Regional Science and Urban Economics 65 (2017) 116–126

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regsciurbeco

Is road infrastructure investment in China excessive? Evidence from productivity of firms☆

Zhigang Li[a], Mingqin Wu[b,⁎], Bin R. Chen[c]

[a] *Asian Development Bank, Philippines*
[b] *School of Economics and Management, South China Normal University, Guangzhou, PR China*
[c] *Business School, Sun Yat-sen University, Guangzhou, PR China*

ARTICLE INFO

JEL classifications:
H54
O18
R42

Keywords:
Road infrastructure
Productivity
China

ABSTRACT

China's road investment boom since 1990 has often been criticized as excessive. In this paper, we estimate the return to road investment in China due to manufacturing firms' increased productivity between 1998 and 2007. To address endogeneity in road investment, we estimate the differential impact of road investment on firms with heterogeneous reliance on transport. Although some investment may be inefficient, our finding does not support the claim that road investment in China is excessive overall. The annual rate of return from productivity gains alone amounts to approximately 11%, partly due to positive spatial spillover. We find little return to road investment in inland China around 2000, but this has significantly improved since the mid-2000s. Our findings are robust to controlling for road quality, railroad investment, and variant markups of firms due to market demand and price shocks.

1. Introduction

During the past two decades, China has carried out massive investment in roads comparable to that of the U.S. prior to 1973. Total road length in China has more than doubled since 1990, while expressways increased from 147 km in 1988 to 98,000 km in 2012, which exceeds the length of the interstate highway system in the U.S. Opponents of this "great leap forward in roads" have criticized it as wasteful, because investment incentives are distorted. For example, Huang (2008) suggests that China's infrastructure spending was biased by government officials' pursuit of short-term GDP growth through physical investments. In a recent study, Ansar et al. (2016) argue that half of China's infrastructure investment has lowered economic value, since infrastructure investment management is poor. Official data on road length also show that more than 50% of expressways are located in inland China, which produces less than 30% of China's industrial output (Fig. 1). If road investment in China were indeed excessive, the amount of capital misallocation would be much larger than any other economy, given China's size and its road investment intensity.[1] For this reason, we focus on assessing the efficiency of China's investment in roads.

We limit our study to the benefit of road investment via the productivity growth of firms. The productivity effect has been an important research subject (Gramlich, 1994; Gillen, 1996; Boarnet, 1997; Jiang, 2001; Melo et al., 2013).[2] Fernald (1999) uses industry-level data to show that road investment in the U.S. before 1973 was highly productive. To address the endogeneity due to reverse causality, Fernald (1999) estimates the differential effects of road investment on firms with heterogeneous transport reliance. Surprisingly, little research has followed this vein of methodology; in this study, however, we illustrate its great potential. In particular, we extend the model to the firm level, which allows us to explicitly account for firm-specific fixed effects.

In addition to the new evidence that emerges from this study, other

☆ The authors thank the editor and two anonymous referees, for numerous constructive and insightful comments that greatly improved the article. We thank Dr. Yifan Zhang for helping to estimate productivity of China. Wu acknowledges the financial support from Guandong Provincial Department of Science and Technology (project code: 2015A070704047); Chen acknowledges the financial support from National Natural Science Foundation of China (project code: 71302101).

⁎ Corresponding author.
E-mail address: mingqinwu@163.com (M. Wu).

[1] The economic development literature suggests that the productivity effect of investment depends on institutional quality, measured by different kinds of distortions (Hsieh and Klenow, 2010).

[2] Gramlich(1994) reviews the literatures of infrastructure capital, return rate, and productivities. Gillen (1996) and Jiang (2001) review the empirical literatures of transportation infrastructure and economic growth. Boarnet (1997) reviews the literature that examines the effect of highway infrastructure on economic productivity and proposes several policy implications. Melo et al. (2013) conduct a meta-analysis of empirical evidence on the output elasticity of transport infrastructure, based on a sample of 563 estimates obtained from 33 studies.

http://dx.doi.org/10.1016/j.regsciurbeco.2017.05.001
Received 11 August 2015; Received in revised form 6 April 2017; Accepted 3 May 2017
Available online 14 May 2017
0166-0462/

contributions are as follows. First, we allow for imperfect competition in our empirical model (De Loecker, 2011; De Loecker and Warzynski, 2012). This extension is necessary because we observe the value of sales, not the quantity of output. When imperfect competition is present, the prices of goods could also respond to road investment, thus confounding the estimated effects on actual productivity. Our augmented framework, therefore, allows us to empirically distinguish the productivity effect from the markup effect of road investment. Second, while Fernald (1999) uses national-level data for empirical estimation, our study estimates the effect of road investment at the provincial and prefectural levels. This enables us to examine the unevenness of investment performance across different regions of China. Third, we provide evidence on the spatial spillover effect by comparing estimates at different jurisdictional levels.

Has road investment been excessive in China? For the country as a whole, it has not—but some earlier investment, especially in inland China, may have been wasteful. In particular, we find that the overall rate of return to road investment via productivity growth alone amounts to 11.4% during the period 1998–2007. Productivity gains, however, were uneven across China and varied over time. We find that around 2000, the productivity effect was significant in coastal China, but nearly zero in inland China. This is consistent with the observation of “empty” roads in inland China, which, according to Huang (2008), could be explained by inefficient investment decisions. Interestingly, this gap has narrowed over time, as the performance of road investment in both of these subregions of China has grown stronger.

Our study falls into a large strand of literature on the effect of infrastructure on economic growth or development. Studies in developed economies include Fernald (1999), Chandra and Thompson (2000), Baum-Snow (2007), Michaels (2008), and Donaldson and Hornbeck (2013). There has been a rising wave of research on developing economies. Among them, Datta (2012), Ghani et al. (2016), and Donaldson (forthcoming) focus on India; Gollin and Rogerson (2010) and Storeygard (2013) estimate the effect of infrastructure in Africa; and Bai and Qian (2010), Banerjee et al. (2012), and Li and Li (2013) focus on China. Few studies, however, have estimated the productivity effect of highways using firm-level data[3]; the study most closely related to ours is Fernald (1999).

The remainder of the paper is organized as follows. Section 2 describes the pattern of road investment in China, and Section 3 presents our empirical model and identification strategy. Data and empirical findings are reported in Sections 4 and 5, and Section 6 concludes with policy recommendations.

2. Road investment in China

Since 1978, China has achieved rapid real GDP growth, averaging more than 10%. In addition to high investment rates, increased productivity has been found to be a key driver of this rapid growth. In an early study on state-owned enterprises, Gordon and Li (1995) found that Chinese productivity increased by 4.6% per year in the 1980s, which contributed to almost half of real GDP growth. More recently, this has been confirmed by Zhu (2012), who finds that China's total factor productivity increased by an average of 3.6% annually from 1978 to 2007.

