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Transport Infrastructure Development and Economic Growth in China: Recent Evidence from Dynamic Panel System-GMM Analysis

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Abstract: China's growth miracle has been accompanied by a great leap forward in the development of transport infrastructure. This study examines and compares impacts from the quantity, quality, and structural aspects of transport infrastructure on regional economic growth in China as the country approaches an upper-middle income status. We also incorporate government's development strategies into the framework for evaluating the growth effect of China's transport infrastructure. Using a consistent and robust dynamic panel data system generalized method of moments (system-GMM) estimation for identification, we find strong evidence confirming that transport infrastructure contributes to regional economic growth in China during the period 2007–2015, as the country approaches its upper-middle income status. In particular, quality improvements in roads and railways and the structural upgrading of transport infrastructure significantly contribute to growth. However, we do not find that quantity expansion of the overall land transport network has a significant impact. Moreover, government development strategies that defy local comparative advantages not only detract from the growth rate but also potentially restrict the contribution of transport infrastructure. Lastly, the regional heterogeneity for Western China may differ across transport modes, particularly with respect to goods versus passenger transport and roadways versus railways.

Keywords: transport infrastructure; quality; structure; economic development level; development strategy; dynamic panel system-GMM

1. Introduction

This study assessed the effects of the quantity, quality, and structural aspects of transport infrastructure endowment upgrading on economic growth. Additionally, the study explored the possibility of a relationship between government development strategies and the growth impact from transport infrastructure. Since the 1990s, the World Bank has repeatedly emphasized that policymakers should not exclusively focus on the quantity of infrastructure investments and that improving the quality of infrastructure services is also vital. Moreover, the World Bank has found that in the past, low operating efficiency, inadequate maintenance, and insufficient attention to users' needs have all contributed to reducing the development impact of these investments. Therefore, it is considered essential to improve the effectiveness of infrastructure investments as well as the efficiency of infrastructure service provision. After analyzing and summarizing lessons learned from experiences worldwide, the World Bank noted that infrastructure investment alone does not guarantee growth and that when the overall economic policy conditions are unfavorable, the returns from infrastructure investment decline [1]. In summary, the World Bank's research has provided valuable guidance for countries to develop infrastructure according to their own unique characteristics.

China has experienced rapid economic growth and an expansion of its transport infrastructure over the last 40 years. Since the initiation of reforms in 1978, the Chinese economy has maintained an annual growth rate of 9.5% in real terms, with the rate doubling every eight years on average according to the National Bureau Statistics of China (NBSC). China's transport infrastructure has emerged at an astonishing pace, growing from almost nothing to an extensive network of roadways, expressways, railways, and high-speed rail (HSR), and it is now the most extensive in the world. As China has successfully transitioned from a low-income country to an upper-middle income one with the world's second-largest economy (see Figure 1), the transport infrastructure endowment has diversified from simple quantitative expansions (i.e., an increase in the length of roadways and railways) to quality improvements (i.e., high-speed roadways and railways) and structural upgrading (i.e., increases in the share of government expenditure to improve maintenance and service efficiency in the transport sector; see Figures 2 and 3). These facts set an appropriate context for studying the causal impacts of China's transport infrastructure on its economic growth at different stages of development. The fundamental questions are as follows. When China reaches upper-middle income status, how do different aspects of transport infrastructure endowment upgrading contribute to regional economic growth? Is there heterogeneity in the impact across these aspects? Further, what is the relationship between the transport infrastructure growth impact and the government's development strategies?

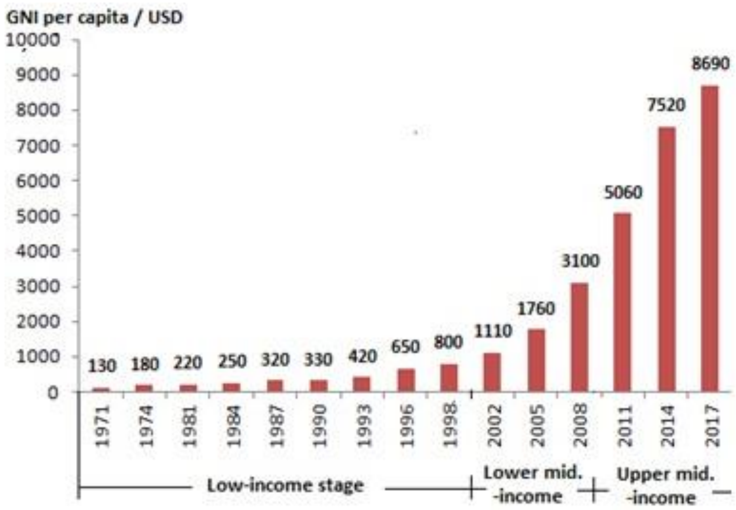

Figure 1. GNI per capita and development stages. Source: Data and thresholds between income groups are from the World Bank [2].

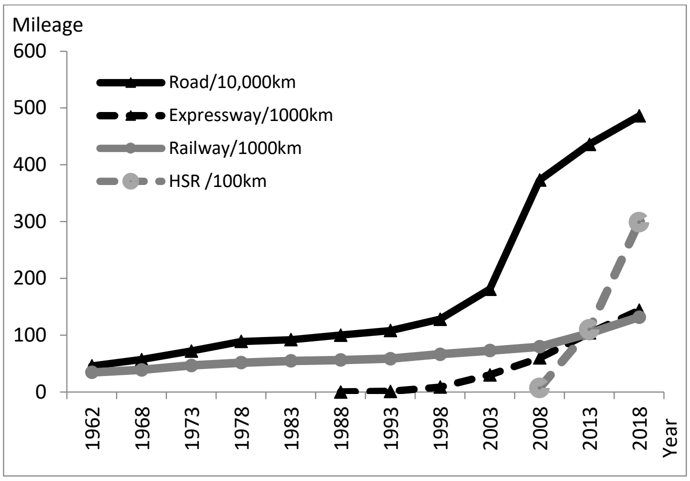

Figure 2. Road, expressway, railway, and high-speed railway mileages. Source: National Bureau Statistics of China (NBSC).

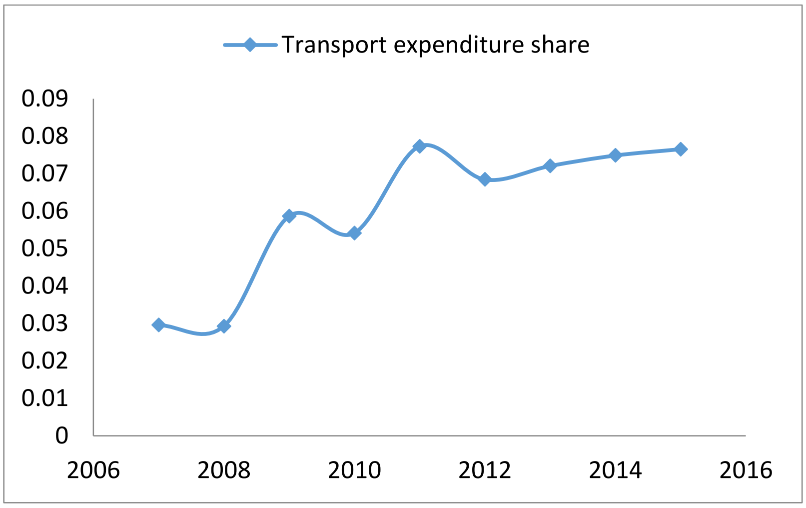

Figure 3. Share of government expenditure in the transport sector, 2007–2015. Source: NBSC.

This study contributes to the growing body of literature that estimates the economic impact of transport infrastructure projects. Recent contributions find that in developed countries, highways and civil aviation promote trade, increase growth, raise skill premia, stimulate innovation, and facilitate decentralization and urban formation [3–5]. See Redding and Turner [6] for an extensive survey.

