Road Infrastructure, Foreign Direct Investment, and Economic Growth in China

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Abstract

Using a panel of Chinese cities from 1999 to 2018, this study examines how foreign direct investment (FDI) and road infrastructure jointly influence local economic growth. Within a human-capital-augmented Solow framework, the analysis shows that FDI is positively associated with growth in GDP per capita, and that this relationship strengthens when cities possess more extensive road networks. The results suggest that transportation infrastructure facilitates the diffusion of technologies and productivity spillovers introduced by foreign firms, thereby amplifying the growth effects of FDI. The complementary interaction between FDI and road infrastructure is most evident in technology-intensive cities, coastal regions, and top-tier urban areas. Multiple robustness checks, including alternative specifications and estimation approaches, support the consistency of these findings.

Keywords: Road Infrastructure, Economic Growth, FDI, Development

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1 Introduction

Transportation infrastructure plays a crucial role in economic development, especially for developing countries, by reducing transport costs, improving regional connectivity, and facilitating trade and access to services. China provides a prominent example, having invested heavily in its road network over the past few decades. The country now boasts one of the world's largest highway systems (the National Trunk Highway System), with an expressway length of about 161,000 kilometers as of 2020 – the longest in the world. These extensive highway investments reflect China's strategy of leveraging infrastructure development to support rapid growth in output and trade. Indeed, the expansion of China's highways has been extraordinary. For instance, since 1990 the growth rate of highway length has far outpaced GDP growth (Figure 1), underscoring the idea that initial access to markets and ideas is a prerequisite for broad-based development (Banerjee et al., 2020). Historically, countries undergo phases of transportation development from establishing basic connectivity to rapidly expanding networks to upgrading services, and China has been swiftly moving through these stages.

In the early reform era, China's transportation infrastructure development lagged behind the pace of economic growth, creating bottlenecks that constrained further progress. Inadequate transport links, especially in interior regions, were a significant factor behind regional growth disparities (Démurger, 2001). Recognizing this, the Chinese government undertook massive highway expansion: since 1978, the total length of highways has increased more than thirty-fold, accompanied by a dramatic rise in freight volumes and connectivity. By 2020, road transport accounted for nearly 74% of China's total freight tonnage, reflecting the pivotal economic role of improved infrastructure (National Bureau of Statistics of China, 2021). Given these trends, this paper focuses on road infrastructure, particularly highways, and its relationship with economic growth, rather than examining all types of infrastructure.

Parallel to infrastructure development, China's economy experienced unprecedented growth after 1978, averaging about 10% annual GDP growth for several decades (Holz, 2008; Whalley and Xin, 2010). A substantial share of this growth has been associated with rising participation in global markets and increased inflows of foreign direct investment (FDI) (Zhao and Du, 2007; Gunby et al., 2017). FDI has played a crucial role by bringing in capital and advanced technology, which often have a larger impact on productivity than domestic investment. Initially, the bulk of FDI gravitated toward the eastern coastal provinces - over 80% of FDI during 1980–2000 went to the coast - due in part to those regions' better market access and infrastructure, as well as policy incentives (Fu, 2004). In contrast, cities in the central and western parts of the country attracted far smaller shares of FDI, constrained by weaker transport networks and less advantageous geographic conditions. Empirical evidence confirms that areas with good infrastructure tend to attract more FDI; for example, Cheng and Kwan (2000a) find that large regional markets and robust infrastructure had a significant positive effect on FDI distribution in China. Over time, as development policies shifted westward and highway connectivity improved across the interior, foreign capital began flowing increasingly into central and western areas. Improved roads have thus expanded the geographic reach of foreign investment, potentially reinforcing growth in regions that were previously left behind (see Figure 2).

The role of FDI in fostering economic growth has received considerable attention in the literature. In addition to supplying external capital, FDI often serves as a conduit for the diffusion of new technologies and managerial practices, generating productivity spillovers for domestic enterprises. As illustrated in Figure 3, the rapid expansion of China's economy since the early 1990s has been accompanied by a marked rise in FDI inflows. The increasing presence of foreign firms has been widely recognized as an important engine of technological upgrading (Blomström and Wang, 1989; Iwasaki and Tokunaga, 2016). Compared with purely domestic investment, FDI is frequently associated with greater growth effects because multinational firms tend to employ more advanced production methods and superior technological capabilities (Borensztein et al., 1998). However, the magnitude of these benefits depends on the host economy's ability to absorb and utilize the incoming technologies. Elements such as human capital, openness, and innovation capability determine how effectively foreign technologies are assimilated. For example, Borensztein et al. (1998) argue that FDI's positive growth impact materializes only when the host country has a minimum threshold of human capital. Thus, while FDI can be a powerful engine of growth through competition and innovation spillovers, its impact is conditional on local circumstances (e.g., education levels, institutional quality) that enable technology absorption (Liu et al., 2001; Fu, 2008; Su and Liu, 2016).

Another strand of literature examines the direct impact of transportation infrastructure on economic performance, a subject of intense academic debate. This discussion dates back to the seminal work of Aschauer (2000), who argued that public capital stocks have a dramatic positive elasticity with respect to output. While early estimates suggested massive returns to infrastructure, subsequent research has scrutinized these magnitudes. Fernald (1999), for instance, highlights that vehicle-intensive industries benefited disproportionately from road building, though the aggregate productivity boost may be more modest once the network is mature. Recent meta-analyses by Bom and Ligthart (2008) and Melo et al. (2013) synthesize this extensive body of work, concluding that while the output elasticity of public capital is indeed positive, the estimates are highly sensitive to the context and econometrics used. Critical surveys by Romp and De Haan (2005) and Lakshmanan (2011) argue that beyond simple productivity calculations, infrastructure investments trigger broader economic consequences, including market expansion and structural shifts. Furthermore, Haughwout (2002) emphasizes the importance of spatial equilibrium, noting that infrastructure benefits in one region may come at the expense of others.

Building on these foundational insights, numerous empirical studies find that better roads and highways enhance productivity and market integration. For instance, major highway investments have been shown to facilitate greater trade flows and regional specialization rather than directly increasing local GDP growth rates (Duranton et al., 2014; Redding and Turner, 2015). In the United States, the expansion of the interstate highway system stimulated economic activity in connected counties and influenced the spatial distribution of industries (Chandra and Thompson, 2000; Michaels, 2008). Similarly, in India, the Golden Quadrilateral national highway project significantly reduced travel times and inventory costs for firms, thereby allowing manufacturers to serve larger markets more efficiently (Datta, 2012). However, while this literature establishes the importance of infrastructure for domestic productivity and trade, it rarely explicitly links these dynamics to foreign capital flows.

Within China, infrastructure investment has proven crucial for regional development and integration. Démurger (2001) finds that transport infrastructure was a key differentiating factor in explaining the growth gap among Chinese provinces - regions with denser highway and rail networks grew significantly faster, contributing to reduced regional disparities. In rural China, Shenggen and Zhang (2004) show that government spending on roads (along with irrigation) significantly boosted agricultural productivity and rural incomes. Recent research also confirms positive impacts of transportation improvements on China's economy. For example, Roberts et al. (2012) and Banerjee et al. (2020) find that the construction of China's national expressway network had a positive causal effect on per capita income levels across regions (even if it did not significantly change short-run GDP growth rates). Investments in other transport modes, such as high-speed rail, have likewise been linked to higher local economic output (e.g., Ke et al. (2017) on the effects of China's high-speed rail). That said, some studies highlight that infrastructure benefits can be unevenly distributed: for instance, Faber (2014) exploits the rollout of the National Trunk Highway System (NTHS) as a natural experiment and finds that while the new highways improved market accessibility, they also led to reduced GDP growth in certain peripheral counties due to economic activity becoming concentrated in major city hubs. On balance, however, the literature suggests that robust road infrastructure is an essential ingredient for enabling trade, reducing geographic isolation, and fostering productivity growth - all of which lay the groundwork for higher long-term growth (Demurger, 2001; Shenggen and Zhang, 2004).

A related body of work investigates how geography and infrastructure influence the location of FDI. In general, foreign investors gravitate toward regions with large markets, good infrastructure, and conducive policies (Cheng and Kwan, 2000b; Halaszovich and Kinra, 2020). Studies of U.S. manufacturing FDI, for example, find that states with more extensive transportation networks attract significantly more foreign investment (Coughlin et al., 1991). In the Chinese context, Cheng and Kwan (2000b) similarly conclude that provinces with better infrastructure (and access to ports) received higher FDI inflows, controlling for other factors. The reason is straightforward: by lowering transportation and transaction costs, infrastructure effectively expands the profitable "reach" of foreign enterprises. Other research emphasizes the role of distance and trade costs in FDI location decisions - for instance, if overseas markets are very distant, multinationals may choose exporting over local investment, unless efficient transport infrastructure mitigates those distance-related costs. Consistent with this, Halaszovich and Kinra (2020) provide evidence that a country's transportation systems moderate the adverse effects of geographical distance on FDI and trade performance.