Despite the rapid economic growth, transport infrastructure investment responded slowly in the late 1970s and the early 1980s, as suggested by the decreasing road stock-GDP ratio (Fig. 3). By 1990, traffic congestion was widespread in China (Park et al., 2002), but road investment began to catch up around 1991. According to calculations based on data from China Statistical Yearbooks, road infrastructure

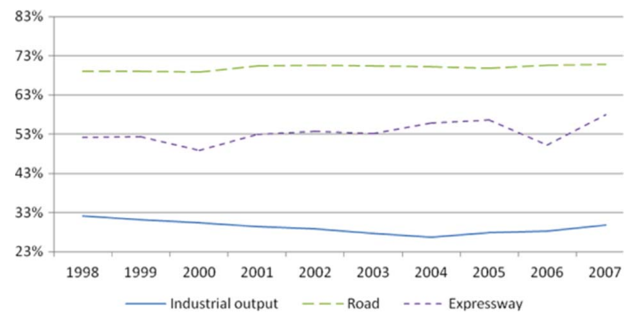

Fig. 1. Inland share of roads, highways, and industrial output in China.
Note: Roads and expressways are measured in length.
Source: China Statistical Yearbooks and ASIF dataset

investment in China had increased from less than 2% of GDP in the mid-1990s to around 6% by the mid-2000s (Fig. 3), well above the 4% average of developing countries (World Bank, 2005). The majority of road investment was for new roads, rather than renovation (Fig. 4). Between 1979 and 2012, total road length almost tripled.[4] The length of expressways increased from zero in 1988 to more than 98,000 km in 2012, exceeding the U.S. interstate highway system's length of 75,932 km. Hence, China's current road stock is primarily the fruit of the boom in road investment that began in the 1990s. In contrast, investment in railways—the highway system's main competitor—has been rather slow, at least before the recent boom in high-speed rail (Table 1 and Fig. 2).

In terms of the degree of centralization (Table 2), the financing structures for roads and railroads differ significantly. Road investment has mostly been financed by local governments through the collection of fees, including road tolls. In contrast, the construction of railroads mainly relies on the central government for financing, as ticket revenue does not accrue to local governments (see Li (2013) for more detailed discussion). This financing structure suggests that while both road and railroad investments may be endogenous in China, road investment is more likely to be endogenously determined by local economic conditions. Careful identification is thus necessary to provide meaningful estimates.

The literature on transport infrastructure investment in China is limited, but available evidence generally supports a positive effect of transport infrastructure investment. For example, Démurger (2001) employs province-level panel data to show that there is a significantly positive relationship between transportation infrastructure and regional growth. An exception is Abhijit et al., who find that the effect of distance to transportation networks on local economic outcomes in China was positive, but the magnitude of the effect was modest. More recent studies provide some microeconometric evidence on how transport infrastructure influences economic growth in China. The mechanisms include social returns from saving transport cost (Li and Chen, 2013), efficiency gains via inventory reduction (Li and Li, 2013), and industrial agglomeration or the geographical distribution of industries (Lu and Chen, 2006).[5]

Industries' reliance on vehIn this section we introduce our empirical strategy for estimating the impact of road investment on firm

[3] Ghani et al. (2016) show evidence on the effect of highway upgrades on firm productivity in corresponding highway districts, but price effects in TFP are not controlled for.

[4] Data source: China Statistical Yearbooks 1978–2013. Before 2005, China Statistical Yearbooks did not include statistics on roads built to connect villages in the measure of road length, though they were included after 2005. Consequently, reported road length increased by 1.47 million km in 2006 alone. We address the effect of this change in measurement criteria by assuming that the growth rate of road length in 2006 is the same as that of 2005. For other years, road length growth is measured by actual growth.

[5] A small number of studies evaluate the return on road investment through specific channels. Li et al. (2012) find that increasing transport speed by 1km per hour can reduce transport costs for Chinese agricultural traders by 0.6%, mainly due to improved fuel efficiency and reduced labor requirements. Li and Chen (2013) find a high social rate of return due to savings on transport costs, while Li and Li (2013) show that China's road investment has a return of 10% as road investment reduces firms' inventory costs.

Table 1
Share of transport infrastructure in total fixed asset investment (%).

Year	1985	1990	1995	2000	2006
Railway	6.4	3.4	4.8	3.8	2.1
Road	2	4.2	4.1	7.9	6.9
Waterway	2.6	2	0.8	0.4	1.1
Airport	1.3	0.5	1.2	1.3	0.5

Source: China Statistical Yearbooks of corresponding years

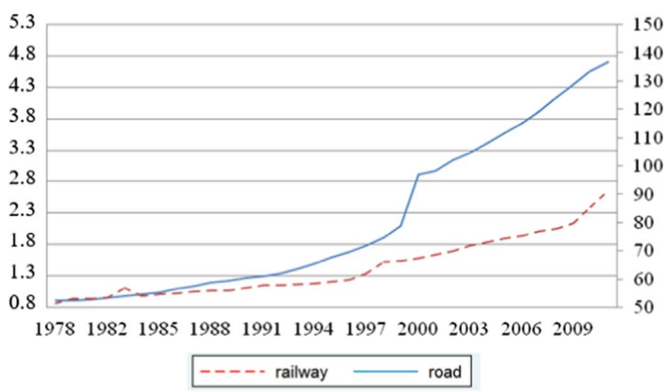

Fig. 2. Road and railway lengths in China.
Note: The length of village roads is not included in the road length. Right Y axis refers to the length of railway, and its unit is 1000 km. The left Y axis refers to the length of road, and its unit is 1000,000 km.
Source: China Statistical Yearbooks

Table 2
Spending by central and local governments on transport infrastructure (bn RMB).

	2004		2008	
	Central	Local	Central	Local
Railway	75.27 (88.9%)	9.36 (11.1%)	369.48 (90.7%)	37.84 (9.3%)
Road	20.07 (4.3%)	446.48 (95.7%)	31.13 (4.2%)	710.02 (95.8%)

Source: Yearbook of China Transportation & Communications of corresponding years

productivity. We first motivate our empirical specifications based on the existing theory, then show how the endogeneity of road investment can be addressed.

2.1. Theoretical framework

Industries' reliance on vehicles may be heterogeneous. This implies that road investments may have a larger impact on the productivity of firms that use more vehicles, as formally shown by Fernald (1999). This is the key insight for our empirical strategy.

In particular, we define the revenue productivity growth of firm i following Solow's productivity residual:

$$d\tau_i \equiv dr_i - s_{ki}dk_i - s_{li}dl_i \tag{1}$$

where dr_i is the growth of total value added (excluding input materials) of firm i, s_{ki} is the share of expenditure on capital and s_{li} is the share of expenditure on labor. dk_i is the growth of capital, and dl_i is the growth of labor inputs.

Based on a Cobb-Douglas function and cost minimization under perfect competition, Fernald (1999) shows that TFP of an industry is a function of road investment and industry-specific elasticity ξ_j[6]:

$$d\tau_j = \xi_j \cdot dg + du_j \tag{2}$$

where dg is the growth rate of road stock and du_j is idiosyncratic productivity shock to industry j. It can be shown that ξ_j is a function of vehicle reliance of industry j:

$$\xi_j = \phi \cdot s_{vj} \tag{3}$$

Here s_{vj} is the share of costs for vehicles in industry j. In industries in which production relies more on transport service, s_{vj} is larger. For example, the stone- and clay-processing industry may be transport-intensive due to its heavy transport load and the low value of transported goods. In contrast, for the textile industry, the value of products and materials is higher, and they weigh much less. Hence, demand for transport services and the share of expenditures for vehicles may be higher for the stone and clay industry than for the textile industry.

