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Spatiotemporal Accessibility of Rail Transport Systems in the Guangdong–Hong Kong–Macao Greater Bay Area and Its Implications on Economic Equity

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Abstract: Reducing inequality and fostering economic growth is the tenth global goal of the United Nations for sustainable development. Rail transport significantly influences spatial structures, industrial distributions, and is vital for regional economic integration. Despite its importance, the impact of rail transport on economic equity has not been thoroughly explored in current literature. This study aims to fill this gap by evaluating the spatiotemporal characteristics of rail transport accessibility and its implications for economic equity in the Guangdong–Hong Kong–Macao Greater Bay Area. We considered high-speed, intercity, and conventional rail transport and employ three distinct indicators—door-to-door travel time, weighted average travel time, and potential accessibility—to provide a nuanced assessment of accessibility in the region. Each indicator provides a unique perspective on how accessibility affects economic equity, collectively broadening the scope of the analysis. From 1998 to 2020, the evolution of rail transport and its consequent impact on regional economic equity is scrutinized. Advanced econometric methods, namely ordinary least squares, and spatial Durbin models, are combined with the Gini coefficient and Lorenz curve for comprehensive quantitative analysis. This approach highlights the dynamic influence of rail transport development on economic equity, contributing to the sustainable urban development discourse. The results reveal that although rail transport advancements bolster connectivity and economic growth, they also exacerbate regional economic inequality. This study provides valuable insights for urban planning and policymaking by elucidating the complex relationship between rail transport accessibility and economic equity. Our findings underscore the importance of implementing balanced and inclusive transport policies that foster growth and efficiency while mitigating socioeconomic disparities.

Keywords: rail transport system; accessibility; economic equity; spatiotemporal characteristics; Greater Bay Area

1. Introduction

Reducing inequality and fostering economic growth, the United Nations’ tenth global sustainable development goal, underscores the importance of equitable transportation systems, particularly rail infrastructure, in promoting regional economic integration [1,2]. Addressing inequities in transportation is crucial for enhancing public policy and infrastructure, with growing attention to the equity impacts within this domain [3,4].

Over the past few decades, substantial investments in rail transport systems, especially high-speed and intercity railways, have revolutionized intercity travel, adding over 40,000 km of tracks globally [5–7]. In China, the development of high-speed and intercity railways with enhanced capacities and speeds aims to overcome the shortcomings of traditional rail networks and meet the extensive travel needs of densely populated areas [8]. By the end of 2023, China’s high-speed railway network reached a remarkable extent of...
45,000 km, making it the fastest-growing transportation system in the country [9]. Rail transport has been claimed to be the most competitive transport mode, offering short travel times and superior service quality [10] and providing the additional benefits of enhanced reliability, safety, lower energy consumption, and reduced carbon emissions [6,11].

Railway developments have significantly influenced urban economic development by improving intercity accessibility, highlighting the importance of rail transport in national transport and urban economic growth [8,12,13]. Understanding the development and spatial implications of rail transport through comparative analyses across different periods is crucial [14,15]. Research suggests that while transport infrastructure can stimulate economic growth and attract foreign investment, its impact varies greatly based on geographical scale and transport modes [16,17]. Spatial variations in rail transport leads to uneven service accessibility [18–21]. Ensuring transport equity, where all societal groups, especially those in remote and economically disadvantaged areas, have reasonable access to railway services, is essential [19,20,22].

Although equity is essential for sustainable development, the impact of rail transport development on regional economic equity has not been thoroughly studied. Prior research has predominantly focused on single-type rail transit accessibility assessments at specific times using limited methodologies [18,23,24]. In addition, the long-term impact of rail transport development on economic equity remains underexplored. To bridge the gap in understanding the role of rail transport in regional economic equity and provide actionable insights for future infrastructure planning, this study aimed to analyze the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) and explores the impact of rail accessibility on economic equity. This study focuses on balancing development across various regions to promote regional integration, mitigate disparities, and support sustainable development.

Accessibility features from various perspectives are assessed, evaluating the characteristics of accessibility patterns and their impact on regional economic equity owing to rail transport development across different time dimensions. We primarily investigated national railways, focusing on high-speed, intercity, and conventional rails. Indicators were selected to evaluate travel time in different manners, each responding to a distinct concept, and their combined use provides supplementary information regarding accessibility. Door-to-door travel time primarily focuses on the entire journey from origin to destination, weighted average travel time aims to reduce urban transit times, and potential accessibility emphasizes enhancing urban competitiveness or attractiveness by improving accessibility. Rail transport accessibility indicators are estimated to quantify their impact on regional economic equity, capable of quantifying service changes in rail transport accessibility across different regions. The Gini coefficient and Lorenz curve are used to measure economic equity, and the ordinary least squares (OLS) and spatial Durbin model (SDM) models correlate socioeconomic and transportation accessibility variables from 1998 to 2020 in different regions to quantify the equity effects caused by changes in rail transport accessibility. This approach not only calculates the economic impact across four different time periods but also addresses the current gap in using persuasive equity indicators for analysis.

The remainder of this paper is organized as follows. Section 2 reviews the literature on rail transport accessibility and economic equity. Section 3 describes the study area and the methods. Section 4 presents the characteristics of rail accessibility and evaluates its impact on the regional economic equity. Finally, Section 5 summarizes the major findings and discusses the corresponding policy implications, and contributions of the study.

2. Literature Review

Transportation accessibility is a multifaceted concept that involves the potential for interaction [25], user friendliness [26], and overall benefits it brings [27]. Location-based measures, including distance, connectivity, gravity, and potential-based metrics, are pivotal for evaluating rail accessibility, which emphasizes weighted travel times and considers factors such as gross domestic product (GDP) and population [28]. Rail infrastructure,
particularly high-speed and intercity railways, significantly affects urban economies by reducing travel time and enhancing mobility [1,15,29].