Although a large body of work examines the growth effects of FDI and the role of infrastructure development, these two strands of research have generally evolved independently. Much of the existing literature focuses either on how infrastructure shapes the location of foreign investment or on the separate contribution of each factor to economic performance, leaving their combined influence largely unexplored. To our knowledge, no study has directly assessed how transportation infrastructure and FDI jointly contribute to regional growth outcomes. This paper addresses that gap by analyzing whether the growth impact of FDI in China is conditioned by the quality of road networks. Specifically, we ask whether cities that simultaneously enjoy substantial FDI inflows and well-developed road systems achieve faster growth than what would be expected from each factor acting on its own. Our central premise is that these two elements may reinforce one another: a more extensive highway network can enhance the productivity and spillover effects of foreign investment by improving connectivity, while FDI may help regions leverage existing infrastructure more effectively through additional capital, employment opportunities, and technology. Such complementarities could help explain persistent disparities in economic growth across Chinese regions.

Descriptive evidence is consistent with this idea of synergy. Over the past two decades, FDI inflows in China have gradually spread inland from the coast, while highway infrastructure has simultaneously expanded into the interior. The spatial distribution of FDI in 2000 versus 2018 (Figures 4 and 5) shows that many interior cities with minimal FDI in 2000 had become significant FDI recipients by 2018. During the same period, China's highway network grew dramatically, connecting virtually all prefecture-level cities by 2020 (Figures 6 and 7). These parallel trends suggest that roads and FDI have been advancing in tandem. It stands to reason that this co-movement - better infrastructure attracting more FDI, and FDI in turn leveraging the infrastructure - has contributed to faster growth in those regions that benefited from both improvements. This study formally tests and confirms that notion within a growth regression framework.

This study contributes to the existing literature in several ways. First, we employ a panel-data framework grounded in an augmented Solow growth model to analyze the sources of economic growth across Chinese cities. By modeling growth along the transition path toward each city's steady-state income, we tie our empirical strategy closely to the model's theoretical foundations. This structure provides a systematic rationale for including core determinants such as investment, saving behavior, and population dynamics, and it avoids relying on arbitrary variable selection. Our results are consistent with the Solow model's implications: per capita GDP growth is negatively associated with population expansion and positively related to both physical and human capital accumulation. Moreover, within this theoretically guided framework, we show that the development of road infrastructure plays an important role in accelerating transitional growth in per capita income.

Second, unlike many studies that use a crude proxy for infrastructure (such as total road length or paved road area), we compile a more nuanced measure that distinguishes between different types of roads. In particular, we focus on inter-city highways and expressways - the arterial roads that connect economic centers - as opposed to local urban streets. This distinction is important because major highways are the roads most likely to reduce trade costs and integrate markets across regions. Our analysis reveals that the highway system indeed promotes economic growth and, importantly, enhances the effect of FDI on growth. In other words, we find evidence of complementarity: FDI has a larger growth impact in locations with extensive highway networks than in those with poor road connectivity. By contrast, we find that paved urban roads (municipal streets within city limits) do not always significantly intensify FDI's effect on growth. This result suggests it is the broad connectivity provided by highways, rather than local road density per se, that matters more for leveraging FDI. Our refined infrastructure measure thus contributes to the literature by highlighting the differential growth effects of trunk highways versus local roads. It also addresses a measurement gap noted in prior research, which often emphasized the need for better infrastructure metrics when examining productivity (e.g., the "productivity puzzle" around public capital noted by Holts-Eakin (1994), where controlling for regional factors showed much weaker infrastructure effects).

Third, we provide new evidence on the heterogeneity of the FDI–infrastructure growth nexus across regions with different technological profiles. We find that the complementary effect of FDI and highways on growth is especially pronounced in high-tech regions (areas with a greater concentration of technology-intensive industries). In these regions, foreign investments likely bring frontier technologies that, when combined with good infrastructure, yield substantial productivity gains. In contrast, in more labor-intensive (low-tech) regions, we do not observe that road infrastructure has a positive direct impact on growth, and there is little to no additional boost from FDI–road interaction. Moreover, consistent with our earlier finding, paved local roads show significant complementary effect with FDI in only some regions. These heterogeneous results enrich our understanding of how local conditions (industrial structure, tech intensity) mediate the benefits of infrastructure and FDI. They suggest that policymakers in high-tech regions might gain especially high returns from coordinating infrastructure upgrades with efforts to attract FDI, whereas in lower-tech regions the gains from FDI–infrastructure synergy may be more limited.

Finally, our study carefully addresses potential endogeneity concerns. It is possible that causality runs in the reverse direction - i.e., richer or faster-growing cities invest more in roads and attract more FDI, which could bias the results of simple growth regressions. This issue of reverse causality and omitted variable bias in growth–infrastructure studies has been highlighted by prior research (Holts-Eakin, 1994). We tackle this challenge in two ways. First, our panel fixed-effects model accounts for unobserved city-specific factors (such as geography or historical institutions) that could affect both growth and infrastructure investment, thereby mitigating omitted variable bias. Second, we implement an instrumental variable (IV) approach following the strategy of Feng and Wu (2018): we use lagged infrastructure development as an instrument to isolate plausibly exogenous variation in current road infrastructure. The IV regressions yield consistent estimates that reinforce our main findings. In fact, the estimated FDI–road complementarity effect on growth is even stronger when using the IV, suggesting that our baseline may understate the true effect. These robustness checks give us confidence that the positive interaction effect we document is not driven by spurious correlation. Our attention to identification echoes broader concerns in the growth literature (e.g. Hauk Jr (2017) on endogeneity bias) and ensures that our contributions are built on a solid empirical foundation.

To the best of our knowledge, this paper is the first to examine the interactive impact of road infrastructure and FDI on regional economic growth in China. We find that highways and FDI reinforce each other in promoting growth: the presence of a strong road network significantly increases the growth dividends from FDI. We also contribute methodologically by using an augmented Solow framework with improved infrastructure measures and by addressing endogeneity rigorously. These findings have direct relevance for policy, suggesting that investments in transportation infrastructure and efforts to attract FDI can yield greater returns if pursued in tandem. For developing countries like China that seek to sustain growth and reduce regional disparities, fostering this synergy between infrastructure and foreign investment can be an effective strategy.

The remainder of the paper is structured as follows. Section 2 presents the theoretical model and empirical methodology. Section 3 describes the data and variables used in the analysis. Section 4 reports the empirical results, including baseline estimates and various robustness checks. Section 5 conducts heterogeneity analysis and Section 6 discusses policy implications. Section 7 concludes our paper.

2 Theoretical Model

Building on the seminal contributions of Mankiw et al. (1992) and the extension proposed by Su and Liu (2016), we adopt the view that economies converge toward their long-run steady states at different speeds. Within this framework, FDI operates as an important efficiency-enhancing factor that introduces more advanced production technologies into the host economy. By affecting the pace at which new technologies are absorbed, FDI can influence how quickly regions move along their transitional path toward steady-state income.

In our analysis, we adopt the extended Solow growth framework developed by Su and Liu (2016) to explore how regional FDI and road infrastructure jointly shape economic performance. We incorporate both FDI and its interaction with transportation networks into the model, allowing us to evaluate their combined influence on transitional growth. In this setting, FDI represents a channel through which more advanced technologies enter the local economy, while the quality of road infrastructure facilitates the diffusion and effective use of these technologies. The interaction of these two elements not only boosts productivity and raises the implied steady-state income level but also accelerates the pace at which cities converge toward that long-run equilibrium.

Our framework begins with a conventional Cobb–Douglas production function. We assume that technological change takes a labor-augmenting form, so the term A aptures efficiency improvements that raise the productivity of labor and grow at an exogenous rate g. Labor itself expands at an exogenous rate n. In addition, we allow the evolution of technology to be influenced by foreign direct investment, reflecting the idea that FDI can contribute to technological upgrading within the economy.

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

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

Equation (2) can be interpreted as consisting of three components. The first term $A(0)e^{gt}$ captures the exogenous component of technological progress that grows at rate g. The second term $F(t)$ reflects the contribution of FDI over time. The third term $f(Road(t))$ represents the role of road infrastructure, where $Road(t)$ denotes the level of transportation infrastructure at time t. To simplify the empirical specification, we assume A is the exponential function of road infrastructure. $f(Road(t)) = exp(\theta Road(t))$, θ is the parameter. This formulation implies that improvements in road networks enhance productive capacity by enabling more efficient resource allocation and raising overall productivity (Kailthya and Kambhampati, 2018).

The expansion of China's highway system has created crucial transportation links that connect major urban hubs and integrate smaller cities along these corridors. By improving regional accessibility and effectively shrinking travel time and spatial separation, these networks reduce logistical frictions and transaction costs. Enhanced mobility facilitates the movement of goods, people, and information, thereby strengthening economic integration across regions. These improvements ultimately lower the cost of economic activity and support broader macroeconomic growth.