With industry-level elasticity ξ_j, economy-wide aggregate elasticity ξ can be easily calculated by weighted average, using the value added share of each industry as weight. Following Fernald (1999), if national elasticity ξ is available, the annual return to road investment can be approximated as follows:

$$\text{return}=\xi \cdot Y/G \tag{4}$$

where Y is the aggregate value added of all industries considered, and G is the value of total road stock.

2.2. Empirical specification

We extend Eq. (2) to allow for firm-level data and propose the following baseline panel-data specification to estimate road effects on firms' productivity:

$$d\tau_{it} = \alpha_0 + \varphi \cdot s_{vj} \cdot dr_{nt} + \alpha_{nt} + \alpha_i + \varepsilon_{it} \tag{5}$$

Here $d\tau_{it}$ is the productivity growth rate of firm i at time t, as defined in Eq. (1). Of particular interest is φ, the coefficient of the interaction term between the vehicle intensity of industry j, s_{vj}, and road investment in jurisdiction n at time t, dr_{nt}. φ is expected to be positive, meaning that the productivity of firms that rely more on transport service gain more benefit from road investment. We control for jurisdiction-time fixed effects α_{nt} to account for all region-specific shocks over time. These shocks include local policy changes, macro-economic shocks, and different types of public investment, including road investment, dr_{nt}. Even though the linear effect of roads is absorbed by the fixed effect of firms, we can still estimate the differential effect, which is represented by the interaction term between road investment and industry-specific vehicle reliance. In addition, we use firm-specific fixed effects to control for idiosyncratic productivity trends. Vehicle intensity s_{vj} is assumed to be constant during our sample period,[7] so it is also absorbed in α_i.

The jurisdiction's geographic scope should be large enough to cover the spatial spillover effect of roads. We use the province as our baseline administration unit, because it is the largest subnational jurisdiction unit.[8] In the robustness check, we also consider regressions using roads at the prefectural level. If spatial spillover is present between prefectures, estimates using province-level roads should be more significant than those using prefecture-level roads.

We also consider augmented empirical models, which include market demand shocks and price shocks. This is because the theoretical model assumes perfect competition. When the industry features imperfect competition, the prices of firms, as well as the revenue

[6] This is from Eq. (4) of Fernald (1999).

[7] The assumption of constant vehicle intensity means a constant return to vehicle service—i.e., if the output of firms increases by 1%, the demand for vehicle service also increases by 1%, holding road stock fixed. When road stock increases, this would increase the marginal return to vehicle service, so the demand for vehicle service would increase, consistent with the "fundamental law of congestion" of Duranton and Turner (2011).

[8] Beijing, Shanghai, Tianjin, and Chongqing are cities, but because they are directly governed by the central government, we treat them as provinces.

productivity that contains the markup of firms, may be affected by market demand and price shocks. We approximate market demand shocks using the growth rate of total sales of firms in the same industry and jurisdiction. In addition, we use jurisdiction-industry level average price growth as a proxy for price shocks.

2.3. Endogeneity and identification

Several major sources of endogeneity concerns may be present. One is reverse causation, as road investment may be affected by expected productivity growth.[9] Another is measurement error in vehicle share, and the third is the potentially endogenous entry and exit of firms. In this subsection, we discuss these issues' effects on our estimates, and propose identification strategies.

Following Fernald (1999), we first show how model (5) can address reverse causation through province-year fixed effects. We can decompose the disturbance term of Eq. (5) into jurisdiction-level aggregate productivity shock, $\overline{\varpi_{nt}}$, and firm-specific shock υ_{it}, which is orthogonal to the aggregate shock by construction:

$$\varepsilon_{it} = \overline{\varpi_{nt}} + \upsilon_{it} \tag{6}$$

The aggregate productivity shock could drive local governments to invest more in roads, e.g., due to improved fiscal conditions. If $\overline{\varpi_{nt}}$ is missing from the model, it would be a source of endogeneity. In model (4), this issue is addressed by the province-year fixed effect, which fully controls for $\overline{\varpi_{nt}}$. Hence, any bias due to reverse causation is absent in our empirical model. Note that the linear effect of roads on productivity is also absorbed by the province-year fixed effect. Nevertheless, the differential effect of roads on firms with different road reliance can still be estimated.

Another source of endogeneity may arise from measurement errors in vehicle intensity. Under the "classical measurement error" assumption, estimates would be biased toward zero. To address this concern, we use the vehicle intensity calculated from alternative input-output databases of China constructed by a different economic agency, which will be described in detail in Section 4.1.

The third source of endogeneity is the potentially endogenous entry and exit of firms in our sample. According to Wooldridge (2002), if the entry and exit of firms are determined by time-invariant firm-specific characteristics, a firm-specific fixed-effect model can deliver consistent estimates. However, if entry and exit are affected by unobserved shocks that affect the productivity or markup of firms, then estimates would be biased, even with the fixed-effect model. Following Wooldridge (2002) and Verbeek and Nijman (1992), we provide a simple test for selection bias by adding to our regression the lagged selection indicator, $s_{i,t-1}$, which is zero if firm i is missing in the previous period and one otherwise. Under the null hypothesis for consistent estimation, shocks are uncorrelated with $s_{i,r}$ for all r, so selection in the previous time period should not be significant in the equation at time t. Alternatively, we can also add the lead selection indicator, $s_{i,t+1}$, which means that there is greater probability that a firm will leave the sample if its productivity and markup were hurt in the previous year.

3. Data and measurement issues

Data availability and quality have been challenging for studies of the Chinese economy. This section describes how we address these issues.

[9] Beginning with Aschauer (1989), a large body of literature estimates the efficiency of road infrastructure investment (Gramlich, 1994). The key challenge for studies that use aggregate data has been the reverse causality between infrastructure and aggregate output: Although infrastructure investment may increase productivity, economic growth could also create demand for infrastructure, which would bias estimated returns of infrastructure.

3.1. Data

Our empirical analysis is based on three main sources of data. First, to construct measures of firm-level productivity, we use the Annual Survey of Industrial Firms (ASIF) database provided by the National Bureau of Statistics of China for the period 1998–2007. This data set contains detailed accounting information for all state-owned manufacturing firms, as well as for non-state-owned manufacturing enterprises that have annual sales of more than RMB 5 million (US$ 0.6 million at the 2005 exchange rate). More than 100,000 firms are covered each year, and their total output accounts for more than 85% of China's industrial output. As an important micro-level dataset in China, ASIF data have been used in a rapidly growing body of research, including studies by Song et al. (2011), Zhu (2012), and Holz (2013).

ASIF data contain crucial information on the productivity growth of firms, including gross output and the input of capital, labor, and materials. A firm identification code is available to link the same firm over time. Due to the entry and exit of firms, the sample is an unbalanced panel, with around 30,000 firms present in the dataset throughout the whole sample period. The total number of observations in the sample is 2,213,013.

Table 3 summarizes the basic statistics of ASIF variables used in our empirical exercises. In particular, the nominal value added growth of firms averaged 11.0% during the period 1998–2007. In terms of production factors, real capital growth and real labor cost growth averaged 2.5% and 8.6%, respectively. State-owned enterprises account for around 13.5% of observations in the data.