Accessibility metrics have become crucial for assessing the impact of transport infrastructure on regional equity [20,22,30–34]. Accessibility, based on proximity to economic opportunities, posits that closer destinations are more attractive [20,25,35]. These metrics shed light on how easily desired destinations can be reached from specific location. New rail corridors have shifted the accessibility patterns that affect regional equity [36]. These changes in accessibility are key indicators of equity across regions [22].

The development of the rail transport infrastructure has been recognized as a key factor in achieving regional economic equity, particularly in efforts to reduce regional and social disparities and strengthen economic and social cohesion [37]. Consequently, transport policies focused on improving accessibility through high-quality public infrastructure are essential for fostering regional cohesion [38]. Assessing the equity impacts of these policies involves examining how their benefits are distributed across different regions to minimize existing spatial disparities in accessibility [22,39,40].

Geographical equity is essential for ensuring fair access to economic activities and services across different population segments. It is divided into horizontal equity (among capable individuals) and vertical equity (focused on disadvantaged groups), which is often associated with socioeconomic aspects [6,41–43]. Economic equity, a key focus in transport equity studies, encompasses the fair and equitable distribution of economic resources, opportunities, and benefits within society [44].

The Gini coefficient and Lorenz curve are commonly used to measure equity across various indicators [45,46]. Economic equity has been assessed using the Gini coefficient, which is related to per capita GDP. Despite China’s 2023 GDP reaching 126 trillion RMB (CNY), making it the world’s second-largest economy, its Gini coefficient was 0.47, surpassing the international alert line of 0.4, indicating a significant wealth disparity. The development of the transportation infrastructure is considered a vital pathway for promoting China’s economic growth [9,18]. However, studies on the influence of rail systems on economic equity are insufficient. Railways are crucial for bolstering intercity connectivity and accessibility [47]. Enhanced rail accessibility fosters spatial and social development, influences land use, drives urban growth, and ultimately contributes to regional economic development and reduces regional disparities [23,32,33,48–50].

The primary methods for assessing the economic impacts of transportation infrastructure include cost–benefit analysis (CBA), computable general equilibrium (CGE) models, and econometric analyses [5,51]. The CBA approach is predominantly used for pre-assessment, focusing on the marginal benefits of a project’s returns versus its costs, rather than the broader economic impacts [32]. In contrast, CGE models, while comprehensive and intricate, require detailed databases to evaluate individual infrastructure projects due to their complexity [53,54]. Econometric models, such as regression and structural equation models, are commonly employed to quantify the economic impacts of large transportation infrastructure projects, providing a more generalizable approach to understanding these effects in an economic context [24,48].

In the new economic geography, transport infrastructure is recognized as an important means of reducing transport costs and promoting economic agglomeration [55]. Many studies have assessed the impact of rail transport on economic development elucidated its varied impacts [36,56,57]. Rail transport can stimulate growth by facilitating locational choices and increasing housing and land values [18,36]. Although rail transport enhances intercity connectivity and urban development, it poses challenges for economic equity. Its effects on economic growth are not always positive, with some regions experiencing exacerbated disparities [18,58], particularly the more developed regions with concentrated economic activities [18,59–61]. It also promotes economies in core cities at the potential expense of peripheral areas [36,62]. High-speed rail plays a dominant role in the diffusion effect of off-site investments in the Yangtze River Delta region, facilitating the flow of resources from developed to less developed areas, contributing to regional integration, and
narrowing urban–rural disparities [24,48]. Although existing studies often infer changes in equity by comparing economic indicator trends in different regions, a systematic analysis in this area is still lacking.

3. Data and Methods

3.1. Study Area

The Guangdong–Hong Kong–Macao GBA, situated along China’s southern coast, stands as a central focus in the country’s policy agenda. Boasting a robust economy with a GDP of 11.69 trillion RMB in 2019 and a per capita GDP of 2.54 times the national average, the GBA is a beacon of development and economic vitality within China. This region is pivotal for the construction of a globally influential urban cluster and hub for science and technology innovation, holding a unique strategic position in China’s national development plans.

As of 2020, the GBA’s high-speed rail network extends over 710 km, supplemented by 608 km of intercity railways and 457 km of general-speed railways, cumulatively spanning 1775 km. This extensive rail network makes the GBA an ideal case study for examining the intricacies of rail transport accessibility and its influence on economic equity. This study focused on the GBA, encompassing the Hong Kong and Macao special administrative regions and the major cities of Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing, covering a total area of 56,094.91 km² (Figure 1).

3.2. Data

We employed the 2017 edition of the 1:1,000,000 National Basic Geographic Database of the National Basic Geographic Information Centre. The database was calibrated and verified using the administrative division codes released in July 2020 by the Ministry of Civil Affairs of the People’s Republic of China. The analysis units included 36 district-level units, 12 county-level units, two prefectural-level city units, and two special administrative regions (Hong Kong and Macao), amounting to 52 units in total. The unincorporated areas of Dongguan and Zhongshan, characterized by dispersed streets and towns, were treated as individual citywide units. Given their distinct administrative levels, Hong Kong and Macao are considered separate units without further subdivision.

To ensure the integrity of the study and continuity of comparative analyses, we did not account for changes in the administrative divisions of each unit over time. The evolution of the rail transport network in the GBA over four key years, namely, 1998, 2008, 2014, and 2020, was analyzed. This temporal analysis utilized vectorized data from historical atlases and relevant planning maps, complemented by socioeconomic data such as GDP and population statistics from regional Statistical Yearbooks. For consistency, the data for Hong Kong and Macao were recorded in their local currencies and converted to RMB to align with other cities in the study.

3.3. Model Specification and Variables

3.3.1. Door-to-Door Travel Time Measurement

A door-to-door methodology was adopted to calculate the full-chain travel time between regions via rail, aligning with the methodologies used in prior research [63]. The total travel time from a starting point in City A to an endpoint in City B consists of the: (1) travel time from a location within City A to the departure station (T₁), (2) intercity rail travel time (T₂), and (3) travel time from the arrival station in City B to the final destination (T₃). Thus, the full-chain travel time equation is:

\[ \text{DDTT} = T_1 + T_2 + T_3 \]  

where DDTT is the door-to-door travel time.
3.2. Data

We employed the 2017 edition of the 1:1,000,000 National Basic Geographic Database of the National Basic Geographic Information Centre. The database was calibrated and

Cost-distance analysis estimates the travel time within the departure \( T_1 \) and destination cities \( T_3 \), whereas rail network analysis calculates the interstation travel time \( T_2 \). The spatial unit for analysis was a 100 \( \times \) 100 m grid, covering 13,231,100 raster grids across 52 counties. The travel time for each grid was calculated to assess accessibility, and the time cost was attached to each road segment as an attribute according to the route type, calculated as follows:

Figure 1. The Guangdong–Hong Kong–Macao Greater Bay Area (GBA) Region.
\[
\text{Cost} = \frac{100}{V} \times 60 
\]

where \(\text{Cost}\) is the travel time (min/100 m) and \(V\) is the restricted travel speed for each type. The speeds for the nonroad types were adapted from existing literature [11]. Intercity travel times were determined using the average speeds for different types in the GBA. The two types of high-speed trains in China operate at 200–250 km/h on upgraded general-speed and lower-standard high-speed railroads or at 300–350 km/h with a more advanced system. Intercity railways typically accommodate speeds of up to 200 km/h, whereas general-speed railroads range from 80 to 120 km/h based on the number of stops. We used these average speeds to model the travel times for different rail services [63].

To model travel time in a geographic information system (ArcGIS 10.2) environment [1], two primary methods are employed: cost distance analysis and network analysis, which use vector and raster datasets, respectively. By integrating these methods, a hybrid approach can be applied to calculate regional accessibility, addressing the intersection problem of cost distance analysis in road networks and the low spatial resolution of network analysis. Specifically, the travel time within the starting city \((T_1)\) and the destination city \((T_3)\) is calculated using cost distance analysis of the road network, while the travel time between two stations \((T_2)\) is determined through rail transit network analysis.

### 3.3.2. Weighted Average Travel Time Measurement

We employed the weighted average travel time metric to assess interregional connectivity. This metric calculates the travel time from one location to all other locations and incorporates the economic and demographic significance of each destination. A destination’s size, which indicates its economic development and urban scale, is typically quantified using GDP and population data [30]. The weighted average travel time is mathematically represented as:

\[
WATT = \frac{\sum_{j=1}^{n} (M_j \times t_{ij})}{\sum_{j=1}^{n} M_j} 
\]

\[
M_j = \sqrt{\text{GDP}_j \times \text{POP}_j} 
\]

where \(WATT\) is the accessibility of the location \(i\), \(t_{ij}\) is the travel time to the destination \(j\), \(M_j\) is the size of \(j\), and \(n\) denotes the number of study units. Usually, the shortest travel time is used for \(t_{ij}\) and the population size or the total GDP is used for \(M_j\). In this study, \(M_j\) is expressed as the square root of the product of the population and GDP of each city (Equation (4)), \(\text{GDP}_j\) refers to the GDP of the destination city \(j\), and \(\text{POP}_j\) represents the population of the destination city \(j\).

### 3.3.3. Potential Accessibility Measurement

We adopted a potential accessibility measure to gauge the proximity of economic opportunities to various locations. The expression is as follows:

\[
PA = \sum_{j=1}^{n} \frac{M_j}{t_{ij}^a} 
\]

where \(PA\) is the potential accessibility of location \(i\), \(t_{ij}\) is the travel time between locations \(i\) and \(j\), and \(a\) is the distance friction parameter.

### 3.3.4. Gini Coefficient and Lorenz Curve

We employed the Gini coefficient, derived from the Lorenz curve, to measure disparities in the rail transport supply relative to the population distribution in the Guangdong–
Hong Kong–Macao GBA. Originally conceptualized for analyzing wealth distribution [64], the Gini coefficient serves as an effective tool to evaluate geographic equity in transportation accessibility. In a Lorenz graph, a black dashed line represents a perfectly equitable distribution, while a solid red line represents an uneven wealth distribution scenario, where 70% of the population shares only 25% of the income. Notably, the Lorenz curve is a tool for representation and does not advocate perfect equity.

3.3.5. Econometric Methods

OLS and SDM were employed to assess the effect of railway transport on economic disparities by incorporating demographic and economic variables. The focus was on the proximity effect, in which regional economic equity is influenced by new transit infrastructure.

The primary unit for the econometric analysis was the county. The model evaluates how a county’s economic, demographic, and transportation attributes, along with those of neighboring counties, influence economic equity. Economic equity was gauged using the Gini coefficient of GDP per county. The OLS and SDM were calculated as follows:

\[
Y_{pt} = \beta_0 + \beta \cdot X_{pt} + \delta \cdot R_{pt} + \mu_{pt} \tag{6}
\]

\[
Y_{pt} = \alpha \cdot \sum_{q=1}^{N_q} W_{p,q} Y_{qt} + \beta_0 + \beta \cdot X_{pt} + \gamma \cdot \sum_{q=1}^{N_q} W_{p,q} X_{qt} + \delta \cdot R_{qt} + \theta \cdot \sum_{q=1}^{N_q} W_{p,q} R_{qt} + \mu_{pt} \tag{7}
\]

where \(Y_{pt}\) is an indicator of economic equity measured by the Gini coefficient of GDP for each county \(p\) at time \(t\), \(p\) represents each county, \(t\) represents each observation year, \(X_{pt}\) represent explanatory variables of economic, demographic, and transit characteristics of each county at year \(t\), \(R_{pt}\) is a dummy variable indicating the presence of transit (1 if the transit operates, 0 otherwise), \(\beta_0\), \(\beta\), and \(\delta\) denote the coefficients of the corresponding variables, and \(\mu_{pt}\) is the error term with a mean of zero.

Based on the OLS model, the SDM incorporates spatial lag matrices. In Equation (7), \(W_{p,q}\) denotes the spatial lag matrices \(p\) and \(q\), representing the relative locations of counties. \(p\) and \(q\) are distributed to represent the origin and destination counties. In particular, \(W_{p,q}X_{qt}\) and \(W_{p,q}R_{qt}\) characterize the spatial lags of the explanatory variables, and \(W_{p,q}Y_{qt}\) represents the spatial lag of the dependent variable. The spatial lags reflect the effects of economic, demographic, rail development, and economic equity in neighboring counties. \(N_q\) represents the number of counties in the sample. The coefficients \(\alpha\), \(\gamma\), and \(\theta\) estimate the impact of neighboring counties based on the relevant variables. The explanatory variables include GDP per capita, population, proximity to other counties and districts (ADJ_DCM), rail presence, accessibility, and economic potential of rail transport services.

Many studies have established a causal relationship between transportation infrastructure development and economic growth [18,28]. A close link has also been established between economic development (GDP) and economic disparities (GDP Gini coefficient) [18,65]. Thus, the explanatory variables include per capita GDP, population, ADJ_DCM, presence of rail transport, accessibility, and economic potential of rail transport services.

We employed four indicators to characterize rail transport: coverage area of rail transport, door-to-door travel time, weighted average travel time, and potential accessibility. The coverage of rail transport is represented by the dummy variable \(R\), which indicates the presence of rail transport services in a county (Table 1). Door-to-door travel time accessibility, DDTT, measures the full chain travel time between different regions via rail transport [63,66,67]. The accessibility of weighted average travel time, WATT, measures the average of the shortest travel times to reach other regions via rail transport [18,21,24,68]. Economic potential accessibility, PA, quantifies the sum of the GDP over travel time for accessible counties and districts, offering a metric to access the economic opportunities available within a specific timeframe [18,21,24].
Table 1. List of variables and definitions used in econometric methods.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>Gini coefficient of GDP for a county</td>
</tr>
<tr>
<td>GINI_GDP</td>
<td>Gini coefficient of GDP for a county</td>
</tr>
<tr>
<td>Economic, demographic, and geographic location variables</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>Gross regional product of a county</td>
</tr>
<tr>
<td>GDP_PC</td>
<td>Gross regional product per capita in a county</td>
</tr>
<tr>
<td>POP</td>
<td>Permanent residents population</td>
</tr>
<tr>
<td>ADJ_DCM</td>
<td>Dummy variable; equal to 1 if a county is adjacent to counties in Guangzhou and Shenzhen, 0 otherwise</td>
</tr>
</tbody>
</table>

Variables related to rail transport

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>Dummy variable; equal to 1 if in a county area connected to the rail network in the sampling year; 0 otherwise</td>
</tr>
<tr>
<td>DDTT</td>
<td>Door-to-door travel times for the entire chain of rail transport to the counties</td>
</tr>
<tr>
<td>WATT</td>
<td>Weighted average travel time by rail counties</td>
</tr>
<tr>
<td>PA</td>
<td>Economic potential accessibility of counties by rail transport</td>
</tr>
<tr>
<td>GINI_DDTT</td>
<td>Gini coefficient of travel time for the door-to-door travel times of rail transport</td>
</tr>
<tr>
<td>GINI_WATT</td>
<td>Gini coefficient of weighted average travel time for rail transport</td>
</tr>
<tr>
<td>GINI_PA</td>
<td>Gini coefficient for accessibility of economic potential of rail transport</td>
</tr>
</tbody>
</table>

4. Results and Discussion

4.1. Characteristics of Railway Accessibility in the GBA

4.1.1. Door-to-Door Travel Time

The expansion of the rail transport network in the Guangdong–Hong Kong–Macao GBA has significantly reduced door-to-door travel times, enhancing travel convenience for residents. We used the natural discontinuity classification to categorize travel times, revealing a pattern of shorter times centrally and longer times on the eastern and western fringes (Figure 2). From 1998 to 2020, the average travel time in each county and district decreased from 126.62 to 64.90 min, marking an overall reduction of 48.75%.
Guangzhou’s central districts such as Yuexiu and Tianhe, along with Shenzhen’s Futian district, have experienced notable reductions in travel time, affirming their roles as transport hubs. Conversely, peripheral areas such as Huidong County in Huizhou, Taishan City in Jiangmen, Longmen County in Huizhou, and Fenkai County in Zhaoqing, although showing improvements, still endured longer travel times. This disparity underscores the critical influence of rail transport development on regional travel efficiency and highlights the ongoing challenge of balancing development across the GBA.

4.1.2. Weighted Average Travel Time

Between 1998 and 2020, the Guangdong–Hong Kong–Macao GBA witnessed a substantial reduction in weighted average travel time, following a spatial trend of shorter times in central cities and longer times in surrounding counties (Figure 3). During this period, the overall weighted average travel time decreased from 75 to 56 min (25.43%) owing to significant rail network improvements.

Central cities within the region, notably Guangzhou, Shenzhen, and Dongguan, have experienced enhanced accessibility due to strategic rail expansion. Key developments included the Guangzhou–Shenzhen Intercity Railway (2007), Beijing–Guangzhou High Speed Railway, Guangzhou–Shenzhen–Hong Kong High Speed Railway, Xiamen–Shenzhen Railway, Nan–Guangzhou High Speed Railway, Gui–Guangzhou High Speed Railway, Guangzhou–Zhuhai Intercity Railway, and Guangzhou–Zhuhai Railway. These developments have notably reduced travel times in these cities, ending the historical isolation of Zhuhai, Zhongshan, and Jiangmen from rail connectivity.
By 2020, new lines such as the Shenzhen–Mao Railway and Guangzhou–Foshan–Zhaoxing Intercity Railway further optimized regional traffic flows. This led to additional decreases in weighted average travel time in major cities, whereas areas such as Huizhou, Zhaoqing, and Jiangmen continued to experience longer travel times.

4.1.3. Potential Accessibility

From 1998 to 2020, the potential accessibility within the Guangdong–Hong Kong–Macao GBA surged by 7.8 times, indicating a marked increase in intercity attractiveness. Key central areas, notably Guangzhou, Shenzhen, and Foshan, have emerged as focal points because of their high regional attractiveness and robust rail transport infrastructure. Conversely, Zhaoqing, Jiangmen, and Huizhou lagged, with their relative remoteness contributing to lower potential accessibility.

In 2020, the central cities within the region maintained superior potential accessibility, whereas the western, eastern, and southern areas exhibited comparatively lower levels, displaying a diminishing marginal effect (Figure 4). The rail network expansion notably bolstered the potential accessibility of central cities, with Shenzhen increasing by 212.92% and Dongguan increasing by 121.83%. Other regions have experienced moderate growth in potential accessibility. The launch of rail services such as the Guangzhou–Zhuhai Railway and Guangzhou–Zhuhai Intercity improved the potential accessibility of Zhuhai, Zhongshan, and Jiangmen. However, by 2020, the disparities persisted, with Guangzhou and Shenzhen having the highest potential accessibility. Regions such as Zhaoqing, Huizhou, and Jiangmen continued to exhibit lower potential accessibility, reflecting the ongoing uneven development within the GBA.

Figure 4. Spatiotemporal characteristics of potential accessibility of railway transport in the Guangdong–Hong Kong–Macao GBA in 1998–2020.
4.2. Effects of Rail Transport Development on Economic Equity

4.2.1. Regional Economic Equity

The economic growth of different parts of the Guangdong–Hong Kong–Macao GBA varies greatly, and the development and construction of rail transport is also uneven among the regions. Between 1998 and 2020, the Guangdong–Hong Kong–Macao GBA witnessed notable disparities in economic growth and rail transport development. A panel dataset encompassing 52 units for 1998, 2008, 2014, and 2020 was compiled to evaluate these variations.

Figure 5 reveals a decline in the GDP Gini coefficient in the Guangdong–Hong Kong–Macao GBA from 1998 to 2020, indicating a move towards more equitable economic development. Specifically, the Gini coefficient saw a 29.44% decrease from 0.52 in 1998 to 0.36 in 2020, suggesting both growth in average economic output and improved fairness in its distribution. Concurrently, GDP per capita witnessed a significant increase from 21,200 RMB in 1998 to 138,600 RMB in 2020, a 5.53-fold increase. This period also saw enhanced rail service connectivity and accessibility, reduced travel times, and improved potential accessibility.

Although the GDP Gini coefficient showed a significant decrease, the Gini coefficients for the door-to-door and weighted average travel times initially displayed an upward trend. In contrast, the potential accessibility Gini coefficient generally decreased, suggesting a more equitable distribution compared with the other travel time measures. Figure 6 illustrates the changes in the Gini coefficients for GDP, door-to-door travel time, weighted average travel time, and potential accessibility in the Guangdong–Hong Kong–Macao GBA.

Further analyses of travel time and accessibility (Figure 7) revealed notable improvements owing to rail transport development. The average door-to-door travel time decreased by 48.75%, from 126.62 min in 1998 to 64.90 min in 2020. The weighted average travel time also showed a reduction of 25.43%, from 74.97 to 55.91 min over the same period. Meanwhile, potential accessibility significantly increased from 82.47 in 1998 to 641.53 in 2020, indicating a nearly seven-fold rise in intercity attractiveness. These trends highlight the enhanced connectivity and efficiency resulting from the development of rail transport in this region.
Further analyses of travel time and accessibility (Figure 7) revealed notable improvements owing to rail transport development. The average door-to-door travel time decreased by 48.75%, from 126.62 min in 1998 to 64.90 min in 2020. The weighted average travel time also showed a reduction of 25.43%, from 74.97 to 55.91 min over the same period. Meanwhile, potential accessibility significantly increased from 82.47 in 1998 to 641.53 in 2020, indicating a nearly seven-fold rise in intercity attractiveness. These trends highlight the enhanced connectivity and efficiency resulting from the development of rail transport in this region.

The spatial distribution of the GDP Gini coefficients in the Guangdong–Hong Kong–Macao GBA exhibits greater inequity in peripheral regions compared with that in the central area (Figure 8). The development of rail transport has played a significant role in enhancing economic equity, particularly in central cities such as Guangzhou and Shenzhen. In contrast, peripheral areas, such as Zhaoqing and Jiangmen, have experienced less pronounced benefits from rail development. This suggests that, while rail transport development contributes to diminishing economic disparities, its impact varies across regions, with more developed cities witnessing more substantial improvements in economic equity. Concurrently, the GDP Gini coefficient in the Guangdong–Hong Kong–Macao GBA displayed a declining trend.
trend from 1998 to 2020, with the corresponding Lorenz curve nearing the line of equality (Figure 9). This indicates an increasingly equitable economic development for the residents of the area, although the rate of inequality reduction was slow.

The GDP Gini coefficient in the Guangdong–Hong Kong–Macao GBA was 0.5154 in 1998, 0.4124 in 2008, 0.3888 in 2014, and 0.3637 in 2020. Economic inequality in the GBA decreased by 20% from 1998 to 2008, indicating that the gap in economic development enjoyed by residents of cities in the GBA significantly decreased during this period. From 2014 to 2008, economic inequality in the GBA reduced by 5.71%, indicating a further narrowing of the economic gap, although at a decreasing rate. This further reduced by 6.46% from 2014 to 2020, showing that with the passage of time and the improvement of rail transit, residents enjoyed more economic equity, and the gap between the rich and poor narrowed further. Between 1998 and 2020, the GDP Gini coefficient values in the GBA were above 0.4, indicating greater economic disparity among residents during this period. From the beginning of 2014 to 2020, these values decreased to 0.3–0.39, indicating relatively greater economic equity among residents.
4.2.2. OLS and SDM Results

The Gini coefficient rankings across various indicators in the Guangdong–Hong Kong–Macao GBA were highly consistent, reflecting similar patterns in economic and rail transport development levels (Figure 9). This suggests a correlation between economic equity and key variables, such as GDP, population, per capita GDP, and rail transport development. This study demonstrated that economic equity in a region was closely linked to economic development, population, rail transport network, and geographical location. The impact of rail transport on economic equity was further explored using econometric models, such as OLS and SDM, which also considered the neighboring effects of Guangzhou and Shenzhen [24,46,69].

In this study, we conducted a comprehensive econometric analysis using data from 52 counties across 1998, 2008, 2014, and 2020 to form a panel dataset. Spatial weight matrices and Moran’s I tests reveal a positive spatial correlation between economic disparities, as indicated by the GDP Gini coefficient. OLS and SDM were employed to examine the impact of rail transport on economic equity, focusing on the proximity effects around Guangzhou and Shenzhen (Tables 2–4).

The dummy variable $R$ represents whether a district has rail transport. The OLS model was positively correlated with the GDP Gini coefficient, indicating that for each standard deviation increase in the rail transit dummy variable, the GDP Gini coefficient across regions increased by 0.0018–0.0348 standard deviations. This result suggests that the development of rail transport is related to economic equity across regions, and its expansion increases economic inequality among districts. This is consistent with the conclusions of [70], indicating that rail transport development exacerbates urban–rural disparities at the county level.

According to the results of the OLS model, as listed in Section 4.2.3, the Gini coefficients associated with door-to-door full-chain travel time as an accessibility measure tended to negatively correlate with the GDP Gini coefficient, while those associated with weighted average travel time and potential accessibility as measures of accessibility tended to positively correlate with the GDP Gini coefficient. An increase of one standard deviation in door-to-door full-chain travel time reduces the district’s GDP Gini coefficient by 0.0281...
standard deviations, whereas increases in weighted average travel time and potential accessibility each raise it by 0.0195 and 0.0117 standard deviations, respectively. Therefore, when determining economic equity at the district level, the weight of door-to-door full-chain travel time as an accessibility measure exceeds that of weighted average travel time and potential accessibility. Furthermore, a comparison of the different accessibility indicators with their corresponding Gini coefficient indicators reveal that the Gini coefficient indicators have larger coefficients than their respective accessibility indicators, indicating that an equitable distribution of rail transport contributes more to a region’s economic equity than its inequitable distribution.

Table 2. Estimates using door-to-door travel time as the main metric.

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>Main</th>
<th>Spatial Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>SDM</td>
<td></td>
</tr>
<tr>
<td>G_GDP</td>
<td>0.4700 ***</td>
<td>0.4505 ***</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-0.1271 **</td>
<td>-0.0699</td>
<td>-0.1049</td>
</tr>
<tr>
<td>GDP_PC</td>
<td>-0.1428 ***</td>
<td>-0.1751 ***</td>
<td>0.1302 ***</td>
</tr>
<tr>
<td>POP</td>
<td>0.2561 **</td>
<td>0.1322 *</td>
<td>0.1728</td>
</tr>
<tr>
<td>ADJ_DCM</td>
<td>-0.0770 ***</td>
<td>0.01043</td>
<td>-0.0897 ***</td>
</tr>
<tr>
<td>R</td>
<td>0.0238</td>
<td>-0.0328 **</td>
<td>0.0755 ***</td>
</tr>
<tr>
<td>DDTT</td>
<td>-0.0281</td>
<td>0.0821 ***</td>
<td>-0.0954 ***</td>
</tr>
<tr>
<td>G_DDTT</td>
<td>0.0577</td>
<td>0.0838 *</td>
<td>-0.0093</td>
</tr>
<tr>
<td>Constant</td>
<td>1.0722 ***</td>
<td>0.4505 ***</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>208</td>
<td>208</td>
<td>208</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.712</td>
<td>0.815</td>
<td>0.815</td>
</tr>
<tr>
<td>Number of ID</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

*** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.10$.

Table 3. Estimates using weighted average travel time as the main metric.

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>Main</th>
<th>Spatial Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>SDM</td>
<td></td>
</tr>
<tr>
<td>G_GDP</td>
<td>0.5007 ***</td>
<td>0.0802</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-0.1365 ***</td>
<td>-0.0721 *</td>
<td>-0.1232</td>
</tr>
<tr>
<td>GDP_PC</td>
<td>-0.1291 ***</td>
<td>-0.1804 ***</td>
<td>0.1633 ***</td>
</tr>
<tr>
<td>POP</td>
<td>0.2530 **</td>
<td>0.1069</td>
<td>0.1016</td>
</tr>
<tr>
<td>ADJ_DCM</td>
<td>-0.0706 ***</td>
<td>-0.0031</td>
<td>-0.0755 ***</td>
</tr>
<tr>
<td>R</td>
<td>0.0348 **</td>
<td>-0.0354 ***</td>
<td>-0.1076 ***</td>
</tr>
<tr>
<td>WATT</td>
<td>0.0195</td>
<td>0.0084</td>
<td>0.0969 ***</td>
</tr>
<tr>
<td>G_WATT</td>
<td>0.0091</td>
<td>0.1008 **</td>
<td>0.1759 *</td>
</tr>
<tr>
<td>Constant</td>
<td>0.9277 ***</td>
<td>0.0802</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>208</td>
<td>208</td>
<td>208</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.710</td>
<td>0.821</td>
<td>0.821</td>
</tr>
<tr>
<td>Number of ID</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

*** indicates $p < 0.01$, ** indicates $p < 0.05$, * indicates $p < 0.10$. 
Table 4. Estimates using potential accessibility as the main metric.

<table>
<thead>
<tr>
<th>Variable, Main</th>
<th>OLS</th>
<th>SDM</th>
<th>Spatial Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>G_GDP</td>
<td>0.3833 **</td>
<td>16.41</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-0.1317 ***</td>
<td>-0.0792 **</td>
<td>-0.1649 *</td>
</tr>
<tr>
<td>GDP_CC</td>
<td>-0.1606 ***</td>
<td>-0.1802 ***</td>
<td>0.1134 ***</td>
</tr>
<tr>
<td>POP</td>
<td>0.1145</td>
<td>0.0857</td>
<td>0.1541</td>
</tr>
<tr>
<td>ADJ_DCM</td>
<td>-0.0804 ***</td>
<td>-0.0030</td>
<td>-0.0861 ***</td>
</tr>
<tr>
<td>R</td>
<td>0.0018</td>
<td>-0.0394 ***</td>
<td>0.0930 ***</td>
</tr>
<tr>
<td>PA</td>
<td>0.0117 ***</td>
<td>0.0026</td>
<td>0.0034</td>
</tr>
<tr>
<td>G_PA</td>
<td>0.1820 ***</td>
<td>0.1142 ***</td>
<td>0.1155</td>
</tr>
<tr>
<td>Constant</td>
<td>0.8099 ***</td>
<td>0.3663 ***</td>
<td></td>
</tr>
</tbody>
</table>

*** indicates \( p < 0.01 \), ** indicates \( p < 0.05 \), * indicates \( p < 0.10 \).

Regression results indicate significant associations between GDP, GDP per capita, population, and adjacency to Guangzhou and Shenzhen (ADJ_DCM) with the GDP Gini coefficient, with GDP per capita having a relatively greater weight. The relationship between GDP per capita and the GDP Gini coefficient suggests a significant negative correlation between a region’s economic equity and its level of economic development, implying that areas with higher GDP per capita rankings are likely to have lower GDP Gini coefficients. This finding aligns with the spatial distribution characteristics of the GDP Gini coefficient in the Guangdong–Hong Kong–Macao GBA, as previously discussed. This phenomenon can be explained by the siphon effect, in which production factors are redistributed from poorer to richer areas [50]. However, over the longer term, from 1998 to 2020, both the average GDP and economic equity at the regional level in the Guangdong–Hong Kong–Macao GBA have shown improvement.

The population coefficient shows a significant positive correlation with the GDP Gini coefficient, indicating that as the population grows, the wealth gap in the Guangdong–Hong Kong–Macao GBA becomes more pronounced. Additionally, the negative ADJ_DCM coefficient in all models implies that counties neighboring Guangzhou and Shenzhen can have better equity. Guangzhou and Shenzhen substantially benefit from strategic policies and planning, leading to a significant flow of production factors towards these cities and prioritizing the development of transportation infrastructure in neighboring areas, which may spill over into adjacent areas and help improve their economic equity. However, the weight of ADJ_DCM accounts for a smaller proportion of the region’s economic equity compared with the variables related to GDP and R.

4.2.3. Robustness Test

The established panel dataset, which included data on the relevant variables for 52 counties in 1998, 2008, 2014, and 2020, was imported into Stata to form panel data for different periods (Table 5). The 52 units were subjected to a spatial weight matrix, in which the spatial weights were constructed based on face adjacencies. The number of elements was 52, the percentage of spatial connectivity was 8.65%, the average number of neighboring elements was 4.5, the minimum number of neighboring elements was 1, and
the maximum number of neighboring elements was 11. The result was then converted into a 52 × 52 matrix using R language, and w was the spatial matrix inputted ahead of time in the order in which the imported panel data were consistent.

Table 5. Descriptive statistics of variables associated with the spatial Durbin model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average Value</th>
<th>Standard Deviation</th>
<th>Minimum Value</th>
<th>Maximum Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>G_GDP</td>
<td>0.844</td>
<td>0.168</td>
<td>0.364</td>
<td>0.98</td>
</tr>
<tr>
<td>GDP</td>
<td>0.118</td>
<td>0.26</td>
<td>0.001</td>
<td>2.366</td>
</tr>
<tr>
<td>GPC</td>
<td>0.83</td>
<td>0.853</td>
<td>0.028</td>
<td>5.583</td>
</tr>
<tr>
<td>POP</td>
<td>0.112</td>
<td>0.14</td>
<td>0.011</td>
<td>0.839</td>
</tr>
<tr>
<td>ADJ_DCM</td>
<td>0.558</td>
<td>0.498</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>R</td>
<td>0.615</td>
<td>0.488</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>DDTT</td>
<td>1.61</td>
<td>0.68</td>
<td>0.487</td>
<td>4.514</td>
</tr>
<tr>
<td>WATT</td>
<td>1.094</td>
<td>0.424</td>
<td>0.505</td>
<td>2.967</td>
</tr>
<tr>
<td>PA</td>
<td>5.164</td>
<td>4.524</td>
<td>0.418</td>
<td>28.827</td>
</tr>
<tr>
<td>G_DDTT</td>
<td>0.864</td>
<td>0.155</td>
<td>0.418</td>
<td>0.98</td>
</tr>
<tr>
<td>G_WATT</td>
<td>0.865</td>
<td>0.154</td>
<td>0.431</td>
<td>0.98</td>
</tr>
<tr>
<td>G_PA</td>
<td>0.843</td>
<td>0.168</td>
<td>0.382</td>
<td>0.98</td>
</tr>
</tbody>
</table>

According to the Moran’s I test, the dependent variable and the GDP Gini coefficient showed a positive spatial correlation, with Moran indices are all greater than 0, which suggests that the economic differences in neighboring regions influence each other (Table 6).

Table 6. Moran’s I of G_GDP.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran’s I</td>
<td>0.169</td>
<td>0.364</td>
<td>0.473</td>
<td>0.375</td>
</tr>
<tr>
<td>p-value</td>
<td>0.044</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

The results of the Panel Hausman test, detailed in Table 7, confirm the superiority of employing a fixed-effects model over a random-effects model for this dataset, as evidenced by the significant differences observed in the GDP estimators. The statistically significant chi-squared value rejects the null hypothesis, underscoring that the fixed-effects model accounts for unobserved heterogeneity across entities more accurately. This affirmation of the model choice bolsters the robustness and reliability of the findings, ensuring that the results are not biased by inappropriate model specifications.

Table 7. Panel Hausman test.

<table>
<thead>
<tr>
<th></th>
<th>FE (b)</th>
<th>RE (B)</th>
<th>Difference (b-B)</th>
<th>sqrt(diag(V_b-V_B)) S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>0.0106874</td>
<td>-0.1354885</td>
<td>0.1461759</td>
<td>0.0778414</td>
</tr>
<tr>
<td>GPC</td>
<td>-0.100575</td>
<td>-0.1321497</td>
<td>0.0315747</td>
<td>0.0112213</td>
</tr>
<tr>
<td>POP</td>
<td>0.3852637</td>
<td>0.2543786</td>
<td>0.1292451</td>
<td>0.2272865</td>
</tr>
<tr>
<td>R</td>
<td>0.0286399</td>
<td>0.0312685</td>
<td>-0.0026326</td>
<td>0.0132473</td>
</tr>
<tr>
<td>chi2(4)</td>
<td>76.05</td>
<td>0.0002</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5. Conclusions

We meticulously examined the impact of rail transport development on accessibility and economic equity within the Guangdong–Hong Kong–Macao GBA. Research indicates that the introduction of these networks has substantially improved accessibility within the Guangdong–Hong Kong–Macao GBA, dramatically reducing regional travel times and significantly enhancing intercity attractiveness. This is consistent with the findings of [1,22,36]. In particular, the travel times in Guangzhou’s districts rank among the shortest in the region, highlighting their central role in transportation. Similarly, the districts in Shenzhen experienced significant reductions in travel time. However, despite improvements, travel
times in Jiangmen and Zhaoqing, which are located on the eastern and western peripheries of the GBA, continue to lag and remain among the longest in the region. Because Guangzhou and Shenzhen reap substantial benefits from the targeted policies and development strategies, they attract a significant influx of resources. This focus on developing transportation infrastructure in areas adjacent to these cities potentially facilitates economic fairness in neighboring regions.

This study provides a comprehensive analysis of the transformative role of rail transport in shaping the Guangdong–Hong Kong–Macao GBA’s socioeconomic landscape. It highlights the dual-edged nature of rail transport development: serving as a catalyst for regional integration, shrinking travel times, and fostering connectivity, particularly in central urban hubs like Guangzhou and Shenzhen, while simultaneously presenting a challenge by potentially widening the economic divide between well-serviced urban centers and less-connected peripheral regions. These findings underscore the importance of adopting a more holistic and equitable approach to transportation planning and policy formulation. Future strategies must transcend mere infrastructural expansion to include equitable resource distribution and ensure that the benefits of rail transport are uniformly disseminated across the region. This calls for a balanced development paradigm that prioritizes not only the efficiency and expansion of transit networks but also addresses the socioeconomic disparities exacerbated by such developments. In essence, the evolution of the GBA’s rail network should align with the broader goals of sustainable development, promoting not only economic growth, but also social inclusivity and regional cohesion. By doing so, the region can harness the full potential of its transportation infrastructure and serve as a foundation for a more equitable, prosperous, and interconnected future.

Although comprehensive, this study has certain limitations. We included all grid centroids within the research area to ensure a comprehensive analysis of regional accessibility patterns. This approach captures the full spatial variability across the Guangdong–Hong Kong–Macao Greater Bay Area, providing a broad understanding of how rail transport infrastructure impacts accessibility. However, we acknowledge that this methodology does not distinguish between different land use types, such as urban, rural, or natural areas. To address this, future research should integrate high-resolution land use data, allowing for a more nuanced analysis of how land use affects accessibility and economic equity. Additionally, the study relies on traditional data and exclusion of urban subway systems in accessibility modeling. Key recommendations include integrating urban subway systems into accessibility models for a more comprehensive understanding of urban mobility, employing big data to enhance the precision of transport and economic forecasts, and formulating targeted policies to improve connectivity in peripheral regions, such as Jiangmen and Zhaoqing. By aligning these efforts with broader sustainable development goals, the region can better leverage its rail infrastructure for economic growth, social inclusivity, and enhanced regional cohesion, ensuring a prosperous future for all residents.

Author Contributions: Conceptualization, S.O.; methodology, S.O.; software, Ouyang, S; validation, Z.G. and P.Z.; formal analysis, S.O.; investigation, S.O.; resources, Z.G. and P.Z.; data curation, S.O.; writing—original draft preparation, S.O.; writing—review and editing, Z.G. and P.Z.; visualization, S.O.; supervision, Z.G. and P.Z.; project administration, P.Z.; funding acquisition, S.O., P.Z. and Z.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Shenzhen Science and Technology Program (KQTD 2022101039360416, JCYJ20220818100810024), the China Postdoctoral Science Foundation (2023M740039), the Guangdong Basic and Applied Basic Research (2023A1515110733), the National Natural Science Foundation of China (41925003, 42130402), the 2023 Annual Project of Philosophy and Social Sciences Planning in Guangzhou (2023GZQN58).

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest.
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