The final component of the model assumes that FDI contributes positively to technological upgrading through multiple channels. Beyond the direct introduction of advanced technologies, foreign investment generates indirect spillover effects when domestic firms learn from, imitate, or collaborate with FDI-related enterprises, thereby raising their own productivity. A strong road network further strengthens this mechanism by improving interactions between foreign-invested and local firms, which enhances the diffusion of knowledge and technology. To capture this relationship empirically, we allow road infrastructure to influence the elasticity of FDI with respect to productivity.

$$\lambda = \lambda_0 + \lambda_1 \ln(Road(t)) \tag{3}$$

Notably, We allow road infrastructure to affect growth through two distinct channels. First, roads directly raise productivity by reducing transport costs, which we capture through a multiplicative function $f(Road)$. This effect is expected to exhibit diminishing marginal returns, consistent with the standard infrastructure literature (Chandra and Thompson, 2000; Datta, 2012). Second, roads also enhance the productivity of foreign investment: better highways allow foreign firms to access markets, suppliers, and distribution networks more effectively. To capture this, we let the elasticity of FDI with respect to productivity depend on $\ln(Road)$. The logarithmic form implies diminishing marginal returns to infrastructure in enhancing FDI efficiency, but because it enters as an exponent on FDI, the combined effect on growth can be magnified once a sufficient network is in place. This mechanism is consistent with evidence that infrastructure reduces trade costs and shapes firm location decisions (Redding and Turner, 2015), and that better transport networks in China facilitated both industrialization and foreign capital inflows (Cheng and Kwan, 2000a; Faber, 2014). In short, this distinction reconciles the two roles of roads: as a direct, concave productivity factor, and as a compounding force that amplifies the growth benefits of FDI.

In the Solow–Swan framework, saving rates are taken as exogenous, reflecting household preferences or policy choices. Building on this assumption, we specify the accumulation processes for physical and human capital accordingly. The evolution of each type of capital is therefore determined by its respective saving share and the standard depreciation and dilution terms.

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

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

where $\dot{K} = dK/dt$, s_k and s_h represent physical and human capital saving rates, respectively. δ is the depreciation rate. Thee depreciation rates of physical and human capital are assumed to be the same.

To express the production relationship in units of effective labor, we define output, physical capital, and human capital per effective worker as $y(t) = Y(t)/A(t)L(t)$, $k(t) = K(t)/A(t)L(t)$, $h(t) = H(t)/A(t)L(t)$. Using these definitions and combining them with equations (4) and (5), we obtain the dynamic equations that characterize the evolution of physical and human capital per effective worker.

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

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

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

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

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

Substituting equations (8) and (9) into the production function and applying a logarithmic transformation, we derive the expression for the steady-state level of income per capita:

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

Incorporating equations (2) and (3), we introduce an empirical simplification by allowing the elasticity of technological progress with respect to FDI to vary with the level of road infrastructure. Specifically, we assume $\lambda = \lambda_0 + \lambda_1 \ln(Road(t))$. Under this formulation, the steady-state value of income per capita becomes a function of population growth, the saving rates for physical and human capital, inflows of foreign direct investment, and the extent of road infrastructure.

These factors jointly determine the long-run income level implied by the model.

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

Because our analysis is conducted at the city level, characterizing a literal steady state is not meaningful. Instead, we concentrate on the transitional dynamics that describe how an economy evolves toward its long-run equilibrium. Following the approach of Mankiw et al. (1992), we model the path of convergence, where the movement toward the steady state is captured by the following expression:

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

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.

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

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

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

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. ϵ_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($\phi_5 > 0$). The coefficient ϕ_6 is expected to be positive, indicating that road infrastructure amplifies the positive effect of FDI on economic growth, while ϕ_7 represents the direct positive impact of road infrastructure on economic growth.

In the framework of Mankiw et al. (1992), the initial level of technology $A(0)$ is treated as unrelated to the saving rates for physical and human capital or to population growth, effectively abstracting from heterogeneity across economies. Rather than relying solely on a cross-sectional specification, we account for unobserved, location-specific factors by adopting a fixed-effects panel approach, following the methodologies in Knight et al. (1993) and Su and Liu (2016). Under this formulation, the empirical model with fixed effects can be written as:

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

In our panel specification, the data are organized into non-overlapping five-year intervals. With the exception of the initial income term $\ln(y_{i0})$, all explanatory variables are measured as averages within each five-year period. Consequently, the time index t in equation (16) refers to these multi-year subperiods rather than individual years.

3 Data

3.1 Main Resource

The analysis is based on an annual panel dataset covering 265 prefecture-level cities in China from 1999 to 2018. Most of the information is drawn from successive volumes of the China City Statistical Yearbook (1999–2018) and the China Statistical Yearbook for Regional Economy (2000–2014). Because the raw data contain some missing observations, we supplement the dataset with figures obtained from individual city statistical yearbooks and local statistical communiqués, which are manually compiled to ensure completeness and consistency.

The China City Statistical Yearbook, published annually by the National Bureau of Statistics, provides detailed indicators on the economic and social development of urban areas across the country. The geographic scope of this study follows the Yearbook's coverage but excludes Hong Kong, Macao, and Taiwan. In the Yearbook tables, the term "city" refers to the entire administrative unit, which includes the urban core as well as affiliated counties and rural districts.

3.2 Data Summary and Measurement

China's Highway System — The evolution of China's highway network can be broadly divided into three phases: (1) a period of gradual expansion from 1978 to 1997, (2) a phase of rapid, large-scale construction from 1998 to 2015, and (3) a more recent period emphasizing integrated and high-quality development beginning in 2016.

A major turning point occurred in 1998, when China responded to the Asian financial crisis by adopting an active fiscal policy that prioritized infrastructure investment. This policy shift sparked a surge in credit flows toward expressway construction and propelled the rapid nationwide buildup of highway networks. During this time, local governments also began releasing more detailed and consistent statistics on road conditions, greatly improving data availability. Moreover, many convergence studies focus on the earlier years of this expansion, which motivates our choice of 1999 as the starting year for the empirical analysis.

The road dataset used in this study includes all officially designated roads that connect different regions (rural areas, towns, and cities) and are built according to national technical specifications with formal administrative approval. These measures provide a representative indicator of the scale and progress of highway development and form the basis for calculating transportation-network indicators such as regional road density.[1]

Although road length reported in kilometres is widely available in the Statistical Yearbooks, relying solely on this measure may not fully capture the scale of infrastructure investment or improvements in construction quality. To address this limitation, we adopt the embodied-technical-change approach of Hulten (1992) to construct a measure of road capital. This method reflects the idea that technological progress is embodied in newly built roads—better design, higher construction standards, and improved durability. Accordingly, we estimate the capital stock of road infrastructure following the formulation in Hulten (1992):

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

where l is the length of the road, δ is the rate of depreciation, which equals 0.096. ϕ denotes

[1] The series captures the physical length of public roads at the end of each reporting period. It includes highways that run through urban streets, the lengths of bridges and tunnels, and ferry widths. Roads counted are those suitable for motor vehicle travel and that link cities, towns, and villages. Excluded are urban street mileage, dead-end routes, agricultural and forestry roads, and internal roads within industrial or mining enterprises.

the effectiveness differential. Full effectiveness is defined as the state in which road infrastructure is preserved in optimal condition and operated under best-practice efficiency standards. The weighting factor is derived from the proportion of freight traffic volume attributed to the respective infrastructure network segment.

The data on the area of urban streets are obtained from the City Statistical Yearbook of China. It is important to clarify that the term urban street in this context specifically refers to smaller city streets that primarily support daily life activities, such as commuting to work, attending school, or shopping. This definition differs from the broader concept of road infrastructure discussed earlier.

Investment - Earlier studies often relied on fixed asset investment as a straightforward indicator of overall investment activity (Su and Liu, 2016). More recent discussions, however, have highlighted concerns about the accuracy of this measure.[2] One notable issue is that in several provinces, the reported volume of fixed asset investment has exceeded provincial GDP, which strongly suggests inflation or misreporting in the underlying data.

An alternative measure is fixed capital formation, which reflects investment under the expenditure approach to GDP. Before 2005, fixed asset investment and fixed capital formation were nearly identical in value. Since then - especially from 2010 onward - a widening gap between the two has become evident.

Unfortunately, city-level data on fixed capital formation are unavailable. To address this, we calculate the ratio of provincial-level fixed capital formation to fixed asset investment, which serves as an adjustment factor. Then, we apply this ratio to city-level fixed asset investment to derive a more accurate estimate of city-level investment.

Real GDP - Real per capita GDP is obtained directly from the Statistical Yearbooks and converted into constant prices using the GDP deflator, with 1999 chosen as the base year. This provides a consistent measure of income over time that accounts for inflation.

Human Capital - Following the approach in Su and Liu (2016), we proxy the saving rate devoted to human capital formation using the share of the population enrolled in higher education institutions, such as colleges and universities. This measure reflects the extent of investment in advanced skills and educational attainment.

FDI - The Statistical Yearbooks report only annual inflows of foreign direct investment, rather than the accumulated stock. To construct a consistent measure of FDI stock, we apply the perpetual inventory method, following the approach of Zhang (2008). This method, originally developed by Goldsmith (1951), is widely used in both domestic and international research for estimating

[2]Industry analysts have noted inconsistencies in fixed asset investment statistics. In 2021, the National Bureau of Statistics revised the national series to correct misreporting and structural distortions. This adjustment, however, was applied only at the national level and did not update corresponding city-level figures.

capital stock series. The FDI stock is computed using the following expression:

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

where δ 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 for city i. Table (1) reports the description of the variable used.

4 Result

4.1 Cross-section Regression

Table 2 presents the cross-sectional estimation results based on Equation (15), where the dependent variable is the log difference in real GDP per capita between 1999 and 2018. All explanatory variables are measured as city-level averages over the same period. The model assumes a fixed depreciation-adjusted growth rate of 0.05, following the convention of Mankiw et al. (1992).