The second dataset concerns the measurement of vehicle reliance, which is crucial for our identification strategy. We construct an indicator using the national input-output table published by National Bureau of Statistics in China in 2002. This table reports each industry's input value from the transport equipment manufacturing industry. We approximate vehicle reliance of industry j as follows[10]:

$$s_{vj} = \textit{Value of transport equipment as input to industry } j / \textit{Total input value of industry } j.$$

To address estimation bias due to potential measurement errors, we also construct an instrumental variable by recalculating the ratio s_{vj} with an alternative input-output database for China in 2002, which was compiled by the National Information Centre of China.[11] These two measures are highly correlated with a correlation coefficient of 0.99 (Table 4).

The third data set includes province-level road length, which we obtained from China Statistical Yearbooks for the period 1998–2007. Total road length is measured at the end of each year. Village roads were not included in total road length until 2005, which caused a jump in the road length growth rate in 2005. To address this issue, we replace the road length growth rate of each province in 2005 with that of the previous year. In our empirical exercises, we find that our estimates are robust when the year 2005 is dropped from the regression sample. Table 5 summarizes our road length growth rates by province, grouped into western, central, and coastal regions. Interestingly, China's road length growth rate is similar to that of the U.S. before 1973 (average of 4%), according to Fernald (1999).

3.2. Measurement issues

3.2.1. Road investment

A key variable in our empirical exercise is road investment at the provincial level (China has 31 provinces). Two types of measurements

[10] "Vehicle" is a subset of the transport equipment industry. We refer to this ratio as "vehicle share" for convenience of reference. Also note that this proxy does not include rental/outsourcing of transport services.

[11] Information on the National Information Centre of China is available at http://www.sic.gov.cn/

Table 3
Summary statistics on industrial firms (regression sample).

Variable	Description	Obs.	Mean	Standard deviation
Value added (mn RMB)	In nominal terms; sum of total labor costs (wage plus benefits), capital depreciation for accounting, operating profits, and taxes	854,833	11.0	36.0
Real capital growth (%)	Capital is constructed using perpetual inventory approach; Physical depreciation is assumed to be 9%	854,833	2.5	23.3
Real labor cost growth (%)	Labor cost includes wage bill and benefits of workers, deflator by CPI	854,833	8.6	33.2
Labor share (%)	The share of nominal labor cost in nominal value added	854,833	46.3	30.3
Revenue productivity growth (%)	Subtract the growth rate of nominal value added by the weighted sum of real growth of capital and of labor; the weights are the labor share and capital share	854,821	3.6	32.9
Demand shock (%)	Average growth rate of total sales at province-industry level	854,452	16.4	10.1
Price shock (%)	Average growth rate of price at province-industry level	511,733	1.9	3.2

Source: Annual Survey of Industrial Firms database of China (1998–2007)

Table 4
Vehicle share and revenue productivity growth by industry.

Industry	Average vehicle share (%) (China)	Average vehicle share (%) (IV)	Average revenue productivity growth (%)	Number of Obs.
Food and kindred products*	0.38	0.09	4.3	70,753
Textile mill products*	0.27	0.15	3.7	74,052
Apparel & textiles, leather products*	0.19	0.15	1.6	63,693
Wood and Furniture*	0.63	0.34	4.3	24,159
Paper products, printing & publishing*	1.06	0.14	2.2	56,566
Petroleum products*	0.36	0.46	6.0	4,990
Chemicals, rubber & plastics*	0.38	0.09	3.8	133,099
Non-metal mineral products*	0.38	0.09	4.6	71,050
Primary metals*	0.94	0.32	6.6	30,101
Fabricated metals*	0.55	0.32	2.9	47,951
Miscellaneous manufacturing*	1.65	2.3	3.9	94,511
Transport equipment	38.7	24.86	2.6	37,815
Electronic equipment*	0.67	0.46	5.7	17,927
Telecommunication, computers*	0.36	0.46	2.0	42,413
Instruments and related*	0.71	0.46	1.5	21,338
Recycling	0.49	–	0.9	13,797
Electric utilities*	1.55	0.42	4.3	11,533
Gas utilities*	2.24	0.42	9.1	1,113
Water utilities*	2.67	0.42	4.3	2,821

Note: (1) The data are from authors' calculation, China input-output table (2002) issued by National Bureau of Statistics of the People's Republic of China, and ASIF, IV calculation comes from the input-out table issued by State Information Center.
(2) The number of observations are for those with non-missing revenue productivity. "*" indicates industries covered in the IV regressions.

Table 5
Growth in road length and revenue productivity by province.

Province	Road length growth (%)	Average revenue productivity growth (%)	Number of Obs.
Coast	**4.6**	**3.4**	**1,511,462**
Beijing	2.0	0.3	52,747
Tianjin	8.4	0.4	57,320
Hebei	4.1	5.7	86,040
Liaoning	2.3	2.8	90,030
Shanghai	8.0	0.1	118,045
Jiangsu	10.8	2.9	261,595
Zhejiang	3.4	1.1	284,221
Fujian	2.6	2.3	93,811
Shandong	3.1	5.5	195,311
Guangdong	3.0	2.7	272,342
Hainan	2.3	−0.9	5,837
Central	**4.4**	**5.0**	**430,040**
Shanxi	5.1	2.4	39,259
Jilin	5.2	1.7	28,888
Heilongjiang	3.2	2.3	28,993
Anhui	6.3	1.2	47,631
Jiangxi	5.0	3.6	40,129
Henan	4.2	6.2	65,147
Hubei	5.5	2.3	68,561
Hunan	4.2	6.2	65,147
West	**4.9**	**3.2**	**265,622**
Inner Mongolia	4.5	3.9	18,833
Guangxi	3.0	3.0	34,383
Chongqing	5.8	2.2	24,802
Sichuan	5.2	3.6	63,365
Guizhou	4.5	2.0	22,316
Yunnan	7.6	1.7	22,639
Tibet	7.6	2.8	2,749
Shaanxi	3.9	1.8	27,914
Gansu	0.9	0.8	23,118
Qinghai	6.9	1.6	4,489
Ningxia	4.4	0.6	5,433
Xinjiang	8.5	1.4	14,581

Note: The data are from China Statistical Yearbooks and ASIF. The number of observations are for those with non-missing revenue productivity.

have commonly been used in the literature. One considers investment value, as in studies by Barro (1990), Holtz-Eakin et al. (1988), and Shirley and Winston (2004). The advantage of this approach is that it reflects both the quantity and quality of the transportation infrastructure. However, high-quality information on provincial investment value is lacking for most provinces. Alternatively, road length has also been commonly used as a proxy for road investment, especially in developing economies (Donaldson, forthcoming). We argue that the change in road length is a reasonable proxy for road investment in China over the past two decades. Unlike the U.S., where road growth has had relatively little variation since 1973, recent Chinese road investment is mainly for constructing new roads (Fig. 4). Another advantage of using road length is that it is much easier to measure than investment value, and thus reduces measurement errors.

