# Road Infrastructure in China: Assessing the Impact on Foreign Direct Investment and Economic Growth

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**Abstract**

Using a panel of Chinese cities over the period 1999 - 2018, I examine the determinants of economic growth, focusing on the role of foreign direct investment (FDI) and road infrastructure. Consistent with the predictions of a human capital-augmented Solow model, I find that FDI has a positive effect on the per capita GDP growth rate and this effect is intensified by the road infrastructure of the city. The latter suggests that one way that road infrastructure contributes to growth is to serve as a facilitator for technology transfers stemming from FDI. The findings suggest the FDI-road infrastructure complementary effect is stronger for technology-intensive FDI than for labor-intensive FDI. The results are robust to alternative model specifications and estimation methods.

**Keywords:** Road Infrastructure, Economic Growth, FDI, Development

**JEL Codes:** F21, O18, O53, R40,

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# 1 Introduction

Transportation infrastructure holds a crucial position in every country, especially in developing nations, as it underpins economic development, trade, and accessibility to essential services. Adequate transportation networks reduce costs, promote regional development, and facilitate international trade while enhancing overall quality of life. China, serving as a prominent example among developing nations, has earned a reputation for its strong focus on infrastructure development. Specifically, China has made substantial investments in its highway system as part of its broader infrastructure development efforts. The country has an extensive and rapidly expanding network of expressways and highways[1], making it one of the largest and most comprehensive highway systems in the world. [2]

Figure (1) illustrates changes in the growth of the transportation system and real GDP since 1990. Notably, the growth rate of highways stands out as particularly remarkable. This observation aligns with the argument made by Banerjee et al. (2020), which relies on the straightforward logic that to benefit from markets, technology, and ideas, individuals and firms must have initial access to them. In the context of developmental history, the evolution of road networks in developed countries can be categorized into three stages: the establishment of primitive transportation infrastructure, the accelerated improvement of transportation construction, and the upgrading of transportation services.

The early development of road networks in China lagged behind the pace of social and economic growth, acting as a bottleneck that hindered overall progress. Over the past few decades, the Chinese government has undertaken significant efforts to expand the country's transportation network. According to statistics published by the Ministry of Transport of the People's Republic of China, the length of highways has increased more than 30-fold since 1978. The operational mileage of China's highways and the total freight volume have displayed consistent growth trends.

Data from the China Statistical Yearbook indicates that the total mileage of national highways in 2020 reached approximately 5.2 million kilometers, and the total freight volume in the same year amounted to 46.44 billion tons. Road transportation claimed the largest share, accounting for 73.8% of the overall freight transportation industry in the country. Instead of examining all types of infrastructure, this paper focuses on the theoretical and empirical literature concerning the relationship between road infrastructure and economic growth.

[1] Officially known as the National Trunk Highway System

[2] According to data from the World Bank, as of the end of 2020, China's expressway network spanned a total length of 161,000 kilometers (approximately 100,000 miles), making it the world's longest expressway system.

Meanwhile, following the initiation of market-oriented reforms and the opening-up of the Chinese economy in 1978, China has emerged as the world's most rapidly expanding major economy, achieving an average growth rate of 10% over a span of 30 years. This remarkable surge in GDP, characterized by its consistent stability, has captured the attention of numerous scholars who are keen to examine and research the Chinese economy. Without a doubt, the most significant factor contributing to this evolution has been the dramatic increase in international trade and the substantial influx of foreign direct investment(FDI).

As globalization deepens, China has continuously enhanced its ability to attract and effectively utilize foreign capital. The implementation of market-oriented reforms and the opening-up policy has facilitated a significant influx of FDI into China. In 2019, China maintained its position as the second-largest recipient of foreign capital globally for the fourth consecutive year. Between 1980 and 2000, over 80% of the introduced FDI was concentrated in the eastern coastal areas. However, the central and western regions of China received comparatively less FDI due to their underdeveloped infrastructure and less favorable geographical location. Over time, with the progress of development in the western region and the improvement of road infrastructure in both the central and western regions, foreign capital has increasingly flowed into these areas.

Figure (3) depicts the fluctuations in both FDI and real GDP growth since 1990. As observed in the figure, the progression of economic development in China is evident through a significant increase in FDI inflows into the Chinese market. FDI plays a crucial role in facilitating technology transfer. When compared to domestic investment, FDI makes a relatively more substantial contribution to economic growth owing to its utilization of advanced and higher-level technologies (Borensztein et al., 1998).

Nevertheless, the ability of enterprises in a host country to acquire and replicate advanced technologies from foreign-funded companies ultimately hinges on the host country's own capacity to absorb technology. Numerous scholars have expounded on the various elements that constitute absorptive capacity, approaching it from diverse angles, such as human capital, trade openness, and the level of research and innovation capability within host regions (Borensztein et al., 1998; Su and Liu, 2016; Liu et al., 2001; Fu, 2008).

In addition, certain scholars have delved into the location choices made by foreign firms when investing in a host country. According to studies by Coughlin et al. (1991) and Amiti and Smarzynska Javorcik (2008), the primary determinants influencing the entry decisions of foreign firms revolve around market and supplier access. Moreover, production costs, which encompass elements such as transportation expenses, wield significant influence over the influx of FDI, given their direct impact on the cost-efficiency and competitiveness of conducting business within a specific country or region. Taking this viewpoint into account, my research delves into the role of FDI and road infrastructure, with a particular focus on analyzing their interplay, in influencing economic growth in China.

Numerous scholars have conducted research on infrastructure development, FDI, and their impact on economic growth. This paper provides a review of the literature focusing on three key aspects. First and foremost, it examines the relationship between FDI and economic growth. FDI contributes to GDP growth through various channels. One significant factor is the technological transfer effect resulting from FDI, which plays a central role in enhancing GDP growth due to technology's pivotal role in driving overall total factor productivity improvements.

Many scholars have explored the notion that FDI is expected to generate technology spillovers that benefit domestic firms through increased competition. This perspective finds support in research studies by scholars who assert that FDI serves as a crucial channel for introducing new technologies and that its impact on the national economy exceeds that of domestic investment. (Hansen and Rand, 2006; Borensztein et al., 1998; Liu, 2008; Sinani and Meyer, 2004) However, most articles also emphasize that the ability of FDI to exert its technological influence, thus fostering technological progress and economic growth in host countries, hinges on host country conditions. Among these conditions, the level of human capital stands out prominently since it serves as the vehicle for FDI technology spillovers, as discussed by researchers like Su and Liu (2016) and Zhang and Markusen (1999). Additionally, the characteristics of recipient firms, such as their size and ownership structure, can also impact their effectiveness in assimilating new technologies.(Sinani and Meyer, 2004)

Secondly, some scholars have delved into the impact of transportation infrastructure development on economic growth. For instance, Roberts et al. (2012) discovered that the aggregate real income in China witnessed an increase following the establishment of the expressway network. Meanwhile, Banerjee et al. (2020) demonstrated that China's transportation network has a positive causal effect on per capita GDP levels, though it doesn't significantly impact the growth rate of GDP per capita. In the context of this paper, the construction and enhancement of the transportation system are expected to enhance accessibility to treaty ports, bolster export production, and contribute to the improvement of Total Factor Productivity (TFP).

Lastly, a section of the literature discusses the influence of geographical location on FDI. Geographic factors encompass a wide range, leading to varied perspectives in different articles. For instance, Coughlin et al. (1991) employed a conditional logit model to analyze the location decisions of foreign firms investing in the manufacturing industry in the United States. They found a positive correlation between more extensive transportation systems and FDI. Cheng and Kwan (2000) examined Chinese data and reached the conclusion that the regional market, robust infrastructure, and favorable policies had a positive impact on attracting FDI. Moreover, the aforementioned two articles delve into the factors that attract FDI, considering multiple variables. However, Egger and Pfaffermayr (2004) concentrated on the influence of distance, which affects trade costs and the establishment costs of plants, ultimately determining the choices between export and FDI.

It's noteworthy that the majority of these articles primarily focus on the relationship between transportation convenience and FDI, without extensively discussing the interactions' effects on economic growth. Only a select few offer insights into this aspect. For instance, Ma (2006) employed a gravity-type model to illustrate how transportation costs impact the location of trade flows and the behavior of foreign-invested enterprises. This, in turn, leads to wage inequalities and regional economic performance.

Interestingly, none of the articles have explored the consequences of the interaction between transportation infrastructure and foreign investment on economic growth. This paper aims to address the existing gap in the literature by examining the interaction between FDI and road infrastructure within a neoclassical framework. The hypothesis put forth in this study posits a positive influence of the interaction between FDI and road infrastructure on the growth rate of the local economy.

To be more specific, Figure (4) and (5) depict the geographical shift in FDI. Notably, the dark red areas on the map indicate that FDI has been progressively moving towards China's interior regions since 2000. In contrast, Figures (6) and (7) highlight the substantial expansion of road infrastructure that has taken place since 2000. Based on the developmental patterns depicted in the figures, it's evident that both roads and FDI exhibit similar spatial movement and development trends. Hence, it stands to reason that the mutually reinforcing synergy between FDI and road infrastructure has a positive influence on the growth rate.

The novelty and original contributions of this study are multifaceted. First, it employs a panel data specification of the augmented Solow model to establish that road infrastructure has a positive impact on the growth rate. Specifically, it enhances the FDI endowment of each economy.

Secondly, in contrast to many related studies that often utilize the area of paved roads as a proxy for road infrastructure, this paper distinguishes between various types of roads. In our study, road infrastructure encompasses all forms of expressways and highways, facilitating interconnectivity among economies. Conversely, a paved road in this context refers to a road with accompanying structures, sidewalks, and municipal public facilities primarily within the city limits.