Column (1) includes only the baseline Solow-type growth regressors. The coefficient on initial income is significantly negative, consistent with conditional convergence. Both physical capital ($\ln s_k$) and human capital ($\ln s_h$) have positive and statistically significant effects on growth. However, the coefficient on the population growth rate is unexpectedly positive and insignificant, diverging from theoretical predictions. Column (2) adds FDI as a proxy for foreign technology spillovers. Its coefficient is positive but not statistically significant at conventional levels. Column (3) introduces road infrastructure (measured as average stock over time), and again, the coefficient is positive but small and insignificant. Column (4) includes both FDI and road infrastructure simultaneously. While each term alone remains insignificant, column (5) adds an interaction term between FDI and infrastructure - specified as $\ln(F) \times \ln(\text{Road})$. This interaction term has a positive coefficient, suggesting a potential complementarity between FDI and infrastructure in driving regional growth. In other words, while neither FDI nor roads alone show significant independent effects in this cross-sectional setting, their joint presence appears to amplify economic performance.

Taken together, these results lend preliminary support to the hypothesis that FDI and road infrastructure reinforce each other, though the lack of significance on the individual components may reflect limitations inherent to cross-sectional models, especially the inability to fully control for time-invariant unobserved heterogeneity. Therefore, the next section turns to panel data regressions to validate the interaction effect in a more robust setting.

4.2 Panel Regression

Table 3 presents fixed-effects panel regression results over four non-overlapping five-year periods (1999–2003, 2004–2008, 2009–2013, 2014–2018). The dependent variable is the five-year log difference in GDP per capita. This structure allows us to control for unobserved, time-invariant city characteristics and examine within-city variation over time.

Column (1) presents the baseline Solow model. The results align with theoretical expectations: the initial GDP level has a negative and highly significant effect, consistent with conditional convergence. Investment in physical and human capital significantly contributes to growth, while the effective labor growth rate remains statistically insignificant. Columns (2) and (3) incorporate FDI and road infrastructure separately. Both variables exhibit positive and statistically significant effects, suggesting that FDI inflows and improvements in transport infrastructure independently support economic growth. Column (4) includes both FDI and road infrastructure simultaneously. Both remain positive and statistically significant, and the magnitudes are close to those in columns (2)–(3), suggesting their effects are not merely picking up each other. Column (5) provides the most comprehensive specification, and the interaction term - $\ln(F) \times \ln(\text{Road})$ - is significant at the 1% level. This suggests a robust and economically meaningful complementarity between foreign capital and domestic infrastructure. Specifically, road infrastructure appears to reduce logistical frictions, allowing foreign firms to operate more efficiently and enabling domestic firms to better absorb knowledge spillovers.

Compared to the cross-sectional results, the panel approach reveals more stable and significant estimates. The fixed-effects specification helps mitigate bias from unobserved heterogeneity, while the time structure captures dynamic effects of policy and investment. The adjusted R^2 increases to 0.437 in the fully specified model, indicating an improved model fit.

To explore whether alternative measures of infrastructure produce similar patterns, we extend the baseline model to include urban street length as a complementary proxy for local infrastructure. Table A.1 presents the results. Columns (2) and (3) include the urban street length and its logarithm interaction with FDI. Notably, the interaction term between FDI and urban street infrastructure ($\ln(FDI) \times \ln(UrbanStreet)$) is positive and statistically significant, suggesting that the complementarity result is robust to using a more localized measure of infrastructure beyond intercity roads. This supports the interpretation that infrastructure quality - whether regional or urban - enhances the economic returns to FDI. Importantly, the coefficient on $\ln(FDI) \times \ln(Road)$ remains stable when urban infrastructure is added, indicating that road-level and street-level effects are not simply capturing the same variation.

4.3 Endogeneity and Mitigate Bias

A major challenge in identifying the causal effects of FDI and road infrastructure on economic growth is the potential endogeneity of these variables. Reverse causality is a key concern: cities experiencing higher economic growth may attract more FDI and public infrastructure investment, rather than the other way around. Foreign investors often target regions with stronger economic performance, while local governments may respond to growth by expanding infrastructure. To address this issue, we employ two identification strategies.

The first strategy uses the initial-period values of FDI and road infrastructure for each five-year panel as predetermined and plausibly exogenous. Specifically, we construct initial values for each subperiod (e.g., FDI and road levels in 1999 for the 1999–2003 panel) and use these in place of contemporaneous averages. Table 4 reports the results using this approach. Columns (1)–(4) replicate the baseline specifications, confirming the positive and statistically significant roles of FDI and road infrastructure. Column (5) introduces the interaction term between the logarithm of FDI and the logarithm of road infrastructure. The coefficient on the interaction term remains positive and statistically significant at the 1% level. This reinforces the conclusion that FDI and road infrastructure are complementary in promoting economic growth. These results suggest that using initial values reduces simultaneity bias while preserving the core empirical findings.

To further address endogeneity concerns, we implement an instrumental variable (IV) strategy. Following the literature (e.g., Holtz-Eakin, 1992; Su and Liu, 2016), we use lagged values of FDI and road infrastructure, along with their interaction term, as instruments. These lagged instruments are assumed to be correlated with current-period FDI and infrastructure but uncorrelated with the current-period residuals in the growth equation.

Table 7 presents the second-stage IV estimates. Column (1) replicates the OLS benchmark, while Column (2) displays the IV results. The coefficient on the interaction term $\ln(\text{FDI}) \times \ln(\text{Road})$ remains positive and statistically significant at the 1% level, and its magnitude is almost the same as the OLS result. The first-stage and reduced-form regression results for this robustness check are provided in Table A.2. The first-stage regressions in Table A.2 confirm strong instrument relevance. The lagged interaction term, $\ln(F)_{t-1} \times \ln(Road)_{t-1}$, has a statistically significant and large coefficient in the first-stage regression (Column 4), with a corresponding F-statistic well above the conventional threshold (4174.24), alleviating concerns about weak instruments. The reduced-form results (Column 1) also show a strong positive effect of the instruments on the dependent variable. Overall, these diagnostics lend credibility to the IV identification strategy.

In sum, the findings from both OLS regression and the IV strategy 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 Heterogeneity Analysis

5.1 Fixed Estimates for Selected Sub-samples (Rank of Innovation)

While the baseline model assumes that foreign direct investment (FDI) uniformly contributes to technological progress across all cities, this assumption may not hold in practice. FDI inflows differ in their technological intensity, and cities vary in their capacity to absorb such spillovers depending on their local innovation environments. Consequently, the complementary role of road infrastructure in enhancing FDI-driven growth may be more pronounced in cities with greater innovation capacity.

Since detailed city-level data on FDI composition are unavailable, we explore this heterogeneity by dividing cities into subsamples based on two proxies for local innovation capacity: the innovation index[3] and the number of patents[4]. These proxies reflect both innovation inputs and outputs, and are commonly used in empirical growth and development studies. We also examine whether urban street-level infrastructure plays a differential role across these subsamples.

Columns (1) and (2) of Table 5 report results from subsamples split by the top and bottom quartiles of the Innovation Index. The interaction term between FDI and road infrastructure, $\ln(\mathsf{FDI}) \times \ln(\mathsf{Road})$, is positive and statistically significant in the top-innovation cities, indicating a strong complementary relationship. This suggests that cities with high innovation capacity are better equipped to utilize road infrastructure to amplify the productivity of FDI inflows, possibly due to better institutions, absorptive capacity, or a stronger presence of innovation-intensive sectors. In contrast, in low-innovation cities, the interaction term is not significant, and road infrastructure alone has a negative and significant coefficient, implying that without sufficient local innovation capabilities, road investments may not generate meaningful synergies with FDI and may even reflect inefficient overinvestment. Columns (3) and (4) use patent count rankings as an alternative proxy for innovation. The patterns are similar: the interaction term is again positive and significant in the top-patent cities, reinforcing the idea that innovation-intensive cities experience greater gains from FDI when supported by strong infrastructure. In contrast, the interaction term becomes insignificant in the bottom-patent cities.

Incorporating urban infrastructure (see table A.3, we find that $\ln(\mathsf{F}) \times \ln(\mathsf{UrbanStreet})$ is

[3]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.

[4]Patent data are obtained from the China National Intellectual Property Administration (CNIPA).

also positive and significant in high-innovation cities (Columns 1 and 3), but insignificant in their low-innovation counterparts (Columns 2 and 4). This suggests that local infrastructure - both regional and urban - enhances the effectiveness of FDI only when cities possess the technological readiness to exploit these gains. In sum, infrastructure-FDI complementarities are conditional on local innovation intensity.

These findings highlight an important policy insight: the effectiveness of infrastructure investment in catalyzing FDI-driven growth is conditional on local innovation capacity. In technologically advanced cities, road infrastructure not only improves connectivity but also deepens the integration of foreign capital into the local economy, leading to stronger growth multipliers. However, in regions lacking such capacity, roads primarily serve traditional functions like reducing transport costs, and their interaction with FDI is limited. This underscores the importance of aligning infrastructure development strategies with regional innovation policies. For regions with strong R&D and innovation ecosystems, policymakers should prioritize attracting high-tech FDI and upgrading transport infrastructure in tandem. For lagging areas, complementary policies, such as human capital development, support for innovation diffusion, and public R&D investment, may be necessary to fully leverage the potential of infrastructure.