3.2.2. Revenue productivity growth

Another key variable in this study is TFP calculated based on Eq. (1). Specifically, we construct this measure by subtracting the weighted sum of real growth of capital and labor from the growth rate of firms' nominal value added. We construct the annual nominal value added of each firm by summing its total labor costs (wage plus benefits), capital depreciation for accounting, operating profits, and taxes by year. The weight of labor for a firm is the share of the firm's labor costs in its value added. The weight of capital for a firm is one minus the labor share. The growth of both capital and labor are in real terms. Labor growth is the nominal growth of total labor costs minus the provincial consumer price index. For capital growth, we first use a perpetual inventory approach to construct this capital stock for each year, following the method of Brandt et al. (2012). The capital price

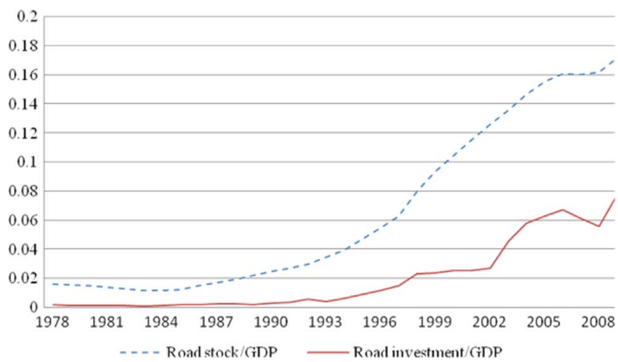

Fig. 3. Road stock and investment as shares of GDP in China.
Note: Road stock is based on the calculation in Xing and Wang (2012). Road investment is calculated through dividing nominal road investment value by deflator from China Statistical Yearbooks.
Source: Authors' calculation, Xing and Wang (2012) and China Statistical Yearbooks

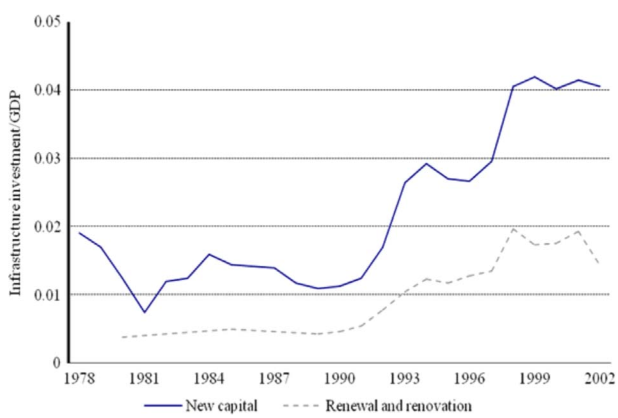

Fig. 4. Infrastructure investment in China (new capital vs. renovation). Notes: Infrastructure includes transportation, storage and telecommunication.
Source: China Transportation Yearbooks

deflator from the National Bureau of Statistics, which is available since 1990, is used as the deflator of nominal investment each year. Annual capital growth is then calculated. Note that our productivity growth contains not only physical productivity growth, but also the change in prices—e.g., due to inflation or change in markup.

For the full sample, average revenue productivity growth is 3.6% (Table 3). This is almost the same as the TFP estimate by Zhu (2012). Tables 4 and 5 summarize average revenue productivity growth rates by industry and province, respectively.

3.2.3. Demand and price shocks

To measure market-level demand shock, we calculate the average annual growth rate of total sales for firms in each province-industry cell. This is similar to De Loecker (2011) measure of demand shifter. In addition, to avoid the confounding effect of entry and exit of firms in our sample, we first compute the nominal sales growth rate of the same firms and then calculate province-industry level averages. The average demand shock in our sample is 16.4%, which is comparable to the rapid industrial growth during this period (Table 3).

Price shocks are particularly challenging to measure at the firm level, as firms typically produce more than one product and information on product composition is not available. In this study, we propose an alternative approach to address the effect of price shocks, using a unique feature of industrial data for China. In the period from 1998 to 2005, managers of firms in China were asked to report two values of their output: the current price and the constant price (using 1990 as the base year). For the constant-price output, managers were instructed to use the same composition of products they manufactured across different years, and multiply the price of

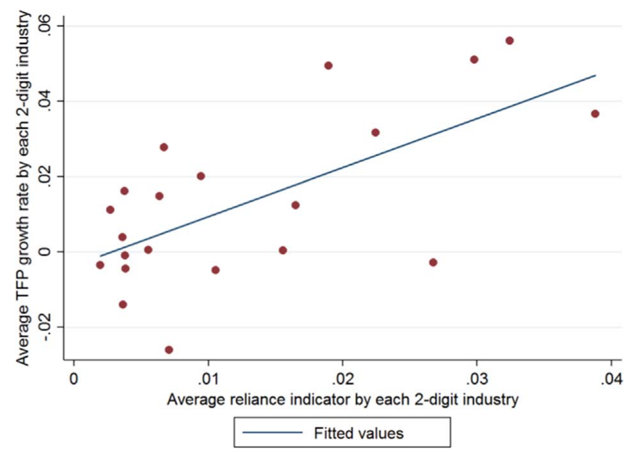

Fig. 5. Vehicle reliance and productivity growth.
Note: (1) Industries with average vehicle share larger than 0.3 are excluded. (2) Industries include: Coal mining and washing; Oil and gas exploration; Ferrous metals mining; Nonmetal minerals mining; Agro food processing, food manufacturing, beverage and tobacco production; Textiles industry; Clothing, shoes, hats, leather and fur manufacturing; Wood, bamboo and furniture industry; Papermaking and paper products, printing and cultural educational and sports goods; Petroleum processing, coking and nuclear fuel processing; Chemical raw materials and chemical products manufacturing; Chemicals, medicine, rubber and plastics industry; Nonmetallic mineral products; Ferrous and non-ferrous metal smelting and rolling processing industry; Metal products; General and special equipment manufacturing; Transportation equipment industry; Electrical machinery and equipment manufacturing; Communications equipment, computers and other electronic equipment manufacturing industry; Culture, office machinery manufacturing; Waste materials recycling processing industry; Electricity, heat, gas production and supply; Water production and supply.

the products in 1990 by their output shares. Hence, we can directly construct a measure of the price growth for each firm, as follows:

$$\mathrm{dp}_{it} = \frac{\mathrm{Y}_{it}^{current}/\mathrm{Y}_{it-1}^{current}}{\mathrm{Y}_{it}^{constant}/\mathrm{Y}_{it-1}^{constant}} \tag{7}$$

Here Y is the reported output value of firms. According to this measure, the average factory price growth rate is 1.9% for 1998–2005 (Table 3).

4. Empirical results

A simple plot of industry-level data (Fig. 5) is consistent with our expectation, which suggests that industries that rely more on transport services experience higher productivity growth. More rigorous estimates are provided in this section. We then infer the implied rate of return to road investment in China at the national level.

4.1. Productivity effect

Tables 6–11 summarize our major estimates of the productivity effect of road investment, with alternative specifications, samples, and estimation methods. Unless otherwise specified, a full data sample is used, and all regressions control for firm-specific fixed effects. Robust standard errors clustered at the province-industry level are reported.

4.1.1. Baseline estimates

To provide a benchmark, we start with a "naive" regression in which the interaction between vehicle intensity and road investment is not included. The dependent variable is productivity growth, which, as discussed in the previous section, is constructed based on Eq. (1). Both current and one-year-lag road investments are included, and we control for firm, province, industry, and year fixed effects. Estimates suggest a negative relationship between road investment and firms' productivity growth, which goes against the typical expectation (Column 1 of Table 6). This result should be treated with caution; as noted previously, it could be affected by a number of endogeneity issues.