Thirdly, this research delves into heterogeneity analysis of technology contents. The findings suggest that the FDI-road infrastructure complementary effect is more pronounced in high-tech regions compared to labor-intensive or low-tech areas. Conversely, road infrastructure exhibits a relatively more prominent and stronger impact on labor-intensive regions, enhancing productivity and stimulating local growth. Importantly, there is no evidence to support the notion that paved roads intensify the effect of FDI.

Furthermore, this study addresses potential endogeneity concerns by incorporating instrumental variables into the empirical analysis. I utilize two instrumental variables: the average geographic slope (gradient) of each sample city as an instrument for road infrastructure and the distance from the coast as an FDI instrument. The instrumental variable (IV) regressions yield consistent estimates, aligning with the fixed effects estimates. Notably, the IV estimates reinforce the idea that the FDI-road infrastructure complementarity has a more substantial and notable impact on the local growth rate.

The rest of this paper is organized as follows: Section (2) outlines the methodology, Section (3) presents the data, Section (4) reports the empirical results along with various robustness checks, and finally, Section (5) concludes the study and offers policy recommendations.

# 2 Model

Building upon the foundational work of Mankiw et al. (1992) and extending the framework introduced by Su and Liu (2016), this paper adopts the Solow framework to investigate the regional relationship between FDI and road infrastructure. In this extension, we introduce FDI and its interaction with road infrastructure to the neoclassical growth model. Drawing from the Solow model, where each country converges to its steady state over the long term, FDI plays a pivotal role as an efficiency factor that brings advanced technology to the equation. This, in turn, affects the rate at which recipient countries converge to their steady states.

The model is based on a standard Cobb-Douglas production function for an economy. Additionally, we assume that technological progress is labor-augmenting, implying that the variable $A$ represents labor-augmenting technological progress, growing exogenously at a rate $g$.Assume labor grows exogenously at rate $n$, and the technology change is a function of FDI.

$$L(t) = L(0)e^{nt} \tag{1}$$

$$A(t) = A(0)e^{gt}F(t)^{\lambda} \cdot f(G(t)) \tag{2}$$

There are three parts of Equation (2). The first part is $A(0)e^{gt}$, which describes the exogenous growth of technological progress. The second part is $F(t)$, representing the FDI. The third part is the $f(G(t))$. $G(t)$ is the level of road infrastrucrure. This assumption defines that road infrastructure has generative effects, which increase income by using resources more effectively. To simplify the empirical specification, I assume $f(G(t)) = e^{\theta G(t)}$, $\theta$ is the parameter.

The third part of the equation operates under the assumption that FDI exerts a positive influence on technological advancements, driven by both direct and indirect effects. The indirect effect, on the other hand, arises from the spillover effect, where domestic firms absorb or acquire technology from foreign investments, consequently leading to improved efficiency and productivity. Additionally, a well-developed road infrastructure fosters collaboration between domestic firms and FDI, further amplifying efficiency gains. To measure the impact of FDI on productivity, we include road infrastructure as a component within the elasticity of FDI.

$$\lambda = \lambda_0 + \lambda_1 f(G(t)) \tag{3}$$

According to the Solow-Swan model, the saving ratios are assumed to be exogenously determined by savers' preferences or government decisions. Therefore, assume that the accumulation of physical capital and human capital are as follows.

$$\dot{K} = s_k Y(t) - \delta K(t) \tag{4}$$

$$\dot{H} = s_h Y(t) - \delta H(t) \tag{5}$$

where $\dot{K} = dK/dt$, $s_k$ and $s_h$ are physical and human capital saving rates. $\delta$ is the depreciation rate. Assume the depreciation rates of physical and human capital are the same.

To specify the production function in terms of per effective labor, let $y(t) = Y(t)/A(t)L(t)$, $k(t) = K(t)/A(t)L(t)$, $h(t) = H(t)/A(t)L(t)$. Then combining with the equation (4) and (5), the change in stock of physical and human capital per effective unit of labor are yielded as following.

$$\dot{k} = s_k y(t) - (n + g + \delta)k(t) \tag{6}$$

$$\dot{h} = s_h y(t) - (n + g + \delta)h(t) \tag{7}$$

In the steady-state, the levels of capital per effective worker are constant. From equations (6) and (7), this assumption implies

$$k^* = \left(\frac{s_k^{1-\beta} s_h^{\beta}}{n + g + \delta}\right)^{\frac{1}{1-\alpha-\beta}} \tag{8}$$

$$h^* = \left(\frac{s_k^{\alpha} s_h^{1-\alpha}}{n+g+\delta}\right)^{\frac{1}{1-\alpha-\beta}} \tag{9}$$

Inserting the equations (8) and (9) into the production function and taking the log of both sides. Then, the steady-state value of income per capita is:

$$\begin{aligned} ln\left(\frac{Y(t)}{L(t)}\right) &= ln(A(t)) - \frac{\alpha+\beta}{1-\alpha-\beta}ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}ln(s_k) \\ &+ \frac{\beta}{1-\alpha-\beta}ln(s_h) \end{aligned} \tag{10}$$

Then together with the equations (2) and (3). To simplify the empirical specification, I assume the elasticity of technological progress concerning FDI is $\lambda = \lambda_0 + \lambda_1 ln(G(t))$. Therefore, the equation of steady-state income level per capita as a function of the population growth, the saving rate of investment in physical and human capital, FDI and road infrastructure.

$$\begin{aligned} ln\left(\frac{Y(t)}{L(t)}\right) &= ln(A(0)) + gt + \lambda_0 ln(F(t)) + \lambda_1 ln(F(t)) \cdot ln(G(t)) + \theta G(t) \\ &- \frac{\alpha+\beta}{1-\alpha-\beta}ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}ln(s_k) \\ &+ \frac{\beta}{1-\alpha-\beta}ln(s_h) \end{aligned} \tag{11}$$

This paper analyzes the city-level economic growth; thus, it is inappropriate to discuss the steady-state. This study focuses on examining the transition dynamics of an economy toward its steady state. Following Mankiw et al. (1992), the economy approaches its steady-state defined by the following equation:

$$\frac{dln(y(t))}{dt} = \eta[ln(y*) - ln(y(t))] \tag{12}$$

where $\eta = (n+g+\delta)(1-\alpha-\beta)$, is the speed of convergence. The equation (12) is a differential equation in $ln(y(t))$ with the solution:

$$ln(y(t)) = (1-e^{-\eta t})ln(y*) + e^{-\eta t}ln(y(0)) \tag{13}$$

Plugging (11) into (13) and subtracting $ln(y(0))$ from both sides, the equation is obtained as following.

$$
\begin{aligned}
ln\left(\frac{Y(t)}{L(t)}\right) - ln\left(\frac{Y(0)}{L(0)}\right) = & \; ln(A(0)) + gt - (1-e^{-\eta t})ln\left(\frac{Y(0)}{L(0)}\right) \\
& + \lambda_0(1-e^{-\eta t})ln(F(t)) + \lambda_1(1-e^{-\eta t})ln(F(t)) \cdot ln(G(t)) \\
& - \frac{\alpha+\beta}{1-\alpha-\beta}ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}(1-e^{-\eta t})ln(s_k) \\
& + \frac{\beta}{1-\alpha-\beta}(1-e^{-\eta t})ln(s_h) + (1-e^{-\eta t})\theta G(t)
\end{aligned} \tag{14}
$$

Re-writing the equation (14), the cross-section regression model is that:

$$
\begin{aligned}
ln(y_{it}) - ln(y_{i0}) = & \; \phi_0 + \phi_1 ln(y_{i0}) + \phi_2 ln(n_i + g + \delta) + \phi_3 ln(s_{k,i}) + \phi_4 ln(s_{h,i}) \\
& + \phi_5 ln(F_i) + \phi_6 ln(F_i) \cdot ln(G_i) + \phi_7 G_i + \epsilon_i
\end{aligned} \tag{15}
$$

In the equation (15), all the independent variables are the average value over the entire period, except the log of initial year income per capita. $\epsilon_i$ in the equation (15) is the error term including $A(0)$ and other random factors. According to equations (14) and (15), the model predicts the negative relationship between population growth rate and income per effective worker ($\phi_2 < 0$). Also, the saving rate of physical and human capital is positively related to income per effective labor ($\phi_3, \phi_4 > 0$). FDI helps increase the economic growth($\phi_5 > 0$). $\phi_6$ should also be positive, meaning road infrastructure helps enhance the positive effect of FDI on economic growth.

Mankiw et al. (1992) assumed $A(0)$ is independent of the saving rate of physical capital, human capital and population growth rate, ignoring the country-specific effects. Instead of using the cross-sectional approach, I also specify the fixed-effects estimation, following the idea from Knight et al. (1993) and Su and Liu (2016). Then, the fixed-effects model is that:

$$
\begin{aligned}
ln(y_{it}) - ln(y_{i0}) = & \; \phi_0 + \phi_1 ln(y_{i0}) + \phi_2 ln(n_{it} + g + \delta) + \phi_3 ln(s_{k,it}) + \phi_4 ln(s_{h,it}) \\
& + \phi_5 ln(F_{it}) + \phi_6 ln(F_{it}) \cdot ln(G_{it}) + \phi_7 G_{it} + \mu_i + \epsilon_{it}
\end{aligned} \tag{16}
$$

The panel approach uses non-overlapping intervals of five years. For the independent variables, except $ln(y_{i0})$, the observations correspond to averages over the five-year intervals. Therefore, the $t$ in the equation (16) indexes sub-periods. Note that the specification of equation (14) is different from the one used in Su and Liu (2016). From their paper, the total product factor consists of two components: initial level of productivity $A_0$, which is economy-specific and time-invariant, and FDI. However, from my paper, the total product factor includes the transportation efficiency component, $f(G) = e^{\theta G}$ and its interaction with

FDI.

The construction of highways has established vital channels for economic connectivity between central cities across the country, while also linking small and medium-sized cities along these routes. This has the effect of reducing spatial distances between different regions, enhancing traffic accessibility, compressing both time and space, and transcending regional boundaries. These developments lead to decreased transportation costs, improved transaction efficiency, and, as a result, contribute to overall macroeconomic growth.

Furthermore, road infrastructure not only supports growth but also facilitates technology spillovers associated with FDI. In addition to this, our empirical estimation includes the consideration of various types of road infrastructure. The category of paved roads comprises roads flanked by buildings, sidewalks, and municipal public facilities within the city districts. Consequently, the model introduces an additional variable denoted as $f(pvd) = e^{\eta * pvd}$ along with an additional interaction term $ln(pvd) * ln(FDI)$.

# 3 Data

## 3.1 *Data Resource*

The dataset comprises annual observations collected from 265 prefecture-level cities in China spanning from 1999 to 2018. The primary data sources include various editions of the China City Statistical Yearbooks (1999-2018) and the China Statistical Yearbooks for Regional Economy (2000-2014). However, it's important to note that some missing values are identified in the compiled dataset. To mitigate the potential bias introduced by missing data, additional information is gathered from the Statistical Yearbooks of specific cities and manually collated from local statistical communiques for the respective cities.

The China City Statistical Yearbook is an annual statistical publication sponsored by the National Bureau of Statistics of China, providing comprehensive insights into the economic and social development of Chinese cities. It's important to note that the study region excludes Hong Kong, Macao, and Taiwan Province. When referring to the whole city in the yearbook tables, it encompasses all administrative areas within the city, including urban areas, counties, and rural areas.

## 3.2 *Data Summary and Measurement*

*China's Highway System* - The development of China's highways can be broadly categorized into three stages: *1. The initial stage of steady development (1978-1997). 2. The stage of rapid and leapfrog development (1998-2015). 3. The stage of comprehensive and* *high-quality development (post-2016)*. Since 1998, during the Asian financial crisis, China implemented a proactive fiscal policy, which included substantial investments in infrastructure construction. This policy shift led to a surge in bank loans directed towards expressway construction, thereby driving the rapid expansion of expressways across China. Simultaneously, local governments actively released detailed road-related data, facilitating the collection of information and consistent variables related to road infrastructure. Additionally, it's worth noting that more convergence studies are available for the early period. Hence, I have chosen 1999 as the starting point for my analysis.

Regarding the road data used in this paper, it encompasses roads designed for connecting various areas, including rural areas, urban areas, and cities, and conforms to national technical standards with proper authorities' approvals. This data serves as a crucial indicator, reflecting the scale of highway construction development and acts as the primary data source for calculating metrics such as transportation network density.[3]

The road data presented in Statistical Yearbooks is calculated in terms of kilometres. However, solely relying on kilometres as a measure to gauge the investment and construction scale of highway projects may not provide an accurate picture. To address this, I've employed the embodied technical change model developed by Hulten (1992) to estimate the capital associated with road infrastructure. This measurement captures the intuitive notion that technical progress is linked to improvements in the design of new road construction. The equation for road capital stock follows the method in Hulten (1992):

$$G(t) = \sum_{\tau=0}^{t}(1-\delta)^{\tau} l(t-\tau) \tag{17}$$

where $l$ is the length of the road.

*China's Paved Road* - The data related to the area of paved roads have been sourced from the City Statistical Yearbook of China. The measurement method employed for paved road stock remains consistent with the approach from Hulten (1992) by Equation (17). It's crucial to reiterate that the term 'paved road' in this context refers to the smaller streets within the city that predominantly serve daily life functions such as commuting to work, attending school, or shopping. This definition is distinct from the broader road infrastructure concept mentioned earlier.

[3]This data pertains to the actual length of roads at the conclusion of the reporting period. The statistical scope encompasses public roads suitable for automobile travel that connect cities, cities to rural areas, and villages. This includes the lengths of highways that traverse urban streets, highway bridges, tunnel lengths, and ferry widths. However, it excludes urban street mileage, dead-end road mileage, agricultural (or forestry) production road mileage, as well as internal road mileage within industrial (or mining) enterprises.

*Fixed Asset* - Traditionally, much of the previous literature employed fixed asset investment as a direct proxy for the investment amount. However, in recent years, there have been raised concerns about the practice of relying on fixed asset investment data as an accurate representation of investment.[4] This concern stems from the fact that, in some Chinese provinces, fixed asset investment has exceeded GDP, leading to potential overestimation and a distortion of reality.

In China, there are three methods for Gross Domestic Product (GDP) accounting: the production method, the income method, and the expenditure method. Each method offers a unique perspective on the final outcomes of national economic production activities. The expenditure method calculates GDP as the sum of final consumption expenditure, gross capital formation, and net exports of goods and services. Consequently, fixed capital formation serves as an alternative approach for estimating investment paths under the expenditure method.

Prior to 2005, fixed asset investment and fixed asset formation were nearly equivalent in value. However, since 2005, a growing gap has emerged between the two, particularly noticeable in 2010 and subsequent years. As a result, the data used in this paper for the period after 2009 has been replaced with estimates of fixed asset formation derived from the expenditure method.[5]

*Real GDP* - Real GDP per capita is calculated as the gross domestic product per capita, directly sourced from Statistical Yearbooks and adjusted using the GDP deflator, with 1999 as the base year for the deflation process.

*Human Capital* - As per the approach outlined by Mankiw et al. (1992), a valid proxy for the saving rate of human capital was originally based on the percentage of the working-age population in secondary school. However, this measure isn't suitable for my sample period. Consequently, I've employed an alternative measure for the saving rate of human capital, which is based on the share of the total population enrolled in high-level education (college or university).

*FDI* - The statistical yearbooks only include the new flow of FDI annually. Therefore, I follow the idea from Zhang (2008), which uses the perpetual inventory method to construct the suitable proxies of stock of FDI. It is the most commonly used method for domestic and

[4]The credibility of fixed asset investment data has faced criticism from researchers within the industry. However, in 2021, the Bureau of Statistics underwent a systematic revision of the investment data, removing various inaccuracies and distortions. It's important to note that the revision was carried out at the national level and did not encompass revisions at the city level.

[5]However, it's worth noting that data on fixed asset formation is not available for all cities. As a result, I've employed the ratio of fixed asset formation to GDP at the provincial level to estimate this measure.

foreign researchers to measure the capital stock and is pioneered by Goldsmith in 1951. The formula is that:

$$F_{it} = (1 - \delta)F_{i,t-1} + I_{it} \tag{18}$$

where $\delta$ is the rate of replacement, and replacement refers to the maintenance and recovery of production capacity, which equals 0.096. $I_{it}$ is the based year stock of FDI. In the specific treatment, the stock of FDI in the base period is divided by 10% of each economy's total annual FDI in the initial year. Table (1) reports the description of the variable used.

# 4 Result

## 4.1 *Benchmark Result*

*Cross-section Regression* - Table (3) presents the results of the cross-sectional regression model specified in Equation (15). The dependent variable in this model is the difference in the logarithm of real GDP per capita between 1999 and 2018. Meanwhile, all independent variables represent their respective averages across the entire period. In accordance with the approach outlined in Mankiw et al. (1992), this paper operates under the assumption that the sum of the growth rate ($g$) and the depreciation rate ($\delta$) remains constant and equal to 0.05.

In Column (1) of Table (3), only variables from the conventional Solow model are considered. However, the results obtained do not align with the model's predictions. Firstly, the growth rate is not negatively correlated with the population growth rate. On the other hand, the saving rate of investment is consistent with the model's prediction, showing a positive relationship. However, it's noteworthy that the coefficient for the saving rate of physical capital does not demonstrate statistical significance, even at the 10% level. Conversely, the coefficient for the saving rate of human capital exhibits a positive and statistically significant effect on the growth rate, aligning with the findings in Su and Liu (2016).

Overall, the augmented Solow model explains approximately 38.5% of the cross-city variations in the growth rate, a figure closely resembling that found in Su and Liu (2016), where it stood at 42.9% for all cities in China. Column (2) presents the expected results after incorporating transportation infrastructure into the analysis. However, it's important to note that the estimation coefficient for transportation infrastructure is negative, relatively small, and statistically non-significant.

Moving on to Column (4), I introduce the stock of FDI into the model. The estimated result for the stock of FDI is both positive and statistically significant at the 1% level, underscoring FDI's positive contribution to economic growth across various economies. To investigate whether transportation infrastructure complements FDI in promoting economic growth, I turn to Column (5), which includes an interaction term between the stock of FDI and transportation infrastructure. However, the estimation for this interaction term yields a negative and statistically insignificant result.

Columns (5) and (6) in Table 3 introduce the area of paved roads within the city and its interaction with FDI. The findings suggest that these variables have no significant effect on economic growth. It's important to note that cross-sectional estimation may omit numerous city-specific characteristics, potentially leading to biased results. To address this issue, I turn to panel data analysis, as per Equation (16), to account for city-specific time-invariant factors and mitigate the omitted heterogeneity problem.

*Panel Regression* - The dataset has been grouped into four five-year sub-periods, spanning from 1999 to 2003, 2004 to 2008, 2009 to 2013, and 2014 to 2018. The dependent variable in this analysis is the growth rate observed every five years.

Table (2) presents the results of panel data. In Column (1), we adhere to the conventional Solow model. Compared to Column (1) in Table (3), the panel data regression model delivers results that align with the model's predictions. Specifically, the growth rate exhibits a negative correlation with the population growth rate and a positive correlation with the investment rate in physical and human capital. Importantly, all estimations in this panel data regression have the expected signs and demonstrate statistical significance.

Columns (2) and (3) expand the model by introducing FDI and road infrastructure. The estimations indicate that both FDI and road infrastructure make distinct contributions to economic growth. Moving to Column (4), I observe that the impact of FDI on growth is further enhanced by the presence of road infrastructure. Additionally, both road infrastructure and FDI individually stimulate economic growth. However, once I include the interaction term between road infrastructure and FDI, the significance of road infrastructure itself diminishes, and its coefficient size decreases. Nevertheless, the interaction term exhibits a positive and statistically significant impact on the growth rate, with a significance level of 1%.

Columns (5) and (6) introduce data on the infrastructure of paved roads within cities. In Column (6), there is an increase in the coefficient size for the interaction term ($\ln(FDI) \times \ln(G)$). When comparing the results of Column (4) and Column (6), it becomes evident that road infrastructure ($G$) itself becomes more effective. Notably, the coefficients of all variables remain relatively stable across these specifications.

*Robustness Check* - As a robustness check, I employ different values for each period to estimate the results. Table (10) uses the initial values of human capital and FDI, treating them as predetermined variables that are exogenous to the subsequent growth over the following five years. Table (5) utilizes the last values of all variables, creating an alternative constructed panel dataset.

The estimates presented in Table (10) and (5) reveal results that are consistent with those in Table (2). Notably, the estimates for the FDI-road infrastructure interaction term remain positive and statistically significant across different panel datasets. Furthermore, the adjusted R-squared values increase after incorporating the interaction term, indicating a higher proportion of the dependent variable's variance being explained by the model.

## 4.2 *Heterogeneity Analysis*

*Fixed Estimates for Selected Sub-samples (Rank of Innovation)* - I have assumed that all FDI sources contribute equally to technology, as per the model specification. However, this assumption may not always hold true, as the technology embodied in FDI may not be directly proportional to its dollar value. Specifically, sectors characterized by varying levels of technological intensity and labor requirements are treated the same in terms of their contribution to local technology and economic growth.

Moreover, it is reasonable to expect that the complementarity between FDI and road infrastructure is more pronounced in high-tech sectors compared to labor-intensive sectors. Additionally, efficient transportation can facilitate information exchange and enhance production efficiency, although the direct impact of transportation infrastructure may vary slightly across different economies. Consequently, I anticipate that the coefficients of road infrastructure and the FDI-road interaction term may differ under varying circumstances.

Unfortunately, data on the type of FDI at the city level is not available. In response, I have employed an alternative method that leverages cities' characteristics to predict the preferences of foreign investors. It is logical to assume that economies with a stronger R&D capacity or a higher level of innovation would be better positioned to attract technology-intensive foreign firms or investors. However, since data on R&D capacity or expenditure are unavailable for many cities, I have turned to alternative proxies.

In this regard, I have utilized the number of patents and innovation indices as substitute indicators. While it's essential to acknowledge that using the number of patents as a measure of technology within a region may have limitations, it remains a widely applicable metric in various economic studies. In support of this, a study by Dang and his colleagues (2015) has emphasized the utility of patent data in Chinese studies, despite its inherent limitations such as the lack of linkage with enterprise financial data and citation data. Therefore, the number of patents serves as the primary method for ranking cities.

Table (6), Columns (1) through (4), presents panel regressions conducted separately for cities ranked by the number of patents. The patent data for these cities were sourced from the EPS China Data, which is the earliest, largest, and most comprehensive data collection resource in China.

Notably, the coefficient of the FDI-road interaction term ($\ln(FDI) \times \ln(G)$) is higher for cities with a high R&D capacity compared to those with a low R&D capacity. This suggests that the complementarity between FDI and road infrastructure is significantly more pronounced in cities with robust R&D capabilities. However, it's essential to highlight that the coefficients of the FDI-road interaction term are only statistically significant for high R&D-capacity cities.

Comparing Column (2) to Column (4), it becomes apparent that the coefficient for road infrastructure ($G$) is sizable and statistically significant for low R&D capacity cities. While the FDI-road complementarity effects may not be as pronounced in these cities, road infrastructure itself still plays a pivotal role in enhancing production efficiency and stimulating local economic growth.

Another method for assessing the R&D capacity of cities involves utilizing the innovation index provided by the China Innovation and Entrepreneurship Index. This index is developed in collaboration with the Enterprise Big Data Research Center of Peking University and jointly developed by the National Development Research Institute of Peking University and the Longxin Data Research Institute. It offers a set of objective indicators that gauge innovation and entrepreneurship activities at the city level in China.

The regional innovation index is derived from the actual output of innovation and entrepreneurship enterprises within a given region, emphasizing tangible outcomes rather than merely focusing on investments. This index takes into account all industries and enterprises of varying sizes across mainland China, with particular attention to small, medium, and micro enterprises that exhibit high levels of innovation activity and startups. It encompasses a range of comprehensive evaluation indicators that provide a holistic perspective on different facets of innovation and entrepreneurship. Compared to patent data, this innovation index offers a more comprehensive summary of a city's R&D capacity.

Table (6), Columns (5) through (8), presents the results of panel regressions conducted separately for cities ranked based on the innovation index. These findings mirror those in Columns (1) through (4). In cities with a high innovation index, a robust complementary relationship exists between road infrastructure and FDI ($\ln(FDI) \times \ln(G)$). However, the coefficients for road infrastructure in high-innovation cities do not achieve statistical significance, whereas they are substantial and statistically significant for low-innovation cities.

In summary, the distinction between technology-intensive and labor-intensive industrial zones manifests in two primary aspects. First, there is a notable difference in the coefficients of the interaction term ($\ln(FDI) \times \ln(G)$). In technology-intensive areas, road infrastructure significantly benefits FDI, whereas, in technologically underdeveloped regions, the complementary role of road infrastructure and FDI is nearly negligible. Second, there is variation in the direct impact of transportation construction on technology and productivity. In technology-intensive areas, road construction does not exert a substantial impact. This is primarily due to the fact that most technology-intensive areas are concentrated in coastal regions and provincial capital cities, where transportation infrastructure has been relatively developed for a longer time. The data in our analysis begins from the second stage of road construction and development, resulting in positive but statistically insignificant coefficients for road infrastructure's effect on technology in these regions. Conversely, in technologically underdeveloped areas, road infrastructure has a highly significant positive impact on production efficiency and technological development. High-tech regions and underdeveloped regions consistently exhibit these regression results.

*Fixed Estimates for Selected Sub-samples (Geographical or Policy conditions)* - Geographical location, administrative level, and FDI policies are additional factors that influence the technical content. Coastal regions inherently possess unique geographical advantages. The presence of numerous ports has positioned many coastal cities as pioneers in attracting foreign investment, as illustrated in Figure (4) and (5).

In Table (7), Column (1) reports the regression results for cities in coastal areas. Interestingly, road infrastructure alone has not had a substantial impact on technological development in these regions. The coefficient for $G$ is relatively small and statistically insignificant. However, the results for the interaction term ($\ln(FDI) \times \ln(G)$) are both significant and slightly larger than the baseline results. This suggests that while the direct effect of road development on coastal cities may be limited, a well-developed road system plays a crucial role in connecting coastal cities with inland areas, thereby fostering interaction between the highway system and FDI.

Column (2) of Table (7) provides the regression results for non-coastal cities. In the case of interior cities, the coefficient for $\ln(FDI) \times \ln(G)$ is 0.014, which is smaller than the regression result for coastal cities ($= 0.25$). This indicates that the complementary relationship between FDI and road infrastructure is more robust in coastal cities. Nevertheless, the individual effect of road infrastructure remains positive, large, and significant for interior cities. This suggests that an improved road system in these areas facilitates the absorption and acquisition of new technology, contributing to their technological advancement. These findings underscore the importance of considering geographical factors and regional characteristics when assessing the impact of road infrastructure and FDI on technological development.

Additionally, FDI is influenced by government policies. To address this, I categorize all cities based on whether they are provincial capitals or subject to specific foreign investment incentives. Provincial capitals, due to their higher administrative status, may have a greater potential to attract foreign investors compared to other cities.

In Table (7), I present regression results in Columns (3) and (4) separately for provincial and non-provincial cities. Column (3) suggests that provincial cities do not yield evidence that supports the established model. Conversely, for non-provincial cities, I observe a positive and statistically significant complementary relationship between road infrastructure and FDI. This suggests that using administrative rankings alone may not be an appropriate criterion for differentiation. As a result, I divide the cities based on the specific foreign investment policies they offer. In the following paragraph, I explain the criteria used to classify cities into policy and non-policy categories.

Following China's reform and opening up, foreign-funded enterprises have played a significant role in driving the country's economic development. China has responded by introducing various preferential tax policies to attract foreign investment and bolster its domestic economy. The most extensive tax category for foreign-invested enterprises is preferential income tax, which varies across different regions. In a study conducted by Demurger et al. (2002), a preferential policy index was created to assess its impact on FDI. The authors noted that cities within coastal open economic zones, special economic zones, or economic and technological development zones consistently offered high tax discount rates to foreign-invested enterprises.

Post-2000, China has introduced new special zones, with attracting foreign investment as a key development objective for these regions. One such example is the national synthetically reform testing district, also referred to as the new special zone. This zone represents the second wave of special economic zones established after the initial reforms. In my analysis, I use the national synthetically reform testing district as a substitute for economic and technological development zones due to its evolving relevance in attracting foreign investment.

Furthermore, foreign investment within bonded areas or tariff-free zones receives additional tax incentives. Goods of foreign origin stored in these bonded areas are exempt from import duties and can be freely exported, subject only to a small storage fee. As a result, I have categorized cities based on their affiliation with coastal economic development zones, special economic zones, national synthetically reform testing districts, or bonded zones, considering them as cities benefiting from preferential policies (Table (11)). Conversely, cities not falling into these categories are deemed either not enjoying preferential policies or having limited access to such benefits.

In Table (7), Columns (5) and (6) present evidence for these two distinct city types.

Column (5) pertains to cities with policies, where the coefficient for the FDI-road interaction term is 0.031, surpassing the value of 0.012 in Column (6). These estimates highlight that the complementary relationship between road infrastructure and FDI is more pronounced in cities with preferential policies than those without such benefits.

## 4.3 *Endogenous Analysis*

There is a concern that despite using fixed-effects estimates to address some unobserved heterogeneity issues, the estimation results may still be biased due to potential omitted variables or other concerns. In particular, the interaction term between the main explanatory variables, road infrastructure and FDI, is challenging to treat as absolutely exogenous, which could lead to biased parameter estimates. To mitigate this problem, this paper employs an appropriate instrumental variable (IV) to control for endogeneity and yield more reliable analyses.

Effective instrumental variables should exhibit a strong correlation with the endogenous variables while maintaining sufficient exogeneity, meaning they should only impact the explained variables through their influence on the endogenous variables. In this study, the paper leverages data from the digital elevation model provided by the China Geographical National Condition Monitoring Platform and utilizes ArcGIS Pro software to extract average slope data for the sample cities.

Firstly, the slope is chosen as an instrumental variable for transportation infrastructure because it significantly affects road planning, design, and cost. Different cities exhibit varying degrees of terrain complexity within their administrative areas, which directly impacts the form and cost of road construction. For instance, in mountainous cities, highways often need to circumvent the mountains, resulting in longer routes and potentially the construction of tunnels, necessitating substantial road investment. Therefore, from a logical standpoint, it can be inferred that road infrastructure is directly influenced by the slope, satisfying the correlation requirement between the instrumental and endogenous variables.

Secondly, as a natural indicator of topographic variation among the sample cities, the slope serves as an inherent geographic information variable for each city. This equivalence to a natural experiment lends it a relatively exogenous nature, thus fulfilling the exogeneity assumption necessary for valid instrumental variables. The suitability of instrumental variables has been extensively elaborated upon in the preceding paragraphs. However, it's important to acknowledge that this instrumental variable may still exhibit certain limitations concerning data characteristics and economic relationships. Firstly, regarding data characteristics, both the slope and geographic distance are inherent natural attributes of the sample cities. The slope index and geographic distance are essentially cross-sectional data in the dataset dimension, whereas both the endogenous variables and the explained variables are panel data containing city and time information.

I present the first-stage IV estimates in Table (9), specifically in Columns (1) to (3). These initial-stage estimates demonstrate a positive correlation between the average slope and road infrastructure, as well as a correlation between geographic distance and FDI. Additionally, the primary explanatory variable, $ln(G) \times ln(FDI)$, is found to correlate with the interaction term of these two instrumental variables. Importantly, the first-stage F-statistics for all instrumental variables exceed 10, indicating a high degree of correlation with the explanatory variables. This suggests that concerns related to the weak instrumental variable problem can be effectively dismissed.

In Table (8), as reported in Column (2), I present the second-stage estimates. According to the results of the second-stage regression, the coefficient of the FDI-road interaction term ($ln(FDI) \times ln(G)$) remains positive and statistically significant. When compared to the benchmark regression results presented in Column (1) of Table (8), it becomes evident that the complementary effect has intensified. This suggests that the observed complementary relationship between FDI and road infrastructure exerts a substantial impact on local economic growth.

Indeed, while the regression results provide valuable insights, it's essential to acknowledge that there could still be reasons why the exclusion restriction might not be fully satisfied. One such concern is the possibility of a correlation between geographical distance to the coast and other types of government policies. For instance, cities located close to the coast may have a higher likelihood of being designated as special economic zones or free-trade zones.

To address this potential confounding, I have incorporated control variables, specifically dummy variables representing economic special zones and free-trade zones, into the second-stage regression analysis. The results, as reported in Table (8) Column (3), show that the coefficient of $ln(FDI) \times ln(G)$ decreases slightly but remains positive and statistically significant. This adjustment helps mitigate the influence of other government policies correlated with coastal proximity, providing a more robust assessment of the relationship between FDI, road infrastructure, and local economic growth.

Furthermore, as a robustness check, I have also adopted an approach inspired by Su and Liu (2016), using lagged road infrastructure, lagged FDI, and their interaction term as potential instrumental variables. The second-stage results are presented in Table (8), Column (4). Notably, the coefficient of the FDI-road infrastructure interaction term in this specification is 0.046, which is consistent with the result obtained using geographical conditions as instrumental variables. The first-stage regression results for this robustness check are provided in Table (9), specifically in Columns (4) to (6).

In sum, the findings from both OLS regression and instrumental variables consistently support the notion that the complementary relationship between FDI and road infrastructure has a positive and significant impact on local economic growth. Even when controlling for potential omitted variables, the core conclusions of this study remain robust.

# 5 Conclusion

In light of China's remarkable development journey since the initiation of economic reforms in 1978, it's undeniable that the country has achieved substantial growth over nearly four decades. However, as highlighted by the Chinese government, there has been a shift from high-speed growth to an emphasis on high-quality development in recent years. This shift has been accompanied by a growing need to enhance total factor productivity, particularly in the face of increased risks and challenges from the global environment since 2020.

Given this evolving economic landscape, questions arise about the continued relevance of massive infrastructure investment, particularly in road infrastructure. Can increased investment in roads still contribute to spreading and improving economic efficiency and technologies? These questions have not been definitively answered in existing literature. This study addresses these questions by focusing on the interaction between foreign direct investment (FDI) and road infrastructure. It provides compelling evidence that the complementary effects of FDI and road infrastructure positively contribute to economic growth. In doing so, it sheds light on the potential continued significance of infrastructure investment in the context of China's shifting economic priorities and the pursuit of high-quality development.

Initially, this study employs an extended version of the augmented Solow model and compiles a panel dataset to derive empirical estimates. Subsequently, the research assesses the robustness of these findings from various perspectives. To mitigate potential endogeneity concerns, the paper constructs suitable instrumental variables based on the geographical context of the sampled cities. The following conclusions have been drawn: Enhanced transportation infrastructure has a direct positive effect on productivity and the advancement of science and technology. Nevertheless, the direct impact of road infrastructure on economic development varies based on the region's research and development (R&D) capacity and geographical location. It is more pronounced in interior and labor-intensive areas.

Secondly, the study consistently finds a positive and significant impact of FDI and road infrastructure as complementary factors in economic development across multiple robustness tests. Furthermore, once additional instrumental variables are introduced to mitigate endogeneity bias, this positive effect becomes even more pronounced.

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# Figures and Tables

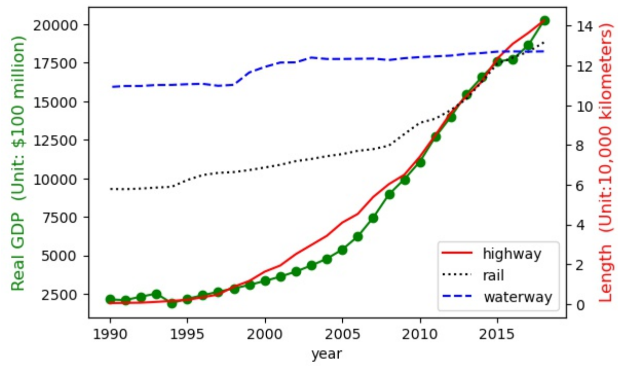


Figure 1 –Transportation vs. real GDP

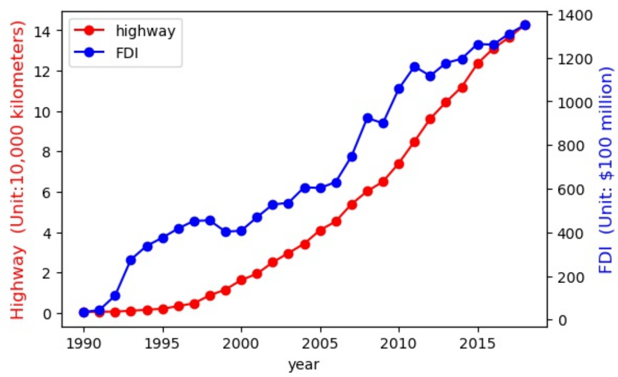


Figure 2 –Highway vs. FDI

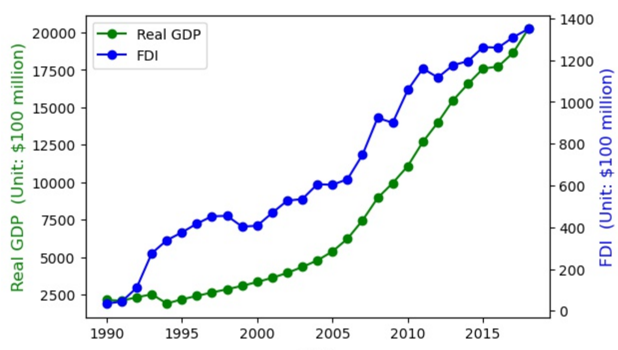


Figure 3 –real GDP vs. FDI

Notes: These three figures describe the time-series real GDP, FDI and transportation infrastructure data at the Country level. Data Source: Statistical Yearbook of China.

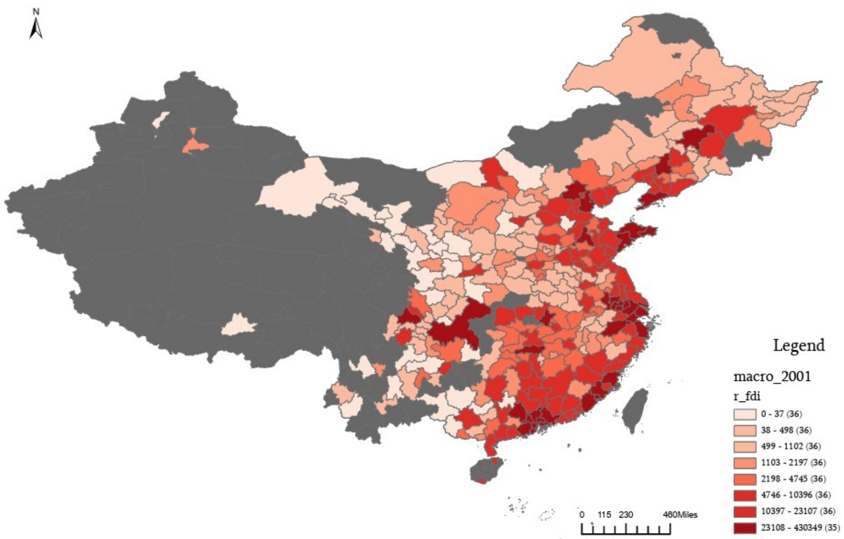


FIGURE 4 –FDI IN 2000

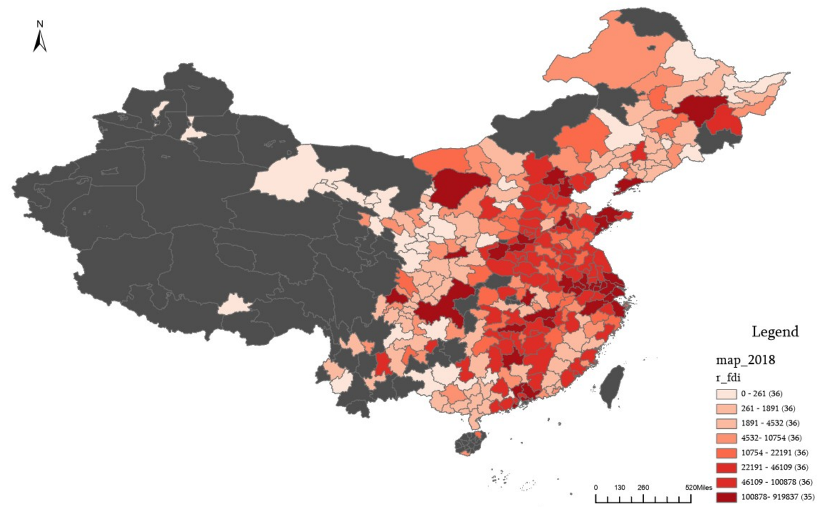


FIGURE 5 –FDI IN 2018

Notes: The two figures depict the new Foreign Direct Investment (FDI) inflow for the years 2000 and 2018. The classification method used for the FDI data is quantile classification, where each class contains an equal number of features. To illustrate, the cities shown in the darkest red color in the figures represent those with the highest levels of FDI for the respective years. The grey areas on the map are excluded from the sample cities, primarily consisting of autonomous regions and a few prefecture-level cities due to the significant amount of missing data.

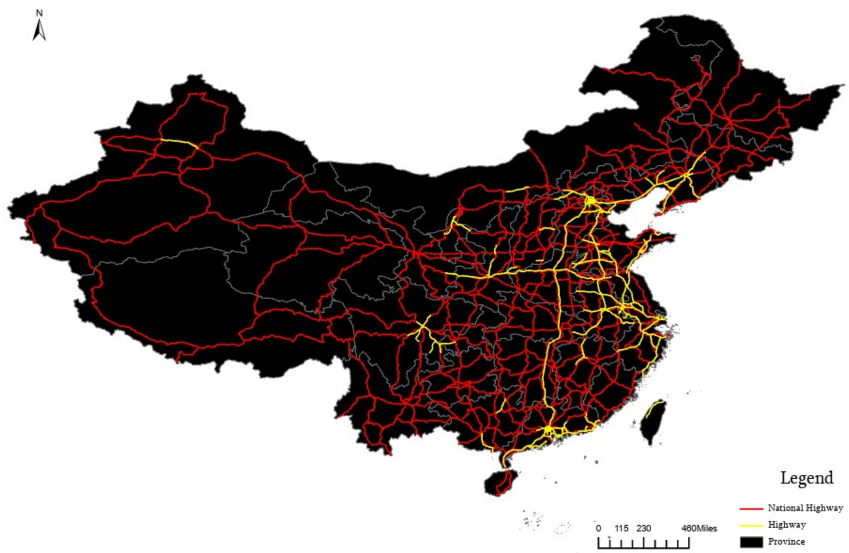


FIGURE **6** –ROAD IN 2000

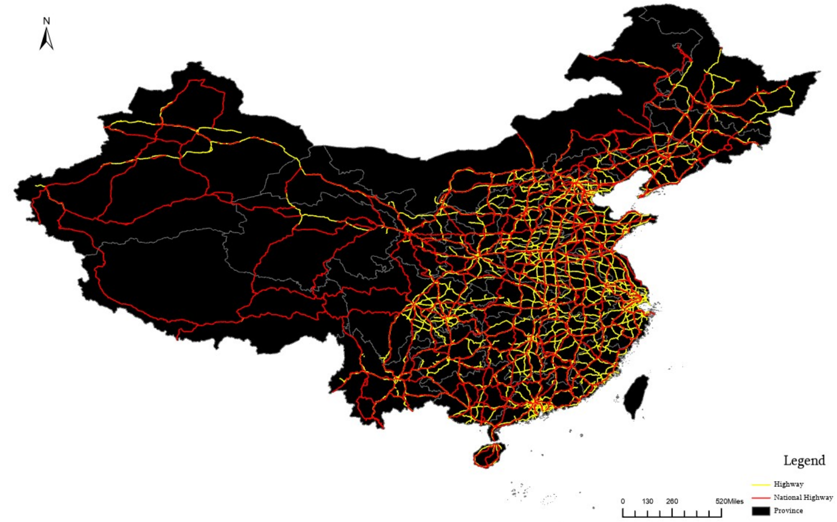


FIGURE **7** –ROAD IN 2020

Notes: The two figures depict the national highway system(red line) and highway system(yellow line) of 2000 and 2020.

# Table 1 –Descriptive Statistics

| | *Variables* | | | | |
|---|---|---|---|---|---|
| | Mean | Std.Dev. | Max | Min | Obs |
| **y** | | | | | |
| real GDP per capital(in Yuan) | 19469.86 | 15178.40 | 109597.01 | 2446.36 | 1064 |
| **n** | | | | | |
| population growth rate | 0.01 | 0.02 | 0.26 | -0.07 | 1064 |
| $\mathbf{s_k}$ | | | | | |
| ratio of investment to GDP | 0.48 | 0.18 | 0.97 | 0.11 | 1064 |
| $\mathbf{s_h}$ | | | | | |
| share of population study in college | 0.01 | 0.02 | 0.13 | 0.00 | 1064 |
| **F** | | | | | |
| stock of FDI (100,000,000 Yuan) | 224.16 | 503.28 | 5028.69 | 0.05 | 968 |
| **G** | | | | | |
| stock of road infrastructure (in 10,000 kilometre) | 4.00 | 3.74 | 59.44 | 0.07 | 1064 |
| **pvd** | | | | | |
| stock of paved road (in square kilometer) | 5367.11 | 8949.77 | 110255.44 | 0.00 | 1064 |

## Table 2 –Panel Data Regression Result

| | Dependent variable: log difference of GDP per capita | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ln(y(0))$ | -0.410*** | -0.485*** | -0.514*** | -0.561*** | -0.562*** | -0.588*** |
| | (0.024) | (0.037) | (0.041) | (0.041) | (0.041) | (0.040) |
| $ln(n+g+\delta)$ | -0.067* | -0.060* | -0.036 | -0.041 | -0.041 | -0.037 |
| | (0.037) | (0.033) | (0.035) | (0.032) | (0.032) | (0.031) |
| $ln(s_k)$ | 0.391*** | 0.354*** | 0.314*** | 0.279*** | 0.269*** | 0.253*** |
| | (0.032) | (0.030) | (0.030) | (0.028) | (0.029) | (0.028) |
| $ln(s_h)$ | 0.033*** | 0.035*** | 0.037*** | 0.037*** | 0.037*** | 0.038*** |
| | (0.008) | (0.008) | (0.009) | (0.009) | (0.010) | (0.009) |
| $G$ | | 0.026** | 0.024** | 0.015* | 0.014 | 0.030*** |
| | | (0.010) | (0.010) | (0.009) | (0.009) | (0.009) |
| $ln(FDI)$ | | | 0.055*** | 0.048*** | 0.046*** | 0.045*** |
| | | | (0.016) | (0.016) | (0.016) | (0.016) |
| $ln(FDI) * ln(G)$ | | | | 0.020*** | 0.024*** | 0.021** |
| | | | | (0.005) | (0.006) | (0.009) |
| $ln(pvd)$ | | | | | -0.002 | -0.003* |
| | | | | | (0.002) | (0.002) |
| $ln(FDI) * ln(pvd)$ | | | | | | 0.000 |
| | | | | | | (0.007) |
| Constant | 4.473*** | 5.079*** | 5.210*** | 5.586*** | 5.595*** | 5.811*** |
| | (0.266) | (0.344) | (0.364) | (0.367) | (0.368) | (0.360) |
| Observations | 1,063 | 1,063 | 967 | 967 | 967 | 963 |
| $R^2$ | 0.453 | 0.486 | 0.492 | 0.507 | 0.508 | 0.519 |

Notes: This table reports the fixed-effect estimation under the four five-year periods. (1999-2003, 2004-2008,2009-2013,2014-2018) The dependent variable is the log difference of GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

Table 3 –Cross-section Data Regression Result

| | Dependent variable: log difference of GDP per capita | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ln(y(0))$ | -0.505*** | -0.506*** | -0.558*** | -0.558*** | -0.566*** | -0.581*** |
| | (0.057) | (0.058) | (0.065) | (0.066) | (0.069) | (0.064) |
| $ln(n+g+\delta)$ | 0.120 | 0.116 | 0.056 | 0.053 | 0.045 | 0.059 |
| | (0.146) | (0.149) | (0.147) | (0.168) | (0.169) | (0.160) |
| $ln(s_k)$ | 0.130 | 0.132 | 0.144 | 0.144 | 0.154* | 0.170* |
| | (0.104) | (0.104) | (0.093) | (0.093) | (0.091) | (0.090) |
| $ln(s_h)$ | 0.147*** | 0.148*** | 0.117*** | 0.117*** | 0.113*** | 0.095*** |
| | (0.026) | (0.026) | (0.023) | (0.023) | (0.023) | (0.024) |
| $G$ | | -0.002 | -0.008 | -0.007 | -0.005 | -0.024 |
| | | (0.007) | (0.008) | (0.015) | (0.016) | (0.025) |
| $ln(FDI)$ | | | 0.051** | 0.053 | 0.050 | 0.016 |
| | | | (0.026) | (0.040) | (0.040) | (0.041) |
| $ln(FDI) * ln(G)$ | | | | -0.001 | -0.004 | 0.004 |
| | | | | (0.016) | (0.017) | (0.019) |
| $ln(pvd)$ | | | | | 0.003 | -0.005 |
| | | | | | (0.003) | (0.004) |
| $ln(FDI) * ln(pvd)$ | | | | | | 0.018 |
| | | | | | | (0.012) |
| Constant | 7.072*** | 7.079*** | 7.044*** | 7.034*** | 7.061*** | 7.267*** |
| | (0.658) | (0.660) | (0.605) | (0.623) | (0.626) | (0.615) |
| Observations | 266 | 266 | 242 | 242 | 242 | 241 |
| $R^2$ | 0.395 | 0.395 | 0.423 | 0.423 | 0.425 | 0.435 |

Notes: This table reports the cross-sectional estimation using the average value of the entire period. The dependent variable is the log difference in GDP per capita between 1999 and 2018. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

Table 4 –Estimation results based on different values during each period - Initial values of each 5-year period

| | Dependent variable: log difference of GDP per capita | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $ln(y(0))$ | -0.410*** | -0.546*** | -0.546*** |
| | (0.024) | (0.040) | (0.044) |
| $ln(n+g+\delta)$ | -0.067* | -0.041 | -0.044 |
| | (0.037) | (0.032) | (0.031) |
| $ln(s_k)$ | 0.391*** | 0.297*** | 0.271*** |
| | (0.032) | (0.029) | (0.028) |
| $ln(s_h)$ | 0.033*** | 0.036*** | 0.036*** |
| | (0.008) | (0.010) | (0.010) |
| $G$ | | 0.015** | 0.025*** |
| | | (0.007) | (0.008) |
| $ln(FDI)$ | | 0.038*** | 0.025 |
| | | (0.014) | (0.016) |
| $ln(FDI) * ln(G)$ | | 0.012*** | 0.015*** |
| | | (0.003) | (0.005) |
| $ln(pvd)$ | | | -0.001 |
| | | | (0.001) |
| $ln(FDI) * ln(pvd)$ | | | -0.003 |
| | | | (0.005) |
| Constant | 4.473*** | 5.559*** | 5.568*** |
| | (0.266) | (0.378) | (0.398) |
| Observations | 1,063 | 967 | 943 |
| $R^2$ | 0.453 | 0.498 | 0.490 |

Notes: The table reports the fixed-effect estimation using the initial values of road infrastructure and FDI stock instead of the average of each period. The dependent variable is the log difference in GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

Table 5 –Estimation results based on different values during each period - Last values of each 5-year period

| | Dependent variable: log difference of GDP per capita | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $ln(y(0))$ | -0.359*** | -0.546*** | -0.592*** |
| | (0.024) | (0.043) | (0.042) |
| $ln(n+g+\delta)$ | -0.008 | 0.019 | 0.017 |
| | (0.044) | (0.045) | (0.046) |
| $ln(s_k)$ | 0.267*** | 0.185*** | 0.156*** |
| | (0.030) | (0.027) | (0.026) |
| $ln(s_h)$ | 0.181*** | 0.138*** | 0.132*** |
| | (0.028) | (0.021) | (0.019) |
| $G$ | | 0.014 | 0.041*** |
| | | (0.011) | (0.010) |
| $ln(FDI)$ | | 0.054*** | 0.050*** |
| | | (0.016) | (0.017) |
| $ln(FDI)*ln(G)$ | | 0.034*** | 0.013 |
| | | (0.007) | (0.012) |
| $ln(pvd)$ | | | -0.005*** |
| | | | (0.002) |
| $ln(FDI)*ln(pvd)$ | | | 0.021** |
| | | | (0.010) |
| Constant | 4.738*** | 5.856*** | 6.153*** |
| | (0.366) | (0.424) | (0.394) |
| Observations | 1,012 | 923 | 919 |
| $R^2$ | 0.413 | 0.509 | 0.534 |

Notes: The table reports the fixed-effect estimation using the last values of all explanatory variables as an alternative constructed panel dataset. The dependent variable is the log difference in GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

Table 6 –Panel Data for Selected Sub-samples(rank of innovation) of Cities

| | Top Quarter by Patent | | Bottom Quarter by Patent | | Top Quarter by innovation | | Bottom Quarter by innovation | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $ln(y(0))$ | -0.582*** | -0.611*** | -0.483*** | -0.539*** | -0.568*** | -0.574*** | -0.428*** | -0.475*** |
| | (0.082) | (0.080) | (0.062) | (0.062) | (0.079) | (0.081) | (0.056) | (0.058) |
| $ln(n+g+\delta)$ | -0.049 | -0.056 | 0.074 | 0.067 | -0.026 | -0.037 | 0.076 | 0.076 |
| | (0.053) | (0.050) | (0.063) | (0.062) | (0.043) | (0.043) | (0.056) | (0.061) |
| $ln(s_k)$ | 0.130*** | 0.083** | 0.263*** | 0.249*** | 0.112*** | 0.084** | 0.273*** | 0.266*** |
| | (0.036) | (0.041) | (0.051) | (0.049) | (0.035) | (0.040) | (0.047) | (0.052) |
| $ln(s_h)$ | 0.006 | 0.003 | 0.035*** | 0.036*** | 0.002 | 0.001 | 0.027*** | 0.027*** |
| | (0.009) | (0.007) | (0.011) | (0.011) | (0.008) | (0.007) | (0.009) | (0.009) |
| $G$ | 0.013 | 0.016 | 0.006 | 0.043** | 0.016 | 0.017 | 0.008* | 0.038** |
| | (0.012) | (0.011) | (0.008) | (0.021) | (0.011) | (0.011) | (0.005) | (0.018) |
| $ln(FDI)$ | 0.063** | 0.044 | 0.055** | 0.061** | 0.034 | 0.019 | 0.059** | 0.064** |
| | (0.032) | (0.032) | (0.023) | (0.026) | (0.033) | (0.034) | (0.025) | (0.027) |
| $ln(FDI)*ln(G)$ | 0.032*** | 0.037** | 0.020 | -0.003 | 0.034*** | 0.030*** | 0.002 | -0.005 |
| | (0.009) | (0.015) | (0.016) | (0.031) | (0.008) | (0.010) | (0.009) | (0.023) |
| $ln(pvd)$ | | -0.005*** | | -0.001 | | -0.004 | | -0.001 |
| | | (0.002) | | (0.034) | | (0.003) | | (0.003) |
| $ln(FDI)*ln(pvd)$ | | 0.008 | | 0.012 | | 0.011 | | -0.000 |
| | | (0.013) | | (0.026) | | (0.012) | | (0.014) |
| Constant | 5.481*** | 5.721*** | 5.172*** | 5.586*** | 5.522*** | 5.540*** | 4.696*** | 5.059*** |
| | (0.815) | (0.780) | (0.542) | (0.549) | (0.728) | (0.731) | (0.459) | (0.482) |
| Observations | 300 | 300 | 240 | 236 | 300 | 300 | 239 | 235 |
| $R^2$ | 0.425 | 0.437 | 0.524 | 0.545 | 0.468 | 0.473 | 0.507 | 0.518 |

Notes: This table reports the fixed-effect estimation under the four five-year periods and the selected sub-samples of cities. The dependent variable is the log difference of GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

Table 7 –Panel Data for Selected Sub-samples(geographical condition or policy condition) of Cities

| | coastal vs. interior cities | | provincial vs. non-provincial | | policy vs. non-policy | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ln(y(0))$ | -0.548*** | -0.593*** | -0.480*** | -0.598*** | -0.534*** | -0.611*** |
| | (0.068) | (0.045) | (0.084) | (0.042) | (0.078) | (0.042) |
| $ln(n+g+\delta)$ | 0.081 | -0.037 | -0.049 | -0.041 | -0.041 | -0.036 |
| | (0.147) | (0.031) | (0.049) | (0.034) | (0.047) | (0.034) |
| $ln(s_k)$ | 0.285*** | 0.262*** | 0.032 | 0.289*** | 0.157*** | 0.279*** |
| | (0.044) | (0.032) | (0.091) | (0.030) | (0.038) | (0.032) |
| $ln(s_h)$ | 0.017 | 0.042*** | 0.136 | 0.037*** | 0.000 | 0.049*** |
| | (0.016) | (0.010) | (0.109) | (0.009) | (0.008) | (0.008) |
| $G$ | 0.008 | 0.033*** | 0.002 | 0.033*** | -0.002 | 0.039*** |
| | (0.009) | (0.010) | (0.020) | (0.009) | (0.003) | (0.009) |
| $ln(FDI)$ | 0.008 | 0.054*** | 0.045 | 0.049*** | 0.074** | 0.052*** |
| | (0.041) | (0.019) | (0.054) | (0.017) | (0.037) | (0.018) |
| $ln(FDI)*ln(G)$ | 0.025*** | 0.014** | 0.020 | 0.013** | 0.031*** | 0.012** |
| | (0.006) | (0.007) | (0.015) | (0.006) | (0.006) | (0.006) |
| Constant | 6.074*** | 5.809*** | 4.985*** | 5.899*** | 4.997*** | 6.050*** |
| | (0.880) | (0.392) | (0.677) | (0.381) | (0.651) | (0.371) |
| Observations | 208 | 755 | 100 | 863 | 186 | 779 |
| $R^2$ | 0.479 | 0.529 | 0.490 | 0.527 | 0.429 | 0.555 |

Notes: This table reports the fixed-effect estimation under the four five-year periods and the selected sub-samples of cities. The dependent variable is log difference of GDP per capita The dependent variable is log difference of GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

TABLE 8 –IV ESTIMATES - THE SECOND-STAGE RESULTS

| | OLS | IV - geographical condition | | IV - lagged value | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | $ln(y)$ | $ln(y)$ | $ln(y)$ | $ln(y)$ | $ln(y)$ |
| $ln(y(0))$ | -0.561*** | -0.838*** | -0.823*** | -0.573*** | -0.574*** |
| | (0.041) | (0.087) | (0.081) | (0.046) | (0.047) |
| $ln(n+g+\delta)$ | -0.042 | -0.066 | -0.068 | -0.075** | -0.075** |
| | (0.032) | (0.049) | (0.049) | (0.037) | (0.037) |
| $ln(s_k)$ | 0.279*** | 0.144** | 0.143** | 0.206*** | 0.211*** |
| | (0.028) | (0.066) | (0.066) | (0.036) | (0.036) |
| $ln(s_h)$ | 0.037*** | 0.041*** | 0.041*** | 0.005 | 0.007 |
| | (0.009) | (0.013) | (0.013) | (0.014) | (0.013) |
| $ln(FDI)$ | 0.048*** | -0.135 | -0.125 | -0.054 | -0.053 |
| | (0.016) | (0.103) | (0.102) | (0.033) | (0.033) |
| $G$ | 0.015* | 0.119*** | 0.122*** | 0.003 | 0.001 |
| | (0.009) | (0.027) | (0.026) | (0.005) | (0.005) |
| $ln(FDI) * ln(G)$ | 0.020*** | 0.047** | 0.043** | 0.046*** | 0.046*** |
| | (0.005) | (0.023) | (0.021) | (0.009) | (0.009) |
| Policy Controls | N | N | Y | N | Y |
| Observations | 967 | 959 | 959 | 725 | 725 |

Notes: This table reports the second stage IV estimation. Column (1) is the benchmark regression(without IVs). The control variables (policy dummy variables) are not shown in the table. All controls are not statistically significant. The dependent variable is log difference of GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

# Table 9 –IV Estimates - the First-stage Results

| | IV - geographical condition | | | IV - lagged value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $G$ | $ln(FDI)$ | $ln(FDI) * ln(G)$ | $G$ | $ln(FDI)$ | $ln(FDI) * ln(G)$ |
| $IV_G$ | 0.178*** | -0.008 | 0.279*** | | | |
| | (0.047) | (0.016) | (0.055) | | | |
| $IV_{FDI}$ | 0.358*** | 0.102*** | 0.413*** | | | |
| | (0.054) | (0.017) | (0.073) | | | |
| $IV_{interaction}$ | -0.057*** | -0.012* | -0.168*** | | | |
| | (0.020) | (0.006) | (0.025) | | | |
| $ln(y(0))$ | 0.978*** | 0.281*** | 2.694*** | 0.094 | 0.200*** | 0.244** |
| | (0.253) | (0.076) | (0.317) | (0.143) | (0.055) | (0.108) |
| $ln(n + g + \delta)$ | 0.252 | -0.166* | 0.106 | 0.123* | -0.079 | -0.006 |
| | (0.349) | (0.101) | (0.375) | (0.070) | (0.053) | (0.101) |
| $ln(s_k)$ | 0.790*** | 0.279*** | 1.840*** | 0.153 | 0.345*** | 0.466*** |
| | (0.197) | (0.073) | (0.268) | (0.100) | (0.064) | (0.118) |
| $ln(s_h)$ | -0.092* | -0.022 | -0.080 | 0.036* | -0.034*** | -0.030 |
| | (0.047) | (0.022) | (0.098) | (0.021) | (0.012) | (0.021) |
| $IV_{G(lag)}$ | | | | 0.850*** | 0.009 | 0.057** |
| | | | | (0.064) | (0.009) | (0.026) |
| $IV_{FDI(lag)}$ | | | | 0.004 | 0.605*** | 0.688*** |
| | | | | (0.040) | (0.034) | (0.055) |
| $IV_{interaction(lag)}$ | | | | 0.007 | -0.014** | 0.483*** |
| | | | | (0.017) | (0.007) | (0.013) |
| Observations | 959 | 959 | 959 | 725 | 725 | 725 |
| F test | 28.47 | 19.49 | 15.17 | 308.01 | 103.69 | 751.03 |
| SW multivariate F test | 25.83 | 18.84 | 52.53 | 776.79 | 401.47 | 4017.47 |

Notes: This table reports the first stage of IV estimation. Columns (1) – (3) report the estimation using geographical conditions. $IV_G = ln(slope) * time. IV_{FDI} = ln(distance) * time. IV_{interaction} = IV_G * IV_{FDI}$. Columns (4) – (6) report the estimation using lagged values. SW F test means Sanderson-Windmeijer multivariate F test of excluded instruments. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

## Table 10 –IV Estimates - the Reduced-form Results

| | IV - geographical condition | | IV - lagged value | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $ln(y)$ | $ln(y)$ | $ln(y)$ | $ln(y)$ |
| $ln(y(0))$ | -0.633*** | -0.634*** | -0.573*** | -0.573*** |
| | (0.036) | (0.036) | (0.039) | (0.039) |
| $ln(n+g+\delta)$ | -0.025 | -0.025 | -0.070* | -0.070* |
| | (0.037) | (0.037) | (0.040) | (0.040) |
| $ln(s_k)$ | 0.295*** | 0.295*** | 0.209*** | 0.214*** |
| | (0.026) | (0.026) | (0.037) | (0.037) |
| $ln(s_h)$ | 0.028*** | 0.028*** | 0.006 | 0.007 |
| | (0.006) | (0.006) | (0.015) | (0.014) |
| $IV_G$ | 0.036*** | 0.036*** | | |
| | (0.005) | (0.005) | | |
| $IV_{FDI}$ | 0.048*** | 0.048*** | | |
| | (0.007) | (0.007) | | |
| $IV_{interaction}$ | -0.013*** | -0.013*** | | |
| | (0.003) | (0.003) | | |
| $IV_{G(lag)}$ | | | 0.004 | 0.003 |
| | | | (0.004) | (0.004) |
| $IV_{FDI(lag)}$ | | | -0.001 | -0.000 |
| | | | (0.021) | (0.021) |
| $IV_{interaction(lag)}$ | | | 0.023*** | 0.023*** |
| | | | (0.004) | (0.004) |
| Policy Controls | N | Y | N | Y |
| Observations | 1,055 | 1,055 | 725 | 725 |

Notes: The table reports the fixed-effect estimation using the initial values of road infrastructure and FDI stock instead of the average of each period. The dependent variable is the log difference in GDP per capita. Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table (1) for variable definitions.

## Table 11 –China's Regional Preferential Policies

| Types | Cities | |
|---|---|---|
| Special Economic Zones | 1988/04 | All cities in Hainan Province |
| | 1989/04 | Shenzhen |
| | 1994/03 | Xiamen |
| | 1996/03 | Zhuhai |
| | 1996/03 | Shantou |
| The National Synthetically Reform Testing District | 2005/6 | Shanghai |
| | 2006/5 | Tianjin |
| | 2007/6 | Chongqing, Chengdu |
| | 2007/12 | Wuhan, Changsha, Xiangtan |
| | 2009/5 | Shenzhen |
| | 2010/04 | Shenyang |
| | 2010/12 | All cities in Shanxi Province |
| | 2011/03 | Yiwu |
| | 2012/08 | Dongxing, Ruili, Manzhouli |
| | 2013/05 | Nantong |
| | 2013/06 | All cities in Heilongjiang Province |
| | 2014/09 | Shantou |
| Bonded Area | 1987 | Shenzhen(Shatou) |
| | 1990 | Shanghai(Gaoqiao) |
| | 1991 | Tianjin, Shenzhen(Futian |
| | 1992 | Haikou, Qingdao, Yantai,Dalian |
| | 1993 | Shantou |
| | 1996 | Shenzhen(Yantian) |
| | 2002 | Ningbo |
| | 2006 | Suzhou |
| | 2008 | Qinzhou, Pingxiang |
| | 2009 | Tianzhu, Suifenhe |
| | 2010 | Chengdu, Chongqing, Zhengzhou |
| | 2011 | Xian, All cities in Xinjiang Province, Wuhan, Weifang |
| | 2012 | Taiyuan, Chifeng, Zhoushan |
| | 2014 | Nanyang, Ganzhou |
| | 2018 | Weihai |
| Coastal Open Economic Zones | 1984 | Dalian, Qinhuangdao, Shanghai, Nantong, Tianjin, Ningbo, Guangzhou, Zhanjiang, Yantai, Fuzhou, Lianyungang, Qingdao |