5.2 Fixed Estimates for Selected Sub-samples (Geographical or Policy conditions)

Geographic characteristics, administrative hierarchies, and local FDI policies also shape the technological sophistication embedded in foreign investment. Coastal areas, in particular, benefit from natural locational advantages—especially the concentration of seaports—which historically enabled these cities to attract foreign capital earlier and more intensively than inland regions, as shown in Figures 4 and 5. In this section, we explore whether the degree of complementarity between road infrastructure and FDI differs across regions, between cities of varying administrative rank, or in locations that offer preferential FDI incentives.

Columns (1) and (2) of Table 6 show the results for coastal and inland cities, respectively. In coastal regions, the interaction term between FDI and road infrastructure is positive and statistically significant at the 1% level (coefficient = 0.016), and notably larger than the corresponding coefficient in inland cities (0.007). This suggests that the complementary effect of FDI and road infrastructure is stronger in coastal areas, likely due to their better connectivity, developed logistics systems, and higher baseline of foreign investment. However, in coastal cities, road infrastructure alone does not have a statistically significant direct effect on economic growth (coefficient = 0.007, p 0.1), likely due to infrastructure saturation. In contrast, inland cities still benefit directly from infrastructure improvements (coefficient = 0.014, significant at 5% level), which reflects their relatively underdeveloped transport networks and greater marginal returns from investment in roads.

Columns (3) and (4) present results for cities classified by administrative level: level 1 (provincial capitals and sub-provincial cities) and level 2–4 (lower-tier cities). In top-tier cities, the interaction term is large and significant (coefficient = 0.027), indicating that FDI and infrastructure are highly complementary. This is expected, as these cities have stronger institutions, better human capital, and more developed ecosystems to absorb and benefit from FDI. Even in lower-tier cities, the interaction term remains positive and statistically significant (coefficient = 0.008), though smaller in magnitude. This suggests that even less developed cities can benefit from complementarities between infrastructure and FDI, albeit to a lesser extent when basic conditions are in place.

Since the beginning of China's reform and opening period, foreign-invested firms have played a major role in driving economic expansion. To attract and retain this investment, the central and local governments introduced a range of preferential tax arrangements—most prominently reduced corporate income tax rates—which differ across regions. Using an index of preferential policies constructed by Demurger et al. (2002), prior research shows that cities located in coastal open economic zones, special economic zones (SEZs), and economic and technological development zones typically provide more generous tax advantages to foreign enterprises. After 2000, additional types of development zones—such as the national comprehensive reform pilot areas, often viewed as a second generation of SEZs—were established with similar goals (see Table A.4). Bonded zones and tariff-free areas also enhance the incentives by allowing foreign goods to enter without import duties. In this study, we classify cities that fall within any of these designated zones as "policy-supported," while those outside these areas are treated as having limited or no preferential FDI policies.

Columns (5) and (6) distinguish cities based on whether they are subject to preferential FDI policies, such as those located in special economic zones (SEZs), bonded zones, or national reform districts. Cities with preferential policies show a strong and significant complementary effect (interaction coefficient = 0.008), reinforcing the idea that targeted policy support amplifies the economic return from combining FDI and infrastructure investment. These cities may also benefit from streamlined administrative processes, tax incentives, and coordinated development planning that further boost FDI effectiveness. In non-policy cities, the interaction term is also positive and significant. This suggests that even without formal preferential treatment, road infrastructure and FDI can work together to support growth, although policy interventions clearly enhance the effect.

Notably, in Table A.5, the interaction between FDI and urban street infrastructure, $\ln(F) \times \ln(UrbanStreet)$, is statistically significant only in the inland subsample (column 2), level-1 (top-tier) cities (column 3), and policy-supported cities (column 5). In contrast, the coefficients are small and imprecisely estimated for coastal cities (column 1), lower-tier (level 2–4) cities (column 4), and non-policy cities (column 6). This pattern suggests that within-city accessibility boosts the growth payoff from FDI where either (i) baseline intercity access is weaker (inland), (ii) administrative/absorptive capacity is high (top-tier), or (iii) supportive investment policies are in place (policy zones). Where these conditions are absent (coastal saturation, lower-tier capacity constraints, no policy support), urban street expansion does not measurably amplify the effect of FDI.

6 Discussion and Policy Implication

Our findings provide new evidence on the complementary relationship between foreign direct investment (FDI) and transportation infrastructure in driving regional economic growth. By extending the Solow growth model to incorporate both the direct productivity effects of road infrastructure and its moderating effect on the returns to FDI, we capture two important and distinct growth mechanisms. The empirical results consistently demonstrate that both FDI and road infrastructure individually contribute to long-term income growth, but more importantly, their interaction term exhibits a statistically significant and economically meaningful effect. This suggests that road infrastructure not only facilitates economic activity directly but also amplifies the efficiency gains from FDI.

This interaction mechanism has strong theoretical support. Roads reduce trade frictions, expand market access, and improve firm-level logistics, all of which make it easier for foreign firms to operate and for domestic firms to integrate into global value chains. The placement of road infrastructure in both the productivity function and the elasticity of FDI within our model reflects this dual role. Regions with better highway networks appear to gain disproportionately more from the presence of foreign capital, due to improved absorptive capacity and connectivity.

From a policy perspective, our results suggest that maximizing the growth impact of FDI requires complementary investments in transportation infrastructure. Regional governments seeking to attract and retain foreign capital should not focus solely on preferential tax policies or industrial parks. Instead, improving the physical connectivity between cities - particularly through the expansion and modernization of highways - can significantly raise the marginal returns to FDI. This is especially critical for third- and fourth-tier cities, which often receive lower levels of FDI due to limited accessibility and logistical bottlenecks.

Our findings also provide a rationale for coordinated national development strategies that integrate transport planning with industrial and investment policy. The observed synergy between infrastructure and FDI implies that fragmented, province-level efforts to attract foreign investment may be suboptimal unless matched with interregional infrastructure investments. The success of China's National Trunk Highway System and the clustering of economic activity around major corridors underscore the importance of such coordinated planning.

Furthermore, these dynamics have implications for regional inequality. Since infrastructure and FDI reinforce each other, their benefits may become concentrated in already well-connected urban hubs. To prevent increasing spatial inequality, policymakers should consider targeting road investment toward lagging or peripheral regions with untapped investment potential. Coupling this with incentives for FDI in those regions could foster more balanced development.

Finally, our paper contributes to the growing literature on endogenous growth by showing that physical infrastructure plays a more complex role than commonly assumed. It is not merely a background condition but a factor that can actively shift the growth trajectory when paired with external capital inflows. This reinforces the idea that infrastructure policy must be designed not just for capacity expansion but for strategic complementarity with broader economic goals.

7 Conclusion

China's economic transformation since 1978 has been underpinned by large-scale infrastructure investments and an openness to foreign capital. As the nation transitions from high-speed growth to high-quality development, policymakers have increasingly emphasized improving total factor productivity (TFP) and fostering more sustainable, innovation-driven economic dynamics. In this context, the role of continued infrastructure investment - especially in road networks - merits reexamination. Can further expansion of transport infrastructure still contribute meaningfully to economic efficiency and technological upgrading, particularly in a more mature growth phase?

This paper addresses that question by developing and testing an extended neoclassical growth framework that integrates foreign direct investment (FDI) and road infrastructure. Distinct from existing studies, our model highlights two growth channels: (1) a direct effect of road infrastructure on productivity via reduced transport costs and market integration, and (2) an indirect effect, where roads enhance the productivity of FDI by improving foreign firms' operational reach and amplifying spillovers to domestic firms. Empirically, we find strong evidence that these two channels jointly contribute to long-run economic growth in China.

Using a province-city panel dataset spanning two decades, we estimate the effects of both FDI and road infrastructure and their interaction. Our baseline results confirm that both FDI and road infrastructure independently raise economic performance. More importantly, their interaction term exhibits a consistently positive and statistically significant effect on income growth, indicating that the marginal benefit of FDI is significantly higher in regions with more developed road networks. This supports the hypothesis that infrastructure enhances the absorptive capacity of host regions and enables foreign capital to be utilized more efficiently.

To address potential endogeneity in infrastructure and FDI placement, we construct and employ lagged and initial-value instrumental variables. The core findings remain robust across specifications, and the interaction effect becomes even more pronounced when instruments are applied. Further heterogeneity analysis suggests that the direct productivity effect of road infrastructure is more salient in inland and labor-intensive regions, where infrastructure constraints may still limit economic activity. In contrast, the FDI–infrastructure interaction effect is more uniformly distributed, pointing to its relevance even in more developed coastal provinces.

Taken together, the results reaffirm the strategic importance of infrastructure investment in China's evolving development model. While road expansion alone may yield diminishing returns in well-connected areas, its role as a productivity amplifier - particularly in combination with FDI - remains vital. Policymakers aiming to raise TFP and promote inclusive growth should therefore consider infrastructure investment not as a sunset policy tool, but as one that must be recalibrated to unlock synergies with capital inflows and regional innovation potential. Future investment strategies should prioritize integrated development plans that jointly coordinate transport infrastructure, foreign investment attraction, and local innovation ecosystems.