Table 6
Effects of road on firms' productivity.

Variables	(1)	(2)	(3) FE - IV	(4) FE - IV Include demand shocks	(5) FE - IV Include demand & price shocks
Road growth *vehicle share		0.153***	0.152***	0.148***	0.122
		(0.038)	(0.033)	(0.033)	(0.088)
Lagged road growth *vehicle share		0.135***	0.138***	0.135***	0.164**
		(0.040)	(0.033)	(0.033)	(0.077)
Road growth	-0.027***				
	(0.008)				
Lagged road growth	0.006				
	(0.007)				
Market demand shock				0.106***	0.016
				(0.012)	(0.026)
Market price shock					0.055
					(0.098)
Year FE	+				
Province FE	+				
Province-year FE		+	+	+	+
Industry FE	+	+	+	+	+
Observations	652,310	639,375	623,114	622,966	362,073
R-squared	0.400	0.404	0.024	0.024	0.031

Note: (1) FE refers to fixed effect estimation. All FE regressions control for firm-specific fixed effects. Robust standard errors clustered at province-industry level in parentheses.
(2) The estimation methods in Column (2) and (3) are different in Table 6. In Column (2), the estimation is ordinary least squares regression controlling for fixed effects, and its R-squared includes the variance explained by the absorbed dummies in the regression. In Column (3), it is panel fixed effect model, and its R-squared does not include the variance explained by the absorbed dummies in the regression, i.e. its R-squared is interpreted as the amount of time variation in the dependent variable that is explained by the time variation in the explanatory variables (Wooldridge, 2012) . Hence the R-squared is smaller in panel fixed effect regression.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$

Table 7
Effect of road on price growth rate.

Variables	(1)	(2) FE without missing data	(3) FE - IV
Road growth *vehicle share	0.104	0.098	0.099
	(0.080)	(0.208)	(0.209)
Lagged road growth *vehicle share	0.098	0.092	0.073
	(0.071)	(0.183)	(0.184)
Province-year FE	+	+	+
Industry FE	+	+	+
Observations	517,737	504,654	504,654
R-squared	0.589	0.004	0.006

Note: (1) Dependent variable is price growth rate.
(2) FE refers to fixed effect estimation. All FE regressions control for firm-specific fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$,
* $p < 0.1$

To address endogeneity concerns, we turn to estimating model (4). This model includes the interaction term of road investment and firms' vehicle share of expenditure. Furthermore, we replace province-specific fixed effect with province-year fixed effect to control for all province-level unobserved shocks, such as productivity shocks, policy changes, and public investments. Estimates are reported in Column 2 of Table 6. According to the coefficients of the interaction between road investment and vehicle share, both the current and lagged effects of road investment are now positive and highly significant, and the effects of road investment are larger for firms with higher vehicle share.

Table 8
Robustness checks (IV).

Variables	(1) Excluding outliers	(2) Road quality	(3) Railway	(4) With all control variables
Road growth *vehicle share	0.143***	0.245***	0.148***	0.216***
	(0.029)	(0.064)	(0.033)	(0.064)
Lagged road growth *vehicle share	0.132***	0.209***	0.142***	0.198***
	(0.029)	(0.062)	(0.033)	(0.063)
Road quality change *vehicle share		0.019*		0.015
		(0.011)		(0.011)
Lagged road quality change *vehicle share		0.013		0.011
		(0.010)		(0.010)
Rail road growth *vehicle share			0.024	0.052
			(0.032)	(0.057)
Lagged rail road growth *vehicle share			0.080***	0.142***
			(0.029)	(0.054)
Market demand shock				0.102***
				(0.012)
Province-year FE	+	+	+	+
Industry FE	+	+	+	+
Observations	611,635	623,114	622,852	622,849
R-squared	0.029	0.024	0.024	0.024

Note: (1) Outliers, defined as the firms whose growth rate of TFP belongs to the highest percentile of 1% and the lowest percentile of 1%, are excluded in Column (1).
(2) In column (4), road quality is the ratio of express road and first road to the total road length
(3) Robust standard errors in parentheses. ** $p < 0.05$
(4) All regression are panel fixed effect with IV estimations.
*** $p < 0.01$
* $p < 0.1$

Table 9
Regressions at different quantiles (IV).

Variables	(1) P25	(2) P50	(3) P75	(4) Mean
Road growth *vehicle share	0.148***	0.137***	0.133***	0.116***
	(0.004)	(0.003)	(0.003)	(0.003)
Lagged road growth *vehicle share	0.113***	0.089***	0.094***	0.100***
	(0.004)	(0.003)	(0.003)	(0.003)
Province-year FE	+	+	+	+
Industry FE	+	+	+	+
Observations	829,259	829,259	829,259	829,259
R-squared	0.62	0.69	0.61	0.64

Note: (1) Dependent variable is firms' productivity
(2) Robust standard errors in parentheses. **$p < 0.05$,
(3) All regression are panel fixed effect with IV estimations.
*** $p < 0.01$,
* $p < 0.1$

To address potential bias due to measurement errors in vehicle share, we provide IV estimates using vehicle share implied by the input-output table of an alternative economic agency (Column 3 of Table 6). The first-stage regression suggests a strong correlation between the two alternative measures of vehicle reliance (1.545). Estimates do not change by much, compared with those in Column (2), suggesting that the effect of measurement errors may be small.

Could this relationship between road investment and productivity be due to omitted demand shocks? This could affect the revenue productivity of firms through changing markup, and could also be affected by an improved road network. To answer this question, we

Table 10
Firms' self-selection effects (IV).

Variables	(1) Lag selection (LGS) indicator	(2) Lead selection (LDS) indicator	(3) Benchmark sample
Road growth *vehicle share	0.152***	0.151***	0.152***
	(0.033)	(0.033)	(0.033)
Lagged road growth *vehicle share	0.138***	0.137***	0.138***
	(0.033)	(0.033)	(0.033)
Selection indicator	-0.004**	0.040***	
	(0.002)	(0.002)	
Province-year FE	+	+	+
Industry FE	+	+	+
Observations	623,114	623,114	623,114
R-squared	0.024	0.025	0.024

Note: (1) Robust standard errors in parentheses.
(2) All regression are panel fixed effect with IV estimations.
*** p < 0.01,
** p < 0.05,
* p < 0.1

Table 11
Results with balanced sample.

Variables	(1)	(2)	(3) FE - IV	(4) FE - IV Include demand shocks	(5) FE - IV Include demand & price shocks
Road growth *vehicle share		0.157***	0.157***	0.155***	0.203
		(0.047)	(0.054)	(0.054)	(0.128)
Lagged road growth *vehicle share		0.107**	0.109**	0.108**	0.232**
		(0.054)	(0.053)	(0.053)	(0.113)
Road growth	-0.019**				
	(0.009)				
Lagged road growth	0.017*				
	(0.008)				
Market demand shock				0.117***	0.036
				(0.019)	(0.039)
Market price shock					0.136
					(0.143)
Year FE	+				
Province FE	+				
Province-year FE		+	+	+	+
Industry FE	+	+	+	+	+
Observations	163,105	159,613	156,532	156,497	113,864
R-squared	0.188	0.195	0.042	0.042	0.050

Note: (1) Balanced sample means that firms in the sample exist in the whole time periods 1998-2007.
(2) FE refers to fixed effect estimation. All FE regressions control for firm-specific fixed effects. Robust standard errors clustered at province-industry level in parentheses.
*** p < 0.01,
** p < 0.05,
* p < 0.1

control for local demand shocks, measured by the annual growth rate of total sales at the province-industry level, following De Loecker (2011).[12] The coefficient of local demand shocks is positive and highly significant, suggesting a positive relationship between demand and markup, as expected (Column 3 of Table 6). Encouragingly, adding demand shocks has little effect on the coefficients of either current or lagged road effects.

Another factor that may be omitted in our model is market price shocks, which could also respond to highway investment. We first provide direct evidence on this by replacing the dependent variable in model (4) with firm-level price shocks. We find a positive but insignificant effect of highway investment on the price growth of firms with both fixed effect estimation and IV regressions (Table 7). Hence, omitting price shocks in the model should not have a significant effect on our estimates. This is confirmed when we augment regression model (4) by adding province-industry level price shocks. Estimates for highway effects remain robust, even though the sample size is reduced by almost half because price data are not available for 2006 and 2007 (Column 5 of Table 6).

4.1.2. Robustness checks

We next conduct a series of robustness checks of the above empirical estimates (Table 8). In the first exercise, we exclude observations with unusually large increases or decreases in productivity (Column 1 of Table 8).[13] The estimated effect of road investment is modestly smaller, but remains positive and highly significant.

Because using road length to measure road stock omits its quality, this could bias our estimated effect of road investment on firms. To address this concern, we add an indicator of road quality, measured by the share of high-quality road in road length at the province level, and interact it with vehicle share.[14] As expected, our estimates show that road quality also has some positive effects on firms' productivity (Column 2 of Table 8). Importantly, after accounting for the quality effect, estimated road-length effects become more significant.

In addition, as railroad and road investment could be complementary, we also consider adding province-level railway length to the regression, as well as its interaction with vehicle share (Column 3 in Table 8). The coefficient of lagged railway is positive and significant, suggesting a possible complementary effect of railway and highways. In addition, we do not find that the estimates of highways investment change much.

In the fourth column of Table 8, we estimate a comprehensive model that includes road quality, railroad investment, and market demand shock as control variables. The signs of their estimated coefficients are all in line with expectations, with the effects of railway and market demand shocks highly significant. Interestingly, the estimated effect of roads becomes more significant than the baseline regressions.

To further understand the effect of road investment on firms' productivity, we also examine firms' productivity responses at different quantiles—specifically, p25, p50, p75, and at the mean level. Regression results are shown in Table 9, and suggest that road investment increases firms' productivity across different quantiles.

In the next exercise, we consider the effect of firms' entry and exit. We calculate the average share of entry or exit in the data sample for the following four groups: (1) road-reliant industries in provinces with rapid road growth,[15] (2) less road-reliant industries in provinces with rapid road growth rate, (3) road-reliant industries in provinces with slow road growth rate, and (4) less road-reliant industries in provinces with slow road growth rate. We find that the shares of entry or exit in the four groups are 0.32, 0.25, 0.22, and 0.18, respectively. Hence, there is some indication that entry and exit are more frequent in road-

[12] To avoid the confounding effect of entry and exit of firms in our sample, we first compute the sales growth rates of the same firms and then aggregate them to province-industry level.

[13] We have deleted the highest percentile of 1% and the lowest percentile of 1% in the data.

[14] High-quality road is measured by the sum of the lengths of expressway and grade I roads in China to total road length. This measure ranges between 0.8% and 12% across provinces of China.

[15] Road-relying industries include those with a road reliance indicator above the median, and provinces with rapid road growth are those with above-median road growth rates.

reliant industries in provinces with more road investment. More rigorously, we conduct tests using the lag and lead selection indicators (see Section 3.3 for discussion). These are added to the baseline model separately, and estimates are reported in the first and second columns of Table 10. In both cases, the coefficients of the selection indicators are significant, suggesting that the productivity effect we estimate could also be due to the entry and exit of firms, but not to the productivity growth within firms. Encouragingly, controlling for the selection indicator has little effect on the estimated coefficients of road investment (compared with estimates for the same sample but without controlling for the selection indicators, in shown Column 3 of Table 10). This may lend support to our estimates (Wooldridge, 2002). As an alternative check, we provide estimates for a constant set of firms in the sample period 1998–2007, following Cherniwchan (2017). Estimates for this balanced sample (Table 11) and for the full sample (Table 6), are similar. This suggests that our estimated effects of roads are mainly in the intensive margin, but may not be driven by the entry and exit of firms (Cherniwchan, 2017).

In all of our regressions so far, we have used province-level road stock; this allows for spatial spillover effects across prefectures within the same province. As an additional robustness check, we follow Banerjee et al. (2012) and Alder (2015) by using prefecture-level road stock to repeat our key regressions (Table 12). This restricts the productivity effect of roads to firms within the same prefecture as the road investment. Coefficient estimates of roads remain positive and significant (Column 1), but are smaller in magnitude than estimates that use provincial-level data (Column 2). This is consistent with positive spatial spillovers between prefectures. For example, the coefficient of the contemporaneous effect of road investment is 0.164 at the provincial level and 0.092 at the prefectural level, a decline of 43%.

4.1.3. Is road investment in China excessive?

According to Huang (2008), China's infrastructure spending has been inefficient because investment decisions were biased by distortions caused by local government incentives. Road investment decisions may be more efficient in coastal regions, as their proximity to international markets—as well as active FDI and trade—may increase the market orientation of local governments. In inland regions, in contrast, where SOEs are still important and the influence of the planning economy is stronger than in coastal regions, road investment efficiency may be lower.

To shed light on this claim, in Table 13 we report the estimates of road productivity by coastal and inland regions of China (see Table 5 for classification of the two regions). Consistent with Huang's (2008)

Table 12
Effect of road growth at prefecture or province level on firm's productivity (IV).

Variables	(1) Prefecture level	(2) Province level
Road growth	0.092*	0.164***
*vehicle share	(0.048)	(0.043)
Lagged road growth	0.073	0.167***
*vehicle share	(0.053)	(0.044)
Road growth		
Prefecture-year FE	+	
Province-year FE		+
Industry FE	+	+
Observations	349,866	349,868
R-squared	0.32	0.313

Note: (1) Road growth is at prefecture level for Column (1) and at province level at Column (2).
(2) Robust standard errors in parentheses. **$p < 0.05$,
(3) All regression are panel fixed effect with IV estimations.
*** $p < 0.01$,
* $p < 0.1$

Table 13
Effect of road on productivity, by region (IV).

Variables	(1) Inland	(2) Coastal	(3) Inland	(4) Coastal
	1998–2002		2003–2007	
Road growth	−0.410	0.089	0.171*	0.199***
*vehicle share	(0.443)	(0.100)	(0.089)	(0.041)
Lagged road growth	−0.564	0.195**	0.120	0.175***
*vehicle share	(0.492)	(0.093)	(0.091)	(0.042)
Province-year FE	+	+	+	+
Industry FE	+	+	+	+
Observations	20,514	157,612	40,901	404,087
R-squared	0.008	0.005	0.024	0.028

Note: (1) Robust standard errors in parentheses.
(2) Inland region includes both central and west provinces in Table 5. Coast region is the same as the provinces in Table 5.
(3) All regression are panel fixed effect with IV estimations.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$

criticism, we find that during the period 1998–2002, road investment shows no positive effect on the productivity of firms in inland China, while the effect was significant in coastal China. This suggests inefficient investment in inland China. However, this does not mean that the road stock in inland China has reached the saturation point. In fact, our estimates for the period 2003–2007 suggest significant improvement in the productivity effect of roads in inland China, which significantly narrows the inland-coastal gap. Taken together, our evidence suggests that the need for road investment still existed in China, but low road investment efficiency was the problem.

4.2. The aggregate rate of return to road investment

To illustrate the magnitude of our estimates, we conduct a simple back-of-the-envelope calculation of the annual return to road investment in China, following Eq. (4). At the national level, the aggregate vehicle share is 3.18%.[16] Multiplying this by the sum of the coefficients of both contemporaneous and lagged road effects gives the elasticity of road investment on productivity at the national level.[17]

Calculating the rate of return also requires information on the national GDP-road stock ratio. China's annual GDP is available from the Statistical Yearbooks of China, but the value of road stock is not available from official sources. Nevertheless, several Chinese researchers have provided estimates of road stock based on the standard perpetual inventory method, but have mostly used different depreciation rates for road stock. Xing and Wang (2012) estimate that in 2009, highway stock was 2195.312 trillion Yuan (in 1990 prices), assuming a depreciation rate of 5.22%. In contrast, Dong and Cen (2011) use higher depreciation rates (7.8% in 2004, declining to 5.3% by 2009) and impute the highway stock as 804.65 trillion Yuan in 2009 (1987 prices). In a third study, Liu and Liu (2007) estimate the joint stock value of highways and waterways. Assuming a depreciation rate of 12.1% during the period 1952–2004, they calculate that from the base year of 1952 to 2004, highway and waterway stock increased by 277 times. In comparison, Xing and Wang (2012) estimate that road stock increased by 876 times from 1952 to 2004. To provide a lower-bound estimate of the rate of return, we adopt the estimates of Xing and Wang

[16] Calculated as the value added of transport equipment divided by national total value added, based on 2002 I-O data from the National Bureau of Statistics.

[17] As data on nonmanufacturing sectors are unavailable, we assume that the productivity effect of roads for the nonmanufacturing sector is the same as that for the manufacturing sector. This could actually cause underestimation of the aggregate return to road investment because, according to estimates by Fernald (1999), the productivity effect of roads is stronger for the nonmanufacturing sector than for manufacturing.

Table 14
Effects of road investment on aggregate productivity (1998–2007).

	Average effect
(1) National aggregate vehicle share (2002)	3.34%
(2) Coefficient of Road Growth * Vehicle Share	0.216
(3) Coefficient of Road Growth * Vehicle Share	0.198
(4) National aggregate ξ	1.32%
(4) = (1) × [(2) + (3)]	
(5) Y/G	8.3
(6) Annual Rate of return	11.4%
(6) = (4) × (5)	

Source: Authors' calculation.

(2012), who suggest that the GDP-road stock ratio averaged 8.3 for the sample period (Table 14). This is higher than the U.S. GDP-road stock ratio of 4 (Fernald, 1999), which suggests that China's road network still lags behind that of the U.S road network before 2007.

Multiplying aggregate elasticity ξ by the GDP-road stock ratio gives us the annual rate of return to road investment in China during the period 1998–2007. This yields an estimate of 11% for China, which is much lower than Fernald's (1999) estimate for the U.S. before 1973 (almost 100%). However, note that our estimate may not be directly comparable to that of Fernald, who uses industry-level productivity data and national-level road stock for estimation purposes. Hence, Fernald's estimates could include productivity spillover between states, and could also reflect the effect of firms' entry and exit on aggregate productivity.

5. Conclusion

We find that road investment in China has contributed to an increase in firms' productivity, based on data for China's manufacturers during the period 1998–2007. The implied annual rate of return averaged 11.4% during the sample period. This is comparable to estimates for China that use different approaches. Using the same data, Li and Li (2013) infer the return to road investment to be nearly 10%, based on firms' inventory saving. Bai and Qian (2010) focus on the private return of listed infrastructure investment firms in China, and estimate a return of approximately 20%. Another important finding of our study is that China's road investment was inefficient in the early 2000s, especially in inland China, but has significantly improved since. Hence, road investment in China was not excessive overall during the period 1998–2007, but some investments were inefficiently managed.

The findings of this study offer several additional implications. First, road investment can generate sizable returns to the economy by raising firms' productivity. This type of benefit is typically omitted in return assessment by infrastructure investors, as traditional methods of assessing return to road investment mainly rely on time costs and vehicle-cost savings. This would likely lead to a biased allocation of investment funds toward passenger-intensive areas, while underinvesting in production-intensive areas. Hence, an improved model of road investment benefit evaluation needs to include productivity gains.

Second, we find evidence for sizable spatial spillover effects of road investment, which account for approximately one-fifth of the total return. This suggests the importance of road network planning and financing at the provincial (or national) level, as well as of offering local officials incentives to coordinate road investment planning across jurisdictions.

Third, although road investment in China has generated reasonably high returns during our sample period, it may be time for China to change its road investment model. While more recent data are unavailable, it is likely that in the next two decades the rate of return to road investment in China will fall significantly if the current investment pace is maintained. According to China's long-term highway investment plan, which was announced in 2013, total road length in China could double in the next two decades.[18] As demonstrated by Eq. (4), however, unless investment efficiency can be further improved, doubling the road stock will decrease the return by half.

References

Alder, S., 2015. Chinese Roads in India: The Effect of Transport Infrastructure on Economic Development. University of North Carolina at Chapel Hill, (working paper).

Ansar, A., Flyvbjerg, B., Budzier, A., Lunn, D., 2016. Does infrastructure investment lead to economic growth or economic fragility? Evidence from China. Oxf. Rev. Econ. Policy 32 (3), 360–390.

Aschauer, D.A., 1989. Is public expenditure productive? J. Monet. Econ. 23 (2), 177–200.

Bai, C., Qian, Y., 2010. Infrastructure development in China: the cases of electricity, highways, and railways. J. Comp. Econ. 38 (1), 34–51.

Banerjee, A., Duflo E., Qian N., 2012. On the road: access to transportation infrastructure and economic growth in China. NBER Working Paper No. 17897.

Barro, R.J., 1990. Government spending in a simple model of endogenous growth. J. Political Econ. 98 (5), 103–125.

Baum-Snow, N., 2007. Did highway cause suburbanization? Q. J. Econ. 122 (2), 775–805.

Boarnet, M., 1997. Highways and economic productivity: interpreting recent evidence. J. Plan. Lit. 11 (4), 476–486.

Brandt, L., Van Biesebroeck, J., Zhang, Y., 2012. Creative accounting or creative destruction: firm level productivity growth in Chinese manufacturing. J. Dev. Econ. 97 (2), 339–351.

Chandra, A., Thompson, