039	2.17	0.058	[-0.004, 0.17]
Highway	0.007	0.005	1.21	0.256	[-0.006, 0.019]

The results of the DDD model are presented in Table 4 above.

The DDD model advances our understanding of CRH stations' economic impact by addressing geographical heterogeneity—a limitation inherent in the previous DID frameworks. The CRH coefficient rises from 15.85 in the DID model to 45.01 in the DDD model, a substantial increase that underlines the importance of accounting for geographic context. The results suggest that simpler DID models underestimate high-speed rail's true economic returns due to unobserved spatial confounders, such as historical underinvestment in peripheral cities. By explicitly modeling distance from regional centers, the DDD framework reveals that CRH stations drive GDP growth more powerfully than previously estimated.

The interaction term between CRH and distance is statistically significant (-0.066 , $p = 0.049$), indicating that the economic benefits of CRH stations decrease as the distance from regional centers increases. This finding supports the hypothesis that proximity to major economic hubs enhances the gains from high-speed rail infrastructure, likely due to stronger labor market integration, business agglomeration, and improved supply chain efficiency. Unlike previous results, where distance effects were ambiguous, the updated estimates suggest that while CRH stations generate substantial growth, their impact is spatially concentrated, favoring cities closer to regional economic centers.

These results also clarify the unique role of high-speed rail relative to other infrastructure. For example, highway investments remain statistically insignificant in influencing GDP (0.007 , $p = 0.256$), reinforcing the idea that reduced long-distance travel time, a hallmark of CRH, is essential to unlocking economic potential. In addition, this suggests that high-speed rail's economic effects, as opposed to traditional transport infrastructure, operate through distinct channels, such as fostering high-value service industries and facilitating workforce mobility at an intercity scale.

3.3.4. Conclusion

This study evaluates the economic impact of China Railway High-Speed (CRH) station construction on prefecture-level cities, employing a generalized Difference-in-Differences (DID) framework to estimate the causal effect of CRH on GDP. The DID results confirm that CRH stations generate significant economic benefits, with GDP gains increasing over time as cities integrate into the high-speed rail network, suggesting that CRH enhances regional connectivity, labor mobility, and investment attraction over time. However, because of the staggered nature of CRH construction across different cities, the DID approach is not able to fully capture treatment effect heterogeneity.

In order to account for staggered treatment timing and selection bias, the Callaway & Sant'Anna Difference-in-Differences (CSDID) methodology is applied, where propensity score re-weighting and group-time specific ATT estimation are utilized. The CSDID results reinforce the DID estimates by confirming that CRH stations contribute to sustained economic growth while providing a more refined view of treatment effects across different time periods. The validation of the parallel trends assumption further confirms the counterfactual framework, strengthening the causal interpretation of the results. Although the last post-treatment effect is statistically insignificant, this is likely due to data limitation rather than a decline in economic impact, which emphasizes the need for long-term observation.

The study also extends the analysis with a Difference-in-Difference-in-Differences (DDD) model to account for spatial heterogeneity in CRH's economic effects. The DDD results reveal that proximity to regional economic centers significantly moderates the economic benefits of CRH, with cities closer to these hubs experiencing greater gains. The results suggest that while CRH boosts the regional economy, its effects are not uniformly distributed. Peripheral cities, though benefiting from CRH connectivity, may require complementary infrastructure investments to fully capitalize on CRH access.

Despite these contributions, this study also identifies areas for further exploration. Future research could incorporate additional spatial variables, such as population density, industrial diversification, or trade flows, to better capture the mechanisms at play. By identifying economic zones beyond administrative boundaries, other clustering methods might enhance the precision of geographical analysis. Additionally, case studies comparing cities with comparable distances from regional centers but different policy support could offer deeper insight into how administrative factors interact with infrastructure investments. These extensions would provide a more nuanced understanding of CRH's economic role and inform infrastructure investments that prioritize both efficiency and regional equity.

The findings suggest that while CRH investments are a powerful driver of regional growth, they should be complemented with targeted policies to maximize their benefits for peripheral cities of a regional cluster. Strengthening local connectivity, fostering business development in newly connected areas, and implementing policies that promote economic agglomeration can help ensure that high-speed rail networks contribute to balanced and inclusive economic development.

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