China's evidence suggests that the transport infrastructure impact differs according to development levels and transport infrastructure attributes. For example, Demurger [7] estimated the impact of transport infrastructure quantity (railway, road, and inland navigable water network length per square kilometer) from 1985 to 1998, when China was a low-income country. The author found that the overall transport quantity had a positive effect on provincial growth, but the impacts decreased with the level of economic development. In a similar research period, Fan and Chan-Kang [8] found that from 1982 to 1999, low-quality roads (mostly rural) rather than high-quality ones (expressways) contributed more to GDP, urban GDP, and poverty reduction. Hong et al. [9] considered both the quantity and quality of transport infrastructure and showed that from 1998 to 2007 (after China became a middle income country), land and water transport's growth impacts were greater than those from airway transport. Lin [10] found that as China approached an upper-middle income level from 2008 to 2013, its HSR promoted urban employment and GDP. Other research has found that transport had zero or negative impacts on development outcomes. For instance, Faber [11] constructed hypothetical instruments and found that from 1997 to 2006, the National Trunk Highway System reduced county GDP growth. Qin [12] exploited an inconsequential units approach and found that from 2002 to 2009, railway speed upgrading reduced county GDP. Feng and Wu [13] showed a negative productivity effect from public infrastructure capital stocks across provinces from 1996 to 2015. Banerjee et al. [14] used an instrumental approach and system-generalized method of moments (GMM) and determined that from 1986 to 2006, the distance of a county from historical transport networks had no impact on per capita GDP growth. In sum, most previous studies have used either public infrastructure investments [15], transport investments [13], or roadway lengths [7] to measure transport infrastructure endowments, but these studies do not capture effects from transport infrastructure quality. Among studies considering both the quantity and quality of transport infrastructure, some identified an overall impact but did not distinguish between the two effects [9].

In addition to the above-mentioned studies, a few papers have focused on infrastructure maintenance and service, and most of the evidence has been based on cross-country analysis. In general, maintenance is defined as those activities that allow public infrastructure to efficiently deliver the outputs for which they were designed [16]. Devarajan et al. [17] examined a panel of 43 developing countries and found that current public expenditures on infrastructure maintenance had a positive effect on output. Rioja [18] modeled the determinants of the optimal share of GDP devoted to infrastructure repair and maintenance, and his quantitative analysis of data from seven Latin American countries suggested that reallocating funds from new investments to maintenance positively affected GDP. Kalaitzidakis and Kalyvitis [19] constructed an infrastructure-led growth model in which the durability of public capital varied according to the maintenance expenditure, and they showed a beneficial role for maintenance expenditure on public capital formation. Despite the consensus on the crucial weight of infrastructure maintenance in the total public investment expenditure, empirical studies on maintenance in developing countries (including China) have received much less attention due to data unavailability [19].

This study also contributes to the literature on the roles of development policies or strategies during countries' early stages of economic development, e.g., Itskhoki and Moll [20] and Tinbergen [21]. In particular, Bruno et al. [22] and Lin [23,24] have provided a series of theoretical and empirical analyses on development strategy impacts in China and other developing countries and transition economies. These studies have argued that most less developed countries in the post-World War II period adopted inappropriate development strategies—or comparative advantage-defying (CAD) strategies—which focused on accelerating the growth of capital-intensive industries even though the countries were capital scarce. Firms in industries with comparative disadvantages became nonviable in open competitive markets, and governments needed to subsidize nonviable firms in prioritized heavy-industry sectors through resource allocation interventions and market distortions [25]. Such development strategies helped shape development outcomes across regions in China. Based on the relevant literature, we argue that if the government adopts a CAD strategy and distorts resource allocation toward the capital-intensive sector, capital returns will be repressed, overall economic conditions will be unfavorable, and returns to transport infrastructure endowment upgrading will be lower. Nevertheless, existing empirical research has ignored the significant role of government development strategies and their influence on transport infrastructure growth impacts in China.

In the context of the rapid rise of China to upper-middle income status, this study constructs a unique dataset to describe the quantity, quality, and structural aspects of the transport infrastructure in China during the period 2007–2015. The dataset has two important characteristics. First, it contains information about regional government expenditures on maintenance in the transport sector, which has been publicly available from the National Bureau Statistics of China (NBSC) since 2007. Following Lin and Fu [26], we identify the share of regional government expenditure for transport that goes toward the structural aspect of transport infrastructure. The second unique characteristic of our dataset is that in contrast to recent studies that used insufficiently aggregated data, we follow Chakrabarti [27] and Hong et al. [9] and select provinces as the geographic units to alleviate concerns about violating the stable unit treatment value assumptions (SUTVA) [28]. This is based on the fact that the economic impacts of the transportation infrastructure can leak beyond the borders of small economic areas such as cities or counties leading to SUTVA violations, as emphasized in Redding and Turner [6], Rephann and Isserman [29], and Baum-Snow and Ferreira [30].

Concerning the econometric methodology, we adopt the system generalized method of moments (system-GMM) estimator for the dynamic panel data model, in which the unobserved province-specific effects and potential endogeneity and measurement error of regressors are controlled for (held constant). GMM was developed by Lars Peter Hansen in Hansen [31] as a generalization of the method of moments, introduced by Karl Pearson in 1894. Hansen shared the 2013 Nobel Prize in Economics in part for this work. The dynamic panel system-GMM estimator was developed by Arellano and Bover [32] and Blundell and Bond [33], building on the first-difference GMM estimation approach proposed earlier by Arellano and Bond [34]. Dynamic panel models permit the use of instrumental variables (internal instruments) for all the explanatory variables so that more precise estimates can be obtained. Thus, the dynamic panel system-GMM method has been widely applied in many areas for example in examining the impact of financial development [35], other institutional improvement [36], etc. In recent years, the method has been exploited to examine the relationship between transport infrastructure and growth, including Chakrabarti [27], Farhadi [37], and Jiwattanakulpaisarn et al. [38]. Indeed, Bond et al. [39] and Hauk and Wacziarg [40] pointed out that the advantage of the dynamic panel system-GMM estimator is that it can address concerns about identification, reverse causality, and to account for the lagged responses of economic growth to any exogenous shock including transport infrastructure, so to obtain consistent and unbiased parameters even in the presence of a measurement error and endogenous right-hand-side variables. As such, we can reliably identify the impacts of the exogenous component of the quantity, quality, and structural aspects of transport infrastructure on regional economic growth in China within the same empirical framework. However, the above-mentioned (external) instrumental variables in the transportation literature cannot achieve our research goal.

Lastly, we consider government development policies in the infrastructure impact evaluation framework for China to investigate how development strategies affect the transport infrastructure growth impact. Following Lin [23,24] and Lin and Wang [25], we adopt the technology choice index (TCI; calculated by the ratio of value-added to labor ratio in manufacturing in a province over the total value-added to labor force in the country) as a measure of the government's inclination to employ a development strategy that is geared toward capital-intensive sectors, in other words, the government's tendency to employ a CAD strategy. For details about government strategies, see Section 5.3.

We found evidence that when China reaches the upper-middle income level, quantity-related bottlenecks in the transport infrastructure have mostly been eliminated; transport infrastructure quality improvement and structural upgrading significantly contributes to regional economic growth. However, we did not find a significant positive impact of the quantity increase in transport infrastructure exclusively. Second, government development strategies that defy local comparative advantages not only lead to declines in the per capita GDP growth rate but also potentially restrict the positive contributions of transport infrastructure. Third, the regional heterogeneity regarding Western China can differ across transportation modes as in goods versus passenger transport and roadways versus railways. Our baseline findings are robust to various sets of control variables, the exclusion of possible outliers, and external instrumental variables for transport infrastructure.

Our contributions to the existing literature are as follows. This study is the first formal assessment of how the quantity, quality, and structure of transport infrastructure contribute to China's economic growth. Moreover, our study is the first to consider government development strategies within an infrastructure impact evaluation framework. We highlight the relationship between a country's level of development and the multiple aspects of transport infrastructure and how government development strategies can affect the impact of transport infrastructure on economic growth. Our results are relevant for policymakers in developing countries and sustainable infrastructure development under the paradigm of Industry 4.0 [41–43].

The rest of the paper is organized as follows. Section 2 reviews the process of transport infrastructure upgrading in China. Section 3 describes the data and variables. Section 4 elaborates on the dynamic panel data model and system-GMM estimation. Section 5 reports baseline estimation results and robustness checks. Section 6 concludes this paper.

2. Transportation Infrastructure Endowment Upgrading in China

Since the founding of the People's Republic of China (PRC), the transportation sector has experienced three phases: Bottleneck restrictions, preliminary mitigation, and basic adaptation [44]. We review the three development stages for the two main forms of land transport: roadways and railways. The two modes of transportation account for around 80% of the freight transport and 96% of the passenger transport volume in China.

2.1. Before the 1990s

In the early days of the founding of P.R.C., China's transportation industry was archaic. There were only 80,700 km of roads and 21,800 km of railways. By 1978, the total mileage of the transportation lines was only 1.235 million kilometers. After the economic reform and opening up in 1978, there was a sharp increase in industrial and agricultural production, and severe deficiencies and bottlenecks began to emerge in the transportation sector. The result was that manufactured products could not be shipped out, and one third of the country's processing capacity was idle. In the mid-1980s, the government began to focus on the construction of high-quality roads.

2.2. From the 1990s to 2007

Since the Eighth Five-Year Plan (1991–1995), investments in infrastructure have become a national priority, leading to a substantial expansion of the transportation network. For instance, the "Five Vertical and Seven Horizontal" national trunk highway lines were connected in 2007, 13 years ahead of schedule. These lines brought roadway operating mileage to 3.583 million kilometers, 41 times the mileage that existed in the early PRC. During the period 1997–2007, the Ministry of Railways conducted six rounds of speed upgrading on existing railway lines and increased railway transport capacity by 50% to ease the bottleneck constraints in China's railway transport, increasing average railway speeds from 48.1 to over 200 km/h. In 2003, the Qinhuangdao-Shenyang passenger-dedicated HSR line was connected, easing passenger and freight congestion along the Shanhaiguan transport corridor. According to the National Railway Administration of China, HSR lines are defined as railway lines running at least with the average speed of 250 km/h or passenger dedicated intercity lines with the average speed of at least 200 km/h. By the end of 2007, China's railway mileage had reached 78,000 km. At this time, land transportation bottlenecks in China were preliminarily mitigated.

2.3. Since 2007

China's transportation sector implemented further reform policies to build an integrated transportation infrastructure network, effectively eliminate poverty, and emphasize railway construction in the central and western regions. By the end of 2018, China's total roadway length had reached 4.85 million kilometers and the expressway mileage jumped to 143,000 km, the highest in the world. Moreover, rural roads connected 99.9% of towns and villages. In terms of railway transport, China's HSR network expanded dramatically with the opening of the Beijing–Tianjin intercity HSR in 2008. By the end of 2018, the national railway operating mileage had reached 131,000 km, with HSR exceeding 29,000 km, accounting for two thirds of the total HSR in the world. At this point, China's rapid passenger transport network based on HSR and supplemented by intercity railways was initially complete.

3. Variables and Data

This section defines variables and describes data. We used province-level data to examine the relationship between transport infrastructure development and economic growth in China. To measure the quantity, quality, and structural aspects of transport infrastructure endowment upgrading, we construct a number of transport infrastructure endowment indicators. In the meanwhile, following Levine et al. [35], we control for different conditioning information sets in our growth regression model to hold constant other factors associated with economic growth.

3.1. Variables

To investigate how the exogenous component of the quantity, quality, and structural aspects of transport infrastructure endowment influences economic growth, we set up a growth regression model with the annual growth rate of real per capita GDP as the dependent variable. The independent variables include a variable representing the transport infrastructure development in the above-mentioned aspects and a conditioning information set controlling for (holding constant) other economic growth factors.

3.1.1. Indicators for Transport Infrastructure Endowment

Following the existing literature and according to the details of China's transport infrastructure development, we selected the available data to construct the following four transport infrastructure endowment indicators:

- Quantity of transport infrastructure (Roadpc): Following Demurger [7] and Hong et al. [9], weuse roadway and railway operation mileage per million people (Roadpc) to characterize the quantity aspect of land transport infrastructure. We also separately use road or railway mileages per million people or per square kilometer as alternative measures and replicate all the regressions. Results still hold and are available upon request.
- Quality of transport infrastructure: We define the quality indicators for roadways and railways as follows.

For roadways (Highroadshare): Fan and Chan-Kang [8] and Hong et al. [9] disaggregate road infrastructure into different classes (expressway, Class 1–4, and substandard) to account for road quality according to the Technical Standard for Highway Engineering in China. Following this literature, we used the share of expressway over total roadway in terms of length (Highroadshare) to characterize the quality of roadways.

For railways(HSR): Chinese trains are split into different types of services: HSR with speeds above 200 km/h and conventional trains with speeds below 140 km/h, according to the China Railway Technology Management Regulations. Hence, we disaggregated railway into HSR (including newly constructed HSR and speed upgrading on existing railway lines) and conventional speed railway to account for the quality of the railway transport. As data on provincial-level HSR mileages are not publicly available, following the recent empirical literature about China's HSR, e.g., Ke et al. [45], Lin [10], and Qin [12], we first defined a "connected" dummy indicating whether city r of province i was connected to HSR in year t. The dummy takes the value zero unless a city is connected to HSR before the end of that year, in which case it takes the value one. Then, we sum up the total number of times that all cities in province i during year t that were connected to HSR as the indicator for railway transport quality (HSR).

- Structure of transport infrastructure (Trstuct1): According to the Ministry of Finance of China, the huge public expenditure for the transport sector is used to improve the maintenance, operation, and service efficiency of transportation covering highways, railways, waterways, and civil aviation. For regional governments' expenditures for the transport sector, the China Statistical Yearbook only provides provincial public finance expenditure data and does not have relevant data on provincial extra-budgetary or other government expenditures [46]. Following Devarajan et al. [17], Kalaitzidakis and Kalyvitis [19], and Rioja [18], we usedthe share of regional government expenditures for transport to characterize the government's effort to increase operating efficiency and provide adequate maintenance. Following Lin and Fu [26], we identified this indicator as the structure of transport infrastructure (Trstuct1). Based on Barro [47], Lin and Fu [26] defined the ratio of public expenditure to output as the structure of the public infrastructure endowment and defined the proportion of public expenditure in a specific sector as the structure of the public infrastructure endowment in that sector.

As China has transitioned from a low-income country to an upper-middle income one, the transport infrastructure endowment has diversified from simple quantitative expansions to quality improvements and structural upgrading. Moreover, most recent causal evidence shows that China's expressways and HSRs help generate new economic activities, e.g., Baum-Snow et al. [48], Ke et al. [45], Lin [10], and Ke and Yan [49]. Additionally, cross-country evidence suggests that public expenditures on maintenance have a positive effect on output and growth, e.g., Devarajan et al. [17] and Rioja [18]. As the quantity-related bottlenecks in the transport infrastructure have mostly been eliminated during our research period 2007–2015, we expected positive coefficients for Highroadshare, HSR, and Trstuct1.

The estimated sign for Roadpc is hard to predict a priori. It could be positive, but we do not expect Roadpc to significantly contribute to the regional growth outcome.

3.1.2. Conditioning Information Sets

Following the common practice in the growth literature, e.g., Levine et al. [35], we used conditioning information sets to capture the influence of factors other than the transport infrastructure development indicators on economic growth. Specifically, we collected data on control variables commonly used in the transportation-growth literature and the literature on China's economic structure's characteristics, e.g., Demurger [7], Sala-i-Martin [50], and Yao [51]. To avoid multicollinearity and poor controls, and to examine the sensitivity of our baseline results, we included the control variables in a stepwise fashion and divided them into four different conditioning information sets defined as follows:

The basic conditioning information set (Basic set): the constant, the logarithm of initial per capita real GDP (l.lgdppc), that is the per capita GDP in yuan of the previous year, to capture the convergence effect, and the logarithm of initial level of education (Enroll), whichis the secondary school enrollment ratio of the previous year, to capture human capital accumulation.

For the expected signs of the estimated coefficients, a negative coefficient wasexpected for l.lgdppc, indicating the existence of conditional convergence among provinces. However, the estimated sign for Enroll is hard to predict a priori, because the role of education in determining economic growth is an area of dispute in the growth empirics as suggested by Sala-i-Martin [50].

The medium conditioning information set (Medium set): the basic set plus the ratio of fixed asset investment formation to GDP (Investrate) to capture the physical capital accumulation impact and the share of state-owned enterprises in fixed asset investment (SOE) as an inverse proxy for the market economy reform process. So, the Medium set includes the constant, l.lgdppc, Enroll, Investrate, and SOE.

For the Investrate, a positive coefficient wasexpected, as greater investment shares have been shown to be positively related toeconomic growth [52]. For SOE, a negative coefficient is expected, as in general the relatively poor performance of state-owned entities has been shown to hurt economic growth [53].

The policy conditioning information set (Policy set): the medium set plus the ratio of export values over GDP (Export) to measure the regional economy's dependence on export, and the ratio of government expenditure over GDP (Govsize) to measure the government size.

A negative coefficient on Exportwasexpected in our research period 2007–2015. As Asia is more reliant on exports than any other region, it is bound to be hurt by the rich world's worst recession since the 1930s owning to the 2008 Financial Crisis, emphasized by The Economist. We expect a negative coefficient for Govsize, as an excessively large government may crowd out private investment and be harmful to growth performance [54].

The full conditioning information set (Full set): thepolicy set plus the share of GDP produced in the agriculture sector (Agrishare) as an imperfect measure for the industry upgrading, and urban population divided by total population (Urbanize) as an imperfect proxy for all types of geographical characteristics related to the provincial economic structure [7].

We expected a negative coefficient for Agrishare, as fast economic growth was associated with rapid structural change as industrialization proceeded [55]. If urban-biased policy is implemented during our research period, then a positive coefficient on Urbanize is expected [7].

Due to the potential nonlinear relationship between economic growth and the explanatory variables, we used the natural logarithms of these variables in regressions. For each of the four indicators for transport infrastructure endowment described in Section 3.1.1, we run regressions for the (1) Basic; (2) Medium; (3) Policy; and (4) Full conditioning information sets.

3.2. Data

We collected a set of balanced panel data from all provinces, municipalities (directly under the central government), and autonomous regions for the period 2007–2015 from the China Statistical Yearbooks. As of 2007, railway speed upgrading information for all cities is from the People's Republic of China Railroad Atlas 2007. Newly constructed HSR information at the city-level wasfrom the China Railway Yearbooks. Table 1 presents the descriptive statistics. We can see that there wasconsiderable variation across provinces.

Table 1. Descriptive statistics.

Variables	Obs.	Mean	Std. Dev	Min	Max
Growth	261	0.091	0.051	−0.086	0.232
Roadpc (kmper 1,000,000 people)	261	3539.000	2171.000	534.000	13,246.000
Highroadshare	261	0.026	0.015	0.004	0.073
HSR (times)	261	10.111	7.573	2.000	32.000
Trstuct1	261	0.061	0.027	0.007	0.161
lgdppc	261	8.796	0.498	7.481	9.851
Enroll	261	0.055	0.014	0.021	0.086
Investrate	261	0.690	0.211	0.254	1.328
SOE	261	0.299	0.102	0.114	0.560
Export	261	0.160	0.181	0.015	0.849
Govsize	261	0.221	0.097	0.087	0.627
Agrishare	261	0.109	0.056	0.004	0.290
Urbanize	261	0.529	0.139	0.282	0.896
TCI	261	7.819	3.366	1.185	15.439

Notes: 1. Real GDP is computed with the implicit deflator provided by the National Bureau Statistics of China (NBSC). Other variables in real terms are deflated using the provincial overall retail price index based on the 1980 price; 2. Technology choice index (TCI) is calculated by the ratio of value-added to labor ratio in manufacturing in a province over the total value-added to labor force in the country following Lin [23,24], and Lin and Wang [25]; and 3. Following the usual practice, Tibet is not included in the sample due to data inconsistency, and the data of Chongqing is added to the Sichuan province.

4. Model and Estimation

An attraction of panel data is the possibility of consistent estimation of the fixed effects model, which allows for unobserved heterogeneity that may be correlated with regressors [56]. Hence, to separately assess the influence of the quantity, quality, and structural aspects of transport infrastructure endowment upgrading, we formulated the empirical growth model following Barro and Sala-i-Martin [57] in a panel data context [58].

$$y_{i,t} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \beta Transport_{i,t} + \delta' X_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t}, \text{ for } i = 1, \ldots, N, \ \ t = 2, \ldots, T \quad (1)$$

where $y_{i,t}$ is the logarithm of per capita real GDP for province i in year t. $y_{i,t-1}$ is the lagged logarithm of per capita real GDP. $Transport_{i,t}$, the main variable of interest in this study, equals eitherthe quantity of transport infrastructure (Roadpc), the quality of roadway transport (Highroadshare), the quality of railway transport (HSR), or the structure of transport infrastructure (Trstuct1) as described in Section 3.1.1. That is, to identify the impact of the quantity of transport infrastructure, $Transport_{i,t}$ equals Roadpc; to identify the impact of the quality of roadway transport, $Transport_{i,t}$ equals Highroadshare; to identify the impact of the quality of railway transport, $Transport_{i,t}$ equals HSR; and to identify the impact of the structure of transport infrastructure, $Transport_{i,t}$ equals Trstuct1.$X_{i,t}$ is a conditioning information set (Basic set, Medium set, Policy set, and Full set). It represents a vector of conditioning information that controls for (holding constant) other factors associated with economic growth, but excluding $y_{i,t-1}$ that Equation (1) has already controlled for. Accordingly, α, β, and δ are the parameters and vectors of parameters to be estimated.

η_i is the fixed effect thatcontrols for (holding constant) the unobserved time-invariant province-specific characteristics [59]. In the transport-growth literature, such unobserved time-invariant heterogeneity is typically climate, topography, history, etc., which influence both growth performance and transport infrastructure development process hence lead to omitted variables bias. λ_t, denotes the unobserved time effect controlling for (holding constant) common shocks (to all provinces) originated from macroeconomic, political, or technological sources [56]. Both the province- and year-effects may also reflect province-specific and period-specific components of measurement errors [58]. Lastly, $\varepsilon_{i,t}$ is the idiosyncratic error term. To account for possible heteroskedasticity, standard errors are clustered at the province level. Equation (1) guarantees that our estimates, in particular for β, are not contaminated by aggregate shocks and trends common to all provinces or by time-invariant provincial factors such as climate, geography, history, and culture.

However, given the potential for unobserved time-varying factors and reverse causality that can induce endogeneity bias and the lagged responses of economic development to exogenous shocks, we used the system-GMM estimator for dynamic panel data model proposed by Arellano and Bond [34]; Arellano and Bover [32], and Blundell and Bond [33]. GMM is a generic method for estimating parameters in statistical models. There are several advantages of using the GMM estimator for the dynamic panel data model. First, it enables us to control for the unobserved province-specific effects, η_i, by treating initial efficiency as time-invariant fixed effects and eliminate its influence through a time-dimensional transformation. More importantly, we can use appropriate lags of the independent variables as (internal) instrumental variables to deal with possible endogeneity in the regressors. Hence, we can reliably examine the impacts of the exogenous component of the quantity, quality, and structural aspects of transport infrastructure on regional economic growth in China at the same time and within the same empirical framework. In fact, the system-GMM method has been widely applied, particularly to identify transport infrastructure impacts in empirical growth research, for example Chakrabarti [27], Farhadi [37], Jiwattanakulpaisarn et al. [38], and Zhang and Fan [60].

Specifically, estimating Equation (1) is equivalent to estimating the dynamic panel data model:

$$y_{i,t} = \alpha y_{i,t-1} + \beta Transport_{i,t} + \delta' X_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t},\ \text{for } i = 1, \ldots,\ N,\ \ t = 2, \ldots, T \tag{2}$$

We take the first difference of Equation (2) to eliminate, η_i, the unobserved time-invariant province-specific characteristics:

$$\begin{gathered} y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta(Transport_{i,t} - Transport_{i,t-1}) + \\ \delta'(X_{i,t} - X_{i,t-1}) + (\lambda_t - \lambda_{t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) \end{gathered} \tag{3}$$

Note that in Equation (3), we need instrumental variables to deal with two issues: (a) the correlation between $\varepsilon_{i,t} - \varepsilon_{i,t-1}$ and $y_{i,t-1} - y_{i,t-2}$ and (b) the endogeneity of $Transport_{i,t} - Transport_{i,t-1}$ and other growth predictors [51]. A simple ordinary least squares regression with two-way fixed effects (FE-OLS) cannot generate unbiased estimates in this situation. The system-GMM estimator building on the first-difference GMM estimator is proposed to address these problems in dynamic panel data modeling [61].

In system-GMM, we estimated the differenced Equation (3) and level Equation (2) simultaneously. The suitable instruments for Equation (3) are lagged explanatory variables. The first-differenced GMM estimator uses lagged explanatory variables as the instrumental variables under two assumptions. First, $\varepsilon_{i,t}$, the idiosyncratic error is not serially correlated. Second, variables contained in $X_{i,t}$ are weakly exogenous [58]. For level Equation (2), the suitable instruments are the lagged differences of the explanatory variables. To ensure the validity of these additional instrumental variables, one more assumption needs to be made, whichis the first differences of the independent variables in Equation (2) that are uncorrelated with η_i [58]. By using instruments from within the available dataset, this approach efficiently addresses the correlations described in (a) and (b). The system-GMM model is also estimated under the assumption of second-order autocorrelation by increasing the lags of instruments one additional time period in both the level and differenced equations [27]. Bond et al. [39] and Hauk and Wacziarg [40] pointed out that the potential for obtaining consistent parameter estimates, even in the presence of measurement error and endogenous right-hand-side variables, is a considerable strength of the system-GMM approach in the empirical growth research.

To use the system-GMM estimator, two criteria must be satisfied: The test for serial correlations in the first-difference error $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$ and the Hansen test for over-identification restrictions. The first test aims to check if serial correlation exists in the error terms. The Hansen test evaluates the validity of the instruments by checking the exogeneity conditions. Furthermore, to alleviate the instrument proliferation problem, we followed theRoodman [62] approach to both collapse instruments and use one or two lags instead of all the available lags for instruments in system-GMM estimators.

5. Estimation Results

5.1. FE-OLS Estimation

As a starting point, Table 2 reports the results from a static panel estimator FE-OLS of Equation (1) under the four conditioning information sets (Basic set, Medium set, Policy set, and Full set) defined in Section 3.1.2. As expected, the coefficients of all four transport infrastructure endowment indicators (Roadpc, Highroadshare, HSR, and Trstuct1) described in Section 3.1.1 werepositive. Only coefficients on the structure of transport infrastructure endowment (Trstuct1) werestatistically significant at the 10% level, suggesting that growth wassignificantly higher when a province spends a larger share of public expenditure on the transport sector to improve maintenance, operation, and service efficiency.

Table 2. Transport infrastructure and growth: ordinary least squares regression with two-way fixed effects (FE-OLS).

Dependent Variable		**Per Capita Real GDP Growth Rate**			
		Roadpc	**Highroadshare**	**HSR**	**Trstuct1**
Conditioning information set		(1)	(2)	(3)	(4)
Basic	Coefficient	0.016	0.004	0.006	0.023 *
	Standard error	(0.013)	(0.006)	(0.008)	(0.012)
Medium	Coefficient	0.017	0.004	0.006	0.023 *
	Standard error	(0.013)	(0.007)	(0.008)	(0.013)
Policy	Coefficient	0.016	0.005	0.005	0.023 *
	Standard error	(0.013)	(0.007)	(0.007)	(0.013)
Full	Coefficient	0.016	0.009	0.005	0.024 *
	Standard error	(0.013)	(0.007)	(0.007)	(0.013)

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in all regressions; 3. The number of observations is 261; and 4. * $p < 0.10$.

Nevertheless, we could not presume that the fixed effect regressions necessarily estimate the causal effect of transport infrastructure, as there are always unobserved time-varying factors that can affect both growth and transport development. Additionally, there is the potential reverse effect. To further correct for this endogeneity and reliably identify the impact of the exogenous components of the various aspects of the transport infrastructure development on economic growth, we followed Chakrabarti [27], Farhadi [37], Jiwattanakulpaisarn et al. [38], and Zhang and Fan [60], and used the system-GMM approach. Specifically, we used the lagged observations of all the growth predictors as internal instruments in a dynamic panel data system-GMM framework to obtain consistent and efficient estimates.

5.2. System-GMM Estimation

Table 3 reports the system-GMM estimates of Equations (2) and (3) with the policy conditioning information setshown in columns(1)–(4) and the full conditioning information set shown in columns

(5)–(8), respectively. In the system-GMM estimations, all estimated standard errors werecorrected for heteroskedasticity, and year dummies wereincluded in all regressions. The initial level of per capita real GDP wastreated as a predetermined variable while the four transport infrastructure endowment indicators (Roadpc, Highroadshare, HSR, and Trstuct1), human capital accumulation, investment rate, and other control variables werepotentially endogenous variables.

Table 3. Transport infrastructure and growth: System-GMM (Policy set and Full set).

Variables	Dependent Variable: Per Capita Real GDP Growth Rate							
	Policy Set				Full Set			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Roadpc	0.016				0.060			
	(0.033)				(0.050)			
Highroadshare		0.039 **				0.045 *		
		(0.018)				(0.026)		
HSR			0.036 **				0.039 *	
			(0.016)				(0.023)	
Trstuct1				0.067 **				0.072 *
				(0.030)				(0.042)
L.lgdppc	−0.036	−0.088	−0.019	−0.164 **	−0.043	−0.040	0.255	−0.233
	(0.064)	(0.060)	(0.050)	(0.079)	(0.150)	(0.107)	(0.424)	(0.148)
Enroll	0.088	−0.092	0.012	−0.204 **	0.160	−0.065	0.029	−0.065
	(0.066)	(0.072)	(0.069)	(0.091)	(0.170)	(0.100)	(0.100)	(0.172)
Investrate	−0.040	0.018	0.057	0.038	0.114	0.048	0.002	0.151
	(0.058)	(0.064)	(0.044)	(0.065)	(0.086)	(0.079)	(0.173)	(0.185)
SOE	−0.112 **	−0.020	0.050	0.002	−0.086	−0.067	−0.002	0.009
	(0.054)	(0.053)	(0.050)	(0.047)	(0.079)	(0.063)	(0.061)	(0.113)
Export	−0.040	−0.033	−0.015	−0.010	−0.061 **	−0.035	−0.023	−0.080
	(0.027)	(0.022)	(0.015)	(0.021)	(0.028)	(0.026)	(0.041)	(0.051)
Govsize	0.038	−0.008	0.027	−0.085	−0.051	0.079	0.042	−0.063
	(0.059)	(0.087)	(0.063)	(0.089)	(0.162)	(0.113)	(0.168)	(0.148)
Agrishare					−0.155 *	0.011	−0.037	−0.117
					(0.083)	(0.030)	(0.123)	(0.088)
Urbanize					−0.061	0.085	−0.659	0.236
					(0.229)	(0.181)	(0.672)	(0.316)
Constant	−0.265	0.571	0.251	0.937	−0.064	0.000	−2.633	1.738
	(0.504)	(0.460)	(0.314)	(0.614)	(1.422)	(0.013)	(3.723)	(1.666)
Hansen test *p* value	0.08	0.06	0.05	0.04	0.16	0.02	0.17	0.06
Difference Hansen J test	0.83	0.77	0.08	0.13	0.17	0.08	0.21	0.13
AR(1) test	0.04	0.08	0.03	0.21	0.03	0.13	0.02	0.24
AR(2) test	0.24	0.19	0.05	0.93	0.52	0.23	0.52	0.53
No. of Instruments	22	22	22	22	26	26	26	26

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in all regressions; 3. The number of observations is 232; 4. We report p-value for AR(1) and AR(2) tests; 5. Tests and estimation results from collapsed instruments with the basic and medium conditioning information sets are in the working paper version of this paper and are available upon request; and 6. * $p < 0.10$; ** $p < 0.05$.

Table 3 suggests that our system-GMM estimations werevalid. The insignificance of all the AR(2) test results implies that there wasno second-order serial correlation of the error term in Equation (3) for all the regression models. The insignificance of the Hansen J test and the difference Hansen J test results together suggest the satisfaction of orthogonal conditions. There wasno instrument proliferation problem as instrument counts ranged between 22 and 24.

For the key variables of interest, Table 3 shows that, as expected, the coefficients of all the four transport infrastructure endowment indicators (Roadpc, Highroadshare, HSR, and Trstuct1) werepositive in our research period. Three werestatistically significant: the quality of roadway transport (Highroadshare); the quality of railway transport (HSR); and the structure of transport infrastructure (Trstuct1). The results werenot only consistent with the most recent evidence that China's expressways and HSRs generate new economic activities [10,45,48,49], but are also in line with cross-country evidence that current public expenditures on maintenance have a positive effect on output and growth [17,18]. In addition, as expected, the coefficients on the transport infrastructure quantity indicator (Roadpc) werestatistically insignificant, which wasin line with the FE-OLS estimates indicating that exclusively the quantity expansion of the transport network didnot have a significant impact on growth. Obviously, the finding runs contrary to the evidence in the early transport literature, for example, Demurger [7], and Fan and Chan-Kang [8]; however, is consistent with our conjecture. We argued that different aspects of transport infrastructure have heterogeneous impacts on growth depending on the economic development level. The research period in Demurger [7] and Fan and Chan-Kang [8] reflected China's low-income stage. In the 1980s and 1990s, the transport infrastructure was still facing bottleneck constraints and the average rate of urbanization was only 27%. At that time, transport infrastructure quantity and low-quality roads were the key factors in regional economic growth. Meanwhile, our study focuses on the period after 2007, when China was approaching upper-middle income status with an average urbanization rate exceeding 50%. During this period, an approach that focused solely on the quantity expansion of the existing transport infrastructure would not even come close to achieving economic development and meeting public needs for more efficient transport services. At this level of development, the rapid development of highly efficient transportation infrastructure—reflected by quality and structure upgrading—becomes the driving force for economic growth.

Most control variables show expected signs although they are not always statistically significant. The coefficients of the lagged per capita real GDP (l.lgdppc) weremostly negative and smaller than one, suggesting evidence of conditional convergence. The coefficients of industry upgrading (Agrishare)werenegative, consistent with Ding and Knight's [55] finding. The estimated coefficients on other variables wereinsignificant.

Lastly, Baum-Snow et al. [48] emphasized that implicit evidence for the process through which infrastructure investments are assigned can plausibly be obtained by comparing the OLS coefficients and instrumental variable/GMM estimates. We found that the system-GMM estimates (Table 4) weremostly larger than the FE-OLS estimates (Table 3), which is consistent with the findings in Baum-Snow [3] and Duranton and Turner [4] in the United States. Thus, any bias served to bias the impact of infrastructure endowment downward. The results suggest that in our research period, the equilibrium allocation process assigned transport infrastructure to locations with slower growth rates rather than to randomly selected locations.

Table 4. Infrastructure and growth: System-GMM (Policy set). Robustness checks with development strategies measured by TCI.

	Dependent Variable: Per Capita Real GDP Growth Rate							
	With TCI				With TCI and Infrastructure Interaction			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Railpc	−0.032 (0.027)				−0.011 (0.030)			
Railpc × TCI					0.094 (0.061)			
Highroadshare		0.032 * (0.017)				0.036 * (0.020)		
Highroadshare × TCI						−0.021 (0.035)		
HSR			0.052 * (0.029)				0.048 ** (0.022)	
HSR × TCI							−0.019 (0.028)	
Trstuct1				0.090 *** (0.027)				0.100 *** (0.033)
Trstuct1 × TCI								−0.040 (0.040)
L.lgdppc	0.023 (0.067)	−0.174 ** (0.081)	−0.051 (0.092)	−0.223 *** (0.074)	0.037 (0.082)	−0.159 * (0.085)	−0.093 (0.096)	−0.254 *** (0.065)

Table 4. *Cont.*

	Dependent Variable: Per Capita Real GDP Growth Rate							
	With TCI				With TCI and Infrastructure Interaction			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Enroll	0.122	−0.095	0.129	−0.164	0.130 *	−0.077	0.142 *	−0.150
	(0.087)	(0.090)	(0.091)	(0.107)	(0.071)	(0.097)	(0.081)	(0.104)
Investrate	0.019	0.090 **	0.043	0.122 *	0.046	0.101 **	0.039	0.063
	(0.056)	(0.040)	(0.082)	(0.068)	(0.063)	(0.045)	(0.128)	(0.061)
SOE	−0.090	−0.037	0.011	−0.030	−0.080	−0.040	0.010	−0.007
	(0.056)	(0.066)	(0.074)	(0.055)	(0.059)	(0.066)	(0.064)	(0.043)
Export	−0.062 **	−0.024	−0.054 **	−0.019	−0.062 **	−0.027	−0.047	−0.014
	(0.026)	(0.019)	(0.026)	(0.023)	(0.025)	(0.018)	(0.028)	(0.027)
Govsize	0.032	−0.038	−0.005	−0.117	−0.004	−0.029	−0.053	−0.177 *
	(0.066)	(0.110)	(0.095)	(0.104)	(0.078)	(0.110)	(0.082)	(0.090)
TCI	−0.080 *	−0.085 **	−0.061	−0.098 **	−0.038	−0.083 **	−0.081 *	−0.101 **
	(0.041)	(0.032)	(0.063)	(0.037)	(0.073)	(0.034)	(0.045)	(0.037)
Hansen test p value	0.11	0.04	0.08	0.59	0.31	0.04	0.09	0.73
Difference Hansen J test	0.11	0.13	0.64	0.69	0.27	0.06	0.51	0.82
AR(1) test	0.03	0.12	0.01	0.16	0.03	0.12	0.01	0.16
AR(2) test	0.12	0.42	0.18	0.94	0.78	0.46	0.23	0.88
No. of Instruments	23	23	23	23	24	24	24	24

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in all regressions; 3. The number of observations is 232; 4. We report ap-value for AR(1) and AR(2) tests; and 5. To construct an indicator capturing whether the regional development strategy falls into a comparative-advantage-defying (CAD) or comparative-advantage-following (CAF) category at the provincial level, following Lin [23] and Bruno et al. [22], we use the technological choice index (TCI), $TCI_{i,t} = (AVM_{i,t}/LM_{i,t})/(GDP_{i,t}/L_{i,t})$. Here, $AVM_{i,t}$ is the value added of manufacturing industries of province i at year t. $GDP_{i,t}$ is the total added value of the whole nation. $LM_{i,t}$ is the labor in the manufacturing industry, and $L_{i,t}$ is the total labor force. Therefore, we expect a higher TCI value when a province follows CAD strategy by investing in the capital-intensive heavy industry than otherwise; 6. TCI values are specified as the difference from the sample mean; and7. For brevity, Table 4 only reports results with the policy conditioning information set. Results with the other conditioning information sets are similar and available upon request; 8. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

5.3. Robustness Checks

We conducted additional robustness checks for development strategies, regional-biased policy, political-biased policy, and external instrumental variables for transport infrastructure.

5.3.1. Development Strategies

One concern wasthat the impact of the infrastructure endowment upgrading could be confounded by the government's development strategies. We also wanted to test whether the contribution of infrastructure endowment upgrading depends on the extent to which development strategies defy local comparative advantages. If the government adopts a CAD strategy, distorting resource allocation toward the capital-intensive sector, the capital return is repressed and hence, aggregate economic growth tends to be low. Moreover, the more distorted the regional economy is away from its comparative advantage, the more unfavorable are the overall economic conditions, and the lower the returns to transport infrastructure quality and structure upgrading.

The basic idea that growth is spurred when a country or region follows a development strategy consistent with its comparative advantages and endowment structure is intuitively and theoretically appealing. However, it is difficult to test. To construct an indicator that captures whether the regional development strategy falls into a CAD or comparative advantage following (CAF) category at the provincial level, we followed Lin [23] and Bruno et al. [22] and used the technological choice index (TCI):

$$TCI_{i,t} = \frac{AVM_{i,t}/LM_{i,t}}{GDP_{i,t}/L_{i,t}} \quad (4)$$

Here, $AVM_{i,t}$ is the valueadded of manufacturing industries in province i at year t; $GDP_{i,t}$ is the total added value of the whole nation; $LM_{i,t}$ is the labor in the manufacturing industry; and $L_{i,t}$ is the total labor force. Therefore, we expected a higher TCI value when a province follows a CAD strategy and invests in a capital-intensive heavy industry than otherwise. Specifically, the numerator of TCI will be relatively larger in contexts where manufacturing firms have larger market shares. This is owing to governments' interventions, where subsidized credit access, inputs, and supernormal profits lead to huge investments into capital, and the value-added generated by that sector is above what it would be otherwise. Less labor will be absorbed by the capital-intensive sectors, further inflating the value-added to labor ratio in the supported sector [22]. The estimated coefficient of TCI is expected to be negative in the empirical growth regression.

First, we included TCI in Table 4, columns (1)–(4), with the policy conditioning information set. Clearly, our system-GMM estimations werevalid and it is notable that the earlier results for transport infrastructure in Table 3 wereall robust to the inclusion of TCI. The coefficients on TCI werenegative and statistically significant, as expected. Growth waslower when a province followed a CAD strategy. This is in line with existing cross-country studies and studies of China in the development strategy literature, e.g., Bruno et al. [22], Lin [24], and Lin and Wang [25].

Further, to test whether the impact of transport infrastructure upgrading on growth varies across provinces according to the extent to which regional development strategies defy comparative advantages, we further added the interaction term between TCI and a transport infrastructure endowment indicator. In these interaction terms, the TCI values are specified as their difference from the sample mean [63]. Thus, the coefficient of the transport infrastructure indicator represents the partial effect of the transport infrastructure endowment upgrading on per capita GDP growth at the mean value of TCI.

Table 4, columns (5)–(8), shows the system-GMM estimates with the policy conditioning information set. Clearly, the system-GMM estimates werevalid. The coefficients on TCI wereall negative and statistically significant in columns (6)–(8), as in columns (1)–(4). Our earlier results for the four transport infrastructure indicators (Roadpc, Highroadshare, HSR, and Trstuct1) all hold.

Notably, for those transport infrastructure endowment indicators having significantly positive relationships with regional economic growth (Highroadshare, HSR, and Trstuct1), the coefficients on their TCI interaction terms wereall negative. These results support our earlier conjecture that the greater the deviation from the local comparative advantage (higher TCI), the lower the contribution of transport infrastructure quality and structure upgrading on regional economic growth. Nevertheless, the coefficients on the interaction terms werestatistically insignificant. The finding indicates that at the national level, 40 years of CAF strategy in China has created favorable overall economic conditions that ensure that transport infrastructure endowment upgrading can promote growth at the aggregate level.

5.3.2. Regional-Biased Policy

To rule out concerns that our results are confounded by regionallybiased policies or regional favoritism [12,48], in this robustness check, we introduced a regional dummy variable to indicate the more developed eastern regions of China and the less developed western region, respectively. Table 5, columns (1)–(4) and (5)–(8), reports the results withthe policy conditioning information set. Clearly, adding a regional dummy does not change our conclusions, suggesting that the strong connections between the quality of roadway transport (Highroadshare), the quality of railway transport (HSR), the structure of transport infrastructure (Trstuct1), and regional growth performance were not associated with whether a province was in the east or west.

Table 5. Transport infrastructure and growth: System-GMM (Policy set). Robustness checks with regional dummy.

	Dependent Variable: Per Capita Real GDP Growth Rate							
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Roadpc	0.023 (0.031)				0.019 (0.038)			
Highroadshare		0.041 ** (0.018)				0.040 ** (0.017)		
HSR			0.045 * (0.025)				0.029 * (0.017)	
Trstuct1				0.070 * (0.038)				0.050 ** (0.022)
East dummy	−0.004 (0.053)	−0.011 (0.068)	0.081 (0.120)	−0.096 (0.108)				
West dummy					0.053 (0.041)	0.063 (0.047)	0.004 (0.026)	0.042 (0.049)
Hansen test p value	0.12	0.04	0.69	0.08	0.12	0.06	0.06	0.05
Difference Hansen J test	0.82	0.13	0.86	0.12	0.79	0.75	0.05	0.26
AR(1) test	0.05	0.06	0.05	0.09	0.05	0.06	0.02	0.14
AR(2) test	0.27	0.19	0.16	0.8	0.31	0.16	0.07	0.61
No. of Instruments	23	23	23	23	23	23	23	23

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in all regressions; 3. The number of observations is 232; 4. We report the p-value for AR(1) and AR(2) tests; and 5. In columns (1)–(6), the east dummy equals 1 for the eleven provinces in Eastern China, including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Otherwise, the east dummy equals 0; 6. In columns (7)–(12), the west dummy equals 1 for the eleven provinces in Western China including Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Xinjiang, Tibet, Ningxia, Inner Mongolia, and Guangxi. Otherwise, the west dummy equals 0. Tibet is excluded from the sample due to missing data;7. For brevity, Table 5 only reports results with the policy conditioning information set. Results with the other conditioning information sets are similar and available upon request; 8. * $p < 0.10$; ** $p < 0.05$.

Although a regionallybiased policy would not bias our baseline results, we recognized that our estimates of the causal effects of transport infrastructure endowment on growth performance mightmask heterogeneity between the east and west [48]. One might expect transport infrastructure upgrading to have a greater effect in more developed eastern coastal regions, as there is greater passenger and freight mobility there than in the inland regions. However, a severe transport infrastructure shortage has long existed in less-developed Western China, which has also had faster growth potential. Hence, one might also expect that transport infrastructure endowment upgrading tends to have a greater impact on western regions when these bottlenecks are overcome.

Following Baum-Snow et al. [48], we examine the extent to which a regional heterogeneous response is important for our results by estimating versions of our baseline regressions from Equation (3) by interacting the transport infrastructure endowment indicators with the regional dummy. We found that we could break China up into a maximum of two regions: the west and the remainder of the country.

Table 6, columns (1)–(4), summarizes the results withthe policy conditioning information set. Clearly, our earlier findings regarding the impact of the quantity, quality, and structural attributes of transport infrastructure wererobust to this regional heterogeneity test. The coefficients on the interaction terms between the west dummy and the quality of roadways (Highroadshare), quality of railways (HSR), and the structure of transportation infrastructure (Trstuct1) werenegative but only significant for HSR. This finding indicates that the contribution of transport infrastructure quality upgrading for passenger-dedicated HSR on regional growth wassignificantly lower in Western China than in Eastern and Central China. This result wasconsistent with the fact that Western China comprises of remote areas with sparsely distributed populations and a less developed economy resulting in insufficient passenger flows and a relatively poor profitability of the HSR as emphasized by the World Bank [64].These results suggest that although transport infrastructure endowment upgrading has significantly positive growth impacts, regional heterogeneity in Western China could differ across transport modes, particularly for goods transport versus passenger transport and roadways versus railways.

Table 6. Transport infrastructure and growth: System-GMM (Policy set). Robustness check with the regional dummy and its interaction term with infrastructure.

	Dependent Variable: Per Capita Real GDP Growth Rate			
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Roadpc	−0.013			
	(0.028)			
Highroadshare		0.041 **		
		(0.017)		
HSR			0.075 **	
			(0.033)	
Trstuct1				0.059 ***
				(0.021)
Roadpc × west	0.010			
	(0.009)			
Highroadshare × west		−0.013		
		(0.010)		
HSR × west			−0.020 *	
			(0.011)	
Trstuct1 × west				−0.020
				(0.020)
Hansen test *p* value	0.04	0.09	0.65	0.05
Difference Hansen J test	0.11	0.06	0.54	0.66
AR(1) test	0.04	0.06	0.02	0.13
AR(2) test	0.21	0.26	0.29	0.55
No. of Instruments	24	24	24	24

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in allregressions; 3. The number of observations is 232; 4. We report a*p*-value for AR(1) and AR(2) tests; and 5. The West dummy equals to 1 for the eleven provinces in western China including Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Xinjiang, Tibet, Ningxia, Inner Mongolia, and Guangxi. Otherwise, the west dummy equals 0. Tibet is excluded from the sample due to missing data; 6. For brevity, Table 6 only reports results with the policy conditioning information set. Results with the other conditioning information sets are similar and available upon request; 7. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

5.3.3. Politically-Biased Policy

Another concern is that planners favor politically strategic locations [11,48]. Early literature has also emphasized that the municipalities directly under the central government have particular characteristics, which reduces their comparability with other provinces [7]. To eliminate this concern, we excluded Beijing, Tianjin, and Shanghai from our baseline sample. Table 7, columns (1)–(4), reports the results withthe policy conditioning information set. Our earlier findings on the growth impact of the four transport infrastructure endowment upgrading indicators wererobust to these special political status outliers.

Table 7. Transport infrastructure and growth: System-GMM (Policy set). Robustness check without municipalities.

	Dependent Variable: Per Capita Real GDP Growth Rate			
	Roadpc	**Highroadshare**	**HSR**	**Trstuct1**
	(1)	**(2)**	**(3)**	**(4)**
Coefficient	−0.033	0.036 *	0.036 **	0.046 *
Standard error	(0.035)	(0.019)	(0.016)	(0.023)
Hansen test *p* value	0.19	0.30	0.06	0.11
Difference Hansen J test	0.18	0.60	0.08	0.11
AR(1) test	0.03	0.28	0.03	0.34
AR(2) test	0.06	0.20	0.05	0.15
No. of Instruments	22	22	22	22

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in allregressions; 3. The number of observations is 208; 4. We report the *p*-value for AR(1) and AR(2) tests; and 5. * $p < 0.10$; ** $p < 0.05$.

5.3.4. External Instruments

Thus far, we had instrumented transport infrastructure endowment upgrading in terms of quantity, quality, and structure by its lags, as in Chakrabarti [27], Farhadi [37], and Jiwattanakulpaisarn et al. [38]. As a further robustness check, we followed Ward and Zheng [65] and used external instruments, the transport infrastructure indicators averaged for the neighboring provinces, for our key variable of interest. We defined a province as a neighboring province of *i* if it shares a common border with that province. For example, Henan's neighbors are Shandong, Anhui, Hebei, Shanxi, Shaanxi, and Hubei. We borrowed this external instrument method from the literature on causal identification within networks, e.g., Bramoulle et al. [66]. The basic idea for the instrument is that the correlation across regions reflects some common global trends and is orthogonal to the specific regional unobserved effects [67]. For instance, it is widely documented in the literature that a distinctive institutional feature of China's economic growth miracle is that under a "GDP tournament" scheme, local governments play an active role in promoting local economic growth, including in infrastructure investment [68,69]. Hence, transport infrastructure investment behavior in one province can mimic that of neighboring provinces. Thus, the quantity, quality, and structural attributes of transport infrastructure tend to be similar across adjacent provinces. Table 8, columns (1)–(8), reports system-GMM estimates using the additional neighbor instruments with the policy and the full conditioning information sets. The coefficient estimates generated by this specification weresimilar to those using the lagged transport infrastructure indicators as the internal instruments. Again, our earlier findings in Table 3 still hold for the external instruments.

Table 8. Transport infrastructure and growth: System-GMM (Policy set and Full set). Robustness check with neighboring provinces' transport indicators as external instruments.

	Dependent Variable: Per Capita Real GDP Growth Rate							
	Policy Set				**Full Set**			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Roadpc	0.029				0.073			
	(0.060)				(0.056)			
Highroadshare		0.035 *				0.045 *		
		(0.019)				(0.025)		
HSR			0.045 *				0.062 *	
			(0.026)				(0.031)	
Trstuct1				0.067 **				0.075 *
				(0.030)				(0.039)
Hansen test *p* value	0.09	0.02	0.41	0.04	0.32	0.06	0.12	0.19
Difference Hansen J test	0.63	0.07	0.37	0.89	0.13	0.15	0.44	0.31
AR(1) test	0.43	0.07	0.90	0.23	0.15	0.11	0.11	0.21
AR(2) test	0.47	0.13	0.34	0.91	0.70	0.31	0.90	0.65
No. of Instruments	23	23	23	23	27	27	27	27

Notes: 1. Robust standard errors clustered by province in brackets; 2. Year dummies are included in all regressions; 3. The number of observations is 232; 4. We report the *p*-value for AR(1) and AR(2) tests; 5. All the regressions use the respective transport infrastructure indicators averaged for the neighboring provinces as additional instruments; and 6. * $p < 0.10$; ** $p < 0.05$.

6. Conclusions

This study identified and compared the upgrading impacts for the quantity, quality, and structural aspects of transport infrastructure on regional economic growth in China from 2007 to 2015, when the country was approaching the upper-middle income stage of development. This is the first study to consider government development strategies in a transport infrastructure impact evaluation framework for China. We constructed a unique dataset to describe the three aspects of the transport infrastructure, and in contrast to recent literature, we selected provinces as the geographic units to alleviate concerns about SUTVA violations [28]. To address concerns about reverse causality and account for lagged responses in economic growth to any exogenous shock including transport infrastructure, we adopted the system-GMM estimator for dynamic panel data and obtained consistent and unbiased parameter estimates [32–34,37,60]. We also compared our results with those in the existing literature, focusing on the differential impacts of various aspects of transport infrastructure on regional economic growth in China at different economic development levels. This approach yields new insights.

Our analysis led us to some general conclusions about the effects of transport infrastructure on growth. First, it appeared that transport infrastructure wasstill significantly contributing to economic growth in China, even as the country had entered the upper-middle income stage. Second, quality improvements in roadways and railways (measured by expressways and HSR development) and structural upgrading of the transport infrastructure (measured by the increasing share of government expenditure for transport) significantly contributed to growth at this development level. However, we didnot find a significant positive impact for overall quantity expansion of the land transport network. Third, government development strategies that defy local comparative advantages not only lead to a lower per capita GDP growth rate but also potentially restrict the contribution of transport infrastructure. Lastly, regional heterogeneity for Western China could differ across transport modes, particularly with respect to goods versus passenger transport and roadways versus railways.

This research enhances our understanding of transport infrastructure impacts on economic growth in China and can inform national transport infrastructure policy. The results are specific to China's context but could be useful for policymakers in other emerging economies and developing countries that are experiencing comparable economic growth and infrastructure development patterns. Economic growth is central to China's economic development mission, and our study suggests that public investments in national high-quality roadways and railways as well as government expenditure for transport maintenance to improve service efficiency can stimulate aggregate economic growth, as China reaches the upper-middle income stage. Compared with the earlier and most recent literature, we found that overall, different aspects of transport infrastructure had heterogeneous impacts on growth depending on the economic development level. Moreover, to ensure that transport infrastructure investment will guarantee growth, government development strategies that are favorable to the overall economic conditions are a vital policy prerequisite.

From a broader perspective, future studies could pay more attention to the function of transport infrastructure to achieve the Sustainable Development Goals adopted by all United Nations Member States in 2015. Moreover, new infrastructure, compared to traditional infrastructure such as roads, railways, and bridges, are built on advanced technology and digitization. Future research may also analyze how the current system of information and communications infrastructure can be used to develop the infrastructure under the paradigm of Industry 4.0 [41–43,70,71].

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