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Figures and Tables

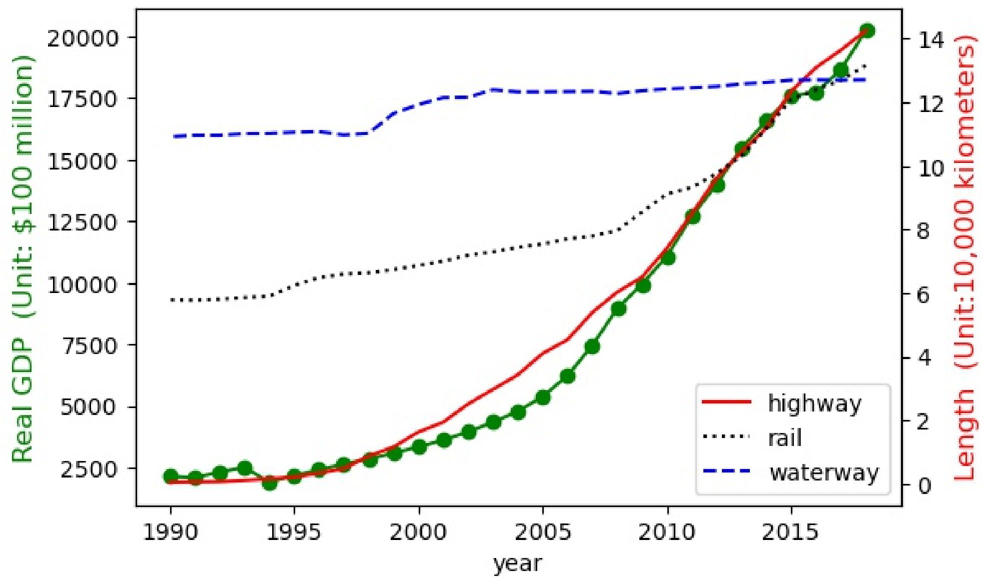

FIGURE 1 –TRANSPORTATION VS. REAL GDP

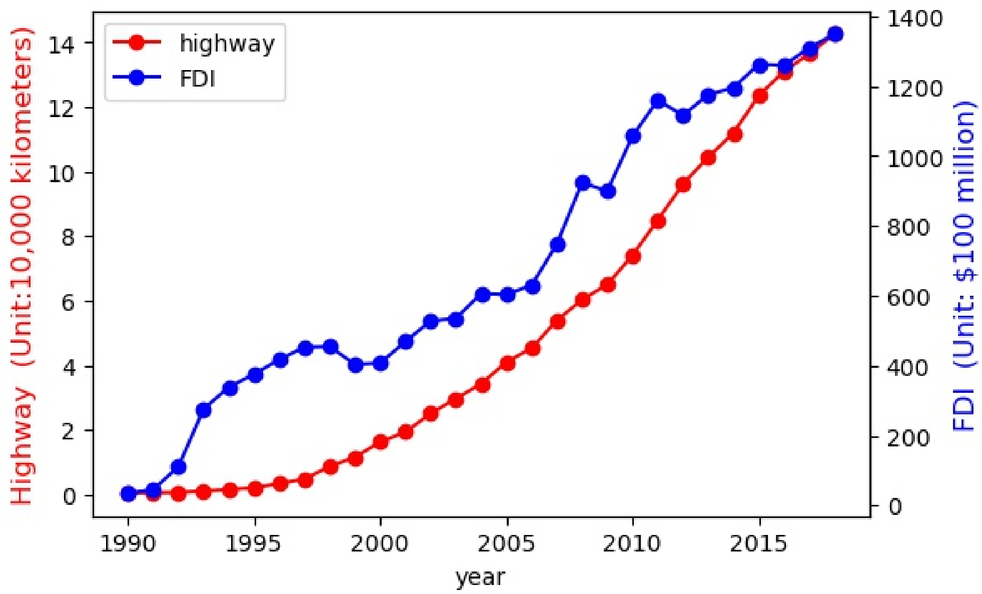

FIGURE 2 –HIGHWAY VS. FDI

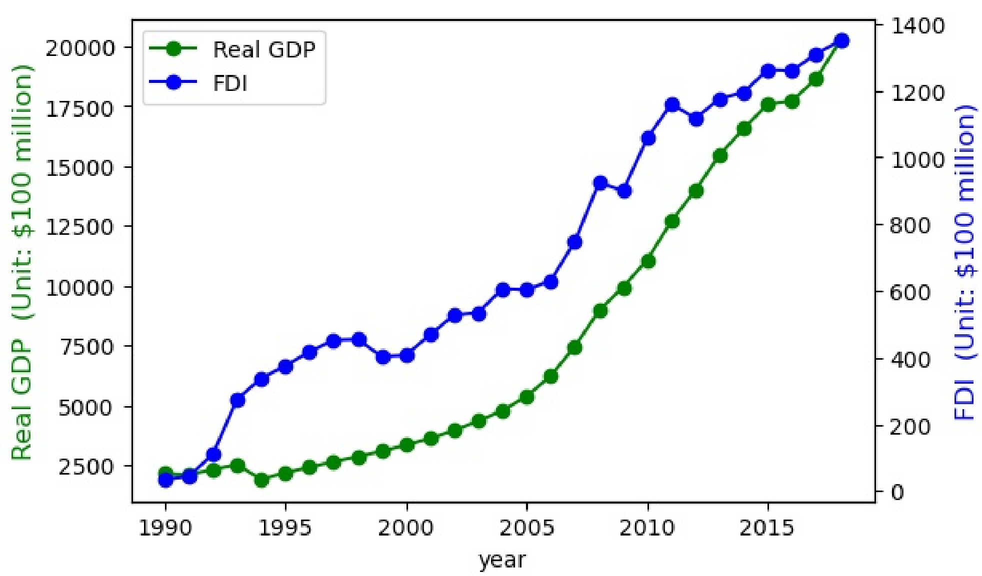

FIGURE 3 –REAL GDP VS. FDI

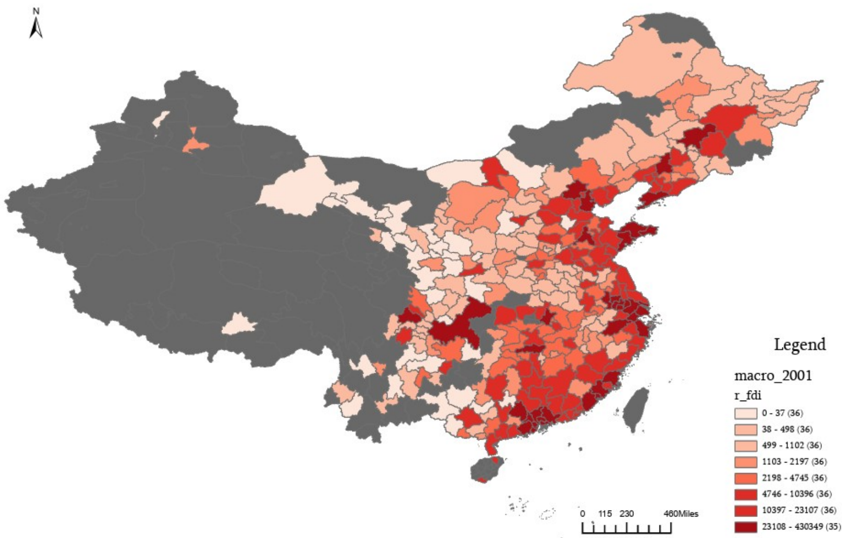

FIGURE 4 –FDI IN 2000

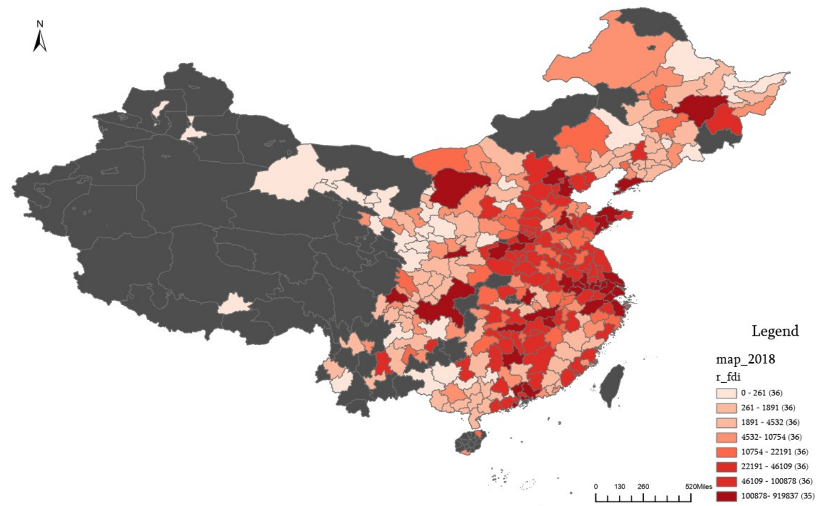

FIGURE 5 –FDI IN 2018

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.

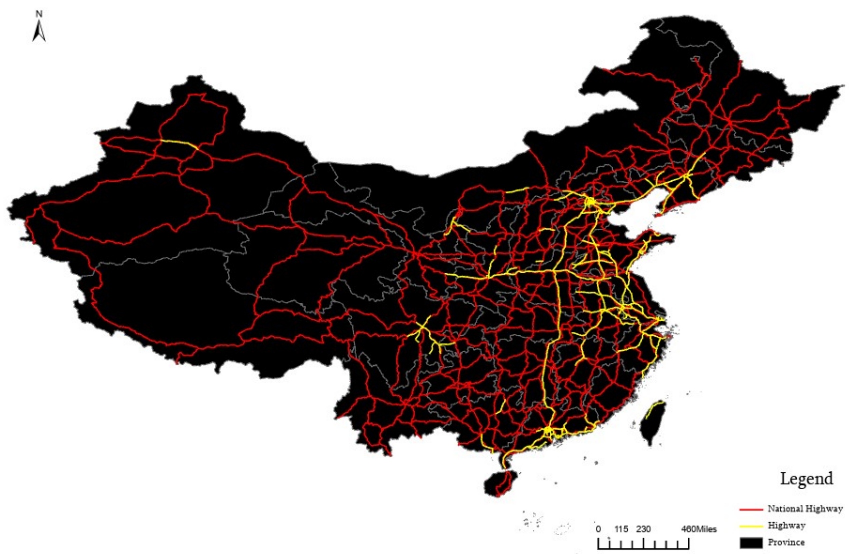

FIGURE 6 –ROAD IN 2000

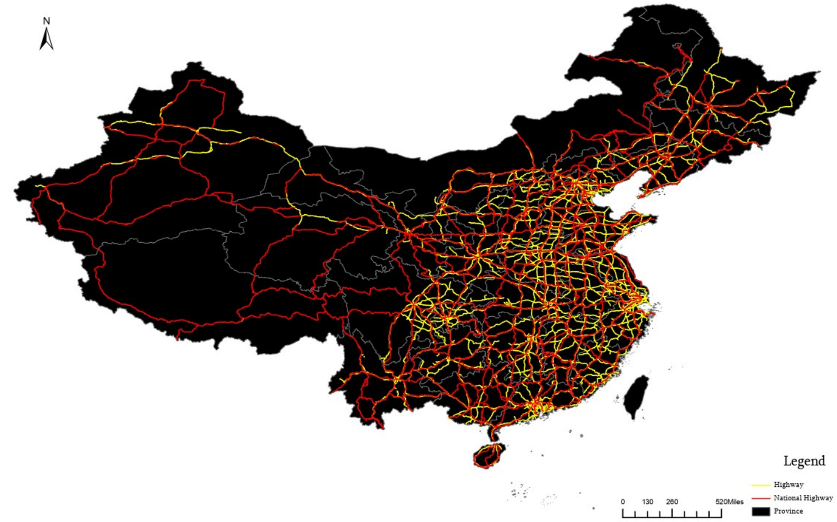

FIGURE 7 –ROAD IN 2020

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

Table 1 –Descriptive Statistics

	Mean	Std.Dev.	Obs
y, real GDP per capita (in Yuan)	21774.85	15807.99	4048
n, population growth rate	0.01	0.04	4048
s_k, ratio of investment to GDP	0.51	0.19	4048
s_h, share of population stduy in College	0.02	0.02	4048
F, stock of FDI (in 100,000,000 Yuan)	252.92	538.09	4048
$Road$, stock of road infrasturcture (in 10,000 kilometre)	4.16	3.98	4048

TABLE 2 –CROSS-SECTION DATA REGRESSION RESULT

	Dependent Variable: logarithm difference of real GDP per capita				
	(1)	(2)	(3)	(4)	(5)
$\ln(y(0))$	-0.435***	-0.464***	-0.432***	-0.464***	-0.464***
	(0.045)	(0.049)	(0.045)	(0.051)	(0.052)
$\ln(n+g+\delta)$	0.140	0.127	0.146	0.127	0.130
	(0.130)	(0.130)	(0.131)	(0.132)	(0.138)
$\ln(s_k)$	0.217**	0.217**	0.216**	0.217**	0.217**
	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
$\ln(s_h)$	0.122***	0.113***	0.121***	0.113***	0.113***
	(0.024)	(0.025)	(0.024)	(0.025)	(0.025)
$\ln(F)$		0.023		0.023	0.022
		(0.017)		(0.018)	(0.022)
$Road$			0.003	-0.000	-0.001
			(0.007)	(0.007)	(0.011)
$\ln(F) \times \ln(Road)$					0.001
					(0.011)
Constant	6.464***	6.536***	6.437***	6.537***	6.547***
	(0.616)	(0.617)	(0.620)	(0.624)	(0.639)
Observations	220	220	220	220	220
R^2	0.354	0.359	0.354	0.359	0.359

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 3 –PANEL DATA REGRESSION RESULT

	Dependent Variable: logarithm difference of real GDP per capita				
	(1)	(2)	(3)	(4)	(5)
$\ln(y(0))$	-0.246***	-0.264***	-0.279***	-0.296***	-0.317***
	(0.019)	(0.022)	(0.023)	(0.026)	(0.027)
$\ln(n+g+\delta)$	-0.037	-0.030	-0.037	-0.031	-0.034
	(0.033)	(0.033)	(0.030)	(0.030)	(0.029)
$\ln(s_k)$	0.150***	0.143***	0.144***	0.138***	0.131***
	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)
$\ln(s_h)$	0.118***	0.117***	0.112***	0.112***	0.096***
	(0.020)	(0.020)	(0.019)	(0.018)	(0.017)
$\ln(F)$		0.027**		0.025**	0.022**
		(0.011)		(0.010)	(0.010)
$Road$			0.011**	0.011**	0.007*
			(0.005)	(0.005)	(0.004)
$\ln(F) \times \ln(Road)$					0.010***
					(0.003)
Constant	3.082***	3.158***	3.321***	3.389***	3.480***
	(0.245)	(0.246)	(0.257)	(0.260)	(0.257)
City Fixed-effect	✓	✓	✓	✓	✓
Observations	870	870	870	870	870
R^2	0.400	0.407	0.421	0.427	0.437

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

	Dependent Variable: logarithm difference of real GDP per capita				
	(1)	(2)	(3)	(4)	(5)
$\ln(y(0))$	-0.246***	-0.254***	-0.279***	-0.287***	-0.303***
	(0.019)	(0.022)	(0.023)	(0.026)	(0.027)
$\ln(n + g + \delta)$	-0.037	-0.034	-0.037	-0.033	-0.035
	(0.033)	(0.033)	(0.030)	(0.030)	(0.029)
$\ln(s_k)$	0.150***	0.150***	0.146***	0.145***	0.140***
	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)
$\ln(s_h)$	0.118***	0.118***	0.113***	0.113***	0.098***
	(0.020)	(0.020)	(0.019)	(0.018)	(0.018)
$\ln(F)$		0.011		0.010	0.014
		(0.011)		(0.010)	(0.011)
$Road$			0.010***	0.010**	0.008**
			(0.004)	(0.004)	(0.004)
$\ln(F) \times \ln(Road)$					0.005***
					(0.002)
Constant	3.082***	3.130***	3.340***	3.384***	3.434***
	(0.245)	(0.255)	(0.261)	(0.273)	(0.267)
City Fixed-effect	✓	✓	✓	✓	✓
Observations	870	870	870	870	870
R^2	0.400	0.401	0.419	0.420	0.428

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 –PANEL DATA FOR SELECTED SUB-SAMPLES(RANK OF INNOVATION/PATENT) OF CITIES

	Innovation Index		Number of Patent	
	(1) Top Quarter	(2) Bottom Quarter	(3) Top Quarter	(4) Bottom Quarter
$\ln(y(0))$	-0.329***	-0.213***	-0.319***	-0.258***
	(0.054)	(0.050)	(0.054)	(0.051)
$\ln(n+g+\delta)$	-0.003	0.066	-0.043*	0.044
	(0.037)	(0.042)	(0.022)	(0.043)
$\ln(s_k)$	0.088**	0.190***	0.060*	0.210***
	(0.036)	(0.050)	(0.033)	(0.045)
$\ln(s_h)$	0.047*	0.025	0.064**	0.034
	(0.026)	(0.019)	(0.030)	(0.021)
$\ln(F)$	0.026	0.053***	0.050**	0.022
	(0.023)	(0.015)	(0.021)	(0.030)
$Road$	0.006	-0.034**	0.009	-0.015
	(0.007)	(0.013)	(0.007)	(0.015)
$\ln(F) \times \ln(Road)$	0.017***	0.018	0.013**	0.015
	(0.005)	(0.018)	(0.006)	(0.020)
Constant	3.403***	2.575***	3.101***	3.015***
	(0.523)	(0.513)	(0.520)	(0.537)
City Fixed-effect	✓	✓	✓	✓
Observations	311	78	287	113
R^2	0.373	0.652	0.396	0.544

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. Because data on the innovation index or patents is unavailable for some cities, the total number of observations is inconsistent.

Table 6 –Panel Data for Selected Sub-samples(geographical/policy) of Cities

	Coastal Region		City Class		FDI Policy	
	(1) Coastal	(2) Inland	(3) level 1	(4) level 2-4	(5) w/	(6) w/o
$\ln(y(0))$	-0.332***	-0.333***	-0.380***	-0.335***	-0.223***	-0.371***
	(0.049)	(0.033)	(0.091)	(0.029)	(0.040)	(0.031)
$\ln(n+g+\delta)$	0.049	-0.034	0.040	-0.042	0.052	-0.046
	(0.134)	(0.028)	(0.059)	(0.028)	(0.037)	(0.029)
$\ln(s_k)$	0.117***	0.131***	0.023	0.139***	0.110***	0.132***
	(0.029)	(0.027)	(0.055)	(0.024)	(0.036)	(0.025)
$\ln(s_h)$	0.060***	0.112***	0.018	0.097***	0.055***	0.110***
	(0.017)	(0.021)	(0.040)	(0.018)	(0.019)	(0.021)
$\ln(F)$	0.003	0.022*	0.025	0.021*	0.020	0.029**
	(0.025)	(0.013)	(0.041)	(0.011)	(0.020)	(0.012)
$Road$	0.007	0.014**	0.000	0.015***	-0.003	0.021***
	(0.006)	(0.006)	(0.010)	(0.005)	(0.006)	(0.005)
$\ln(F) \times \ln(Road)$	0.016***	0.007	0.027***	0.008*	0.008*	0.008*
	(0.004)	(0.005)	(0.009)	(0.004)	(0.005)	(0.004)
Constant	3.824***	3.683***	3.846***	3.626***	2.687***	3.955***
	(0.720)	(0.308)	(0.920)	(0.276)	(0.355)	(0.312)
City Fixed-effect	✓	✓	✓	✓	✓	✓
Observations	202	664	108	758	209	657
R^2	0.417	0.462	0.393	0.459	0.369	0.491

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. 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 –IV Estimates - the Second-stage Results

	OLS	IV
	(1)	(2)
$\ln(y(0))$	-0.317***	-0.305***
	(0.027)	(0.027)
$\ln(n+g+\delta)$	-0.034	-0.037
	(0.029)	(0.029)
$\ln(s_k)$	0.131***	0.136***
	(0.021)	(0.021)
$\ln(s_h)$	0.096***	0.098***
	(0.017)	(0.018)
$\ln(F)$	0.022**	0.010
	(0.010)	(0.012)
$Road$	0.007*	0.007*
	(0.004)	(0.004)
$\ln(F) \times \ln(Road)$	0.010***	0.009***
	(0.003)	(0.003)
Constant	3.480***	3.429***
	(0.257)	(0.260)
City Fixed-effect	✓	✓
Observations	870	870

Notes: This table reports the second stage IV estimation. Column (1) is the benchmark regression(without IVs). All controls are not statistically significant. 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.

Appendix A. Figures and Tables

TABLE **A.1** –PANEL DATA REGRESSION RESULT

	w/o Urban Street	w/ Urban Street	
	(1)	(2)	(3)
$\ln(y(0))$	-0.317***	-0.328***	-0.340***
	(0.027)	(0.033)	(0.034)
$\ln(n+g+\delta)$	-0.034	-0.027	-0.027
	(0.029)	(0.029)	(0.030)
$\ln(s_k)$	0.131***	0.138***	0.133***
	(0.021)	(0.025)	(0.025)
$\ln(s_h)$	0.096***	0.080***	0.079***
	(0.017)	(0.024)	(0.025)
$\ln(F)$	0.022**	0.006	0.009
	(0.010)	(0.011)	(0.012)
$Road$	0.007*	0.010*	0.010*
	(0.004)	(0.005)	(0.005)
$\ln(F) \times \ln(Road)$	0.010***	0.011**	0.008*
	(0.003)	(0.005)	(0.005)
$UrbanStreet$		0.000	0.000
		(0.000)	(0.000)
$\ln(F) \times \ln(UrbanStreet)$			0.008**
			(0.004)
Constant	3.480***	3.599***	3.452***
	(0.257)	(0.331)	(0.320)
City Fixed-effect	✓	✓	✓
Observations	870	724	720

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 A.2 –IV ESTIMATES - THE FIRST-STAGE AND REDUCED-FORM RESULTS

	Reduced-Form	First-stage Result		
	(1)	(2)	(3)	(4)
	$\ln(y)$	Road	$\ln(F)$	$\ln(F) \times \ln(Road)$
$\ln(y(0))$	-0.303***	-0.107**	0.003	0.250***
	(.027)	(0.0517)	(0.025)	(0.076)
$\ln(n+g+\delta)$	-0.035	0.082**	0.030	0.179**
	(0.029)	(0.037)	(0.022)	(0.070)
$\ln(s_k)$	0.140***	.109***	0.202***	0.198***
	(0.021)	(0.032)	(0.029)	(0.069)
$\ln(s_h)$	0.098***	0.081**	0.022	-0.147***
	(0.018)	(0.032)	(0.028)	(0.046)
$Road_{t-1}$	0.008 **	0.951***	0.005	0.084***
	(0.004)	(0.014)	(0.003)	(0.019)
$\ln(F)_{t-1}$	0.014	0.009	0.857***	0.659***
	(0.011)	(0.021)	(0.018)	(0.038)
$\ln(F)_{t-1} \times \ln(Road)_{t-1}$	0.005***	0.001	-0.003	0.593***
	(0.002)	(0.004)	(0.003)	(0.011)
Observations	870	870	870	870
First-stage F statistic	-	11409.49	891.88	4174.24

Notes: Column (1) reports the reduced form of the IV estimation. This table from column (2) to (3) reports the first stage of IV estimation. 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 A.3 –PANEL DATA FOR SELECTED SUB-SAMPLES(RANK OF INNOVATION/PATENT) OF CITIES

	Innovation Index		Number of Patent	
	(1)	(2)	(3)	(4)
	Top Quarter	Bottom Quarter	Top Quarter	Bottom Quarter
$\ln(y(0))$	-0.389***	-0.129	-0.359***	-0.243***
	(0.065)	(0.084)	(0.067)	(0.067)
$\ln(n+g+\delta)$	-0.005	0.004	-0.032	0.032
	(0.036)	(0.038)	(0.024)	(0.039)
$\ln(s_k)$	0.120***	0.164***	0.094**	0.192***
	(0.035)	(0.047)	(0.039)	(0.055)
$\ln(s_h)$	0.009	-0.021	-0.002	0.028
	(0.028)	(0.025)	(0.028)	(0.038)
$\ln(F)$	0.031	0.013	0.054**	0.029
	(0.025)	(0.033)	(0.025)	(0.058)
$Road$	0.008	-0.072***	0.005	-0.014
	(0.008)	(0.019)	(0.008)	(0.022)
$\ln(F) \times \ln(Road)$	0.017***	0.038	0.017***	-0.003
	(0.006)	(0.025)	(0.006)	(0.044)
$UrbanStreet$	0.000	-0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(F) \times \ln(UrbanStreet)$	0.011**	0.030	0.010**	-0.006
	(0.005)	(0.021)	(0.004)	(0.031)
Constant	3.302***	1.219	2.768***	2.928***
	(0.569)	(0.725)	(0.537)	(0.753)
City Fixed-effect	✓	✓	✓	✓
Observations	260	69	239	94
R^2	0.467	0.703	0.505	0.669

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. Because data on the innovation index or patents is unavailable for some cities, the total number of observations is inconsistent.

Table A.4 –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

Table A.5 –Panel Data for Selected Sub-samples(geographical/policy) of Cities

	Coastal Region		City Class		FDI Policy	
	(1) Coastal	(2) Inland	(3) level 1	(4) level 2-4	(5) w/	(6) w/o
$\ln(y(0))$	-0.390***	-0.333***	-0.462***	-0.332***	-0.253***	-0.371***
	(0.069)	(0.041)	(0.114)	(0.037)	(0.047)	(0.043)
$\ln(n+g+\delta)$	-0.013	-0.024	0.043	-0.032	0.049	-0.045
	(0.208)	(0.031)	(0.087)	(0.031)	(0.038)	(0.033)
$\ln(s_k)$	0.101***	0.146***	0.065	0.144***	0.109**	0.142***
	(0.037)	(0.032)	(0.065)	(0.029)	(0.046)	(0.031)
$\ln(s_h)$	0.062*	0.089***	-0.046	0.083***	0.082	0.073***
	(0.034)	(0.031)	(0.046)	(0.026)	(0.053)	(0.028)
$\ln(F)$	-0.002	0.009	0.039	0.005	0.013	0.005
	(0.038)	(0.015)	(0.049)	(0.013)	(0.022)	(0.015)
$Road$	-0.001	0.011*	-0.002	0.010*	-0.000	0.011*
	(0.012)	(0.006)	(0.015)	(0.006)	(0.009)	(0.006)
$\ln(F) \times \ln(Road)$	0.020***	0.006	0.028**	0.008	0.003	0.014**
	(0.007)	(0.008)	(0.011)	(0.007)	(0.007)	(0.007)
$UrbanStreet$	0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(F) \times \ln(UrbanStreet)$	0.012	0.008**	0.019**	0.006	0.014*	0.007
	(0.007)	(0.004)	(0.009)	(0.004)	(0.007)	(0.004)
Constant	3.776***	3.447***	3.255***	3.484***	2.652***	3.705***
	(0.913)	(0.403)	(0.929)	(0.348)	(0.426)	(0.401)
City Fixed-effect	✓	✓	✓	✓	✓	✓
Observations	170	550	93	627	179	541
R^2	0.475	0.511	0.501	0.504	0.410	0.537

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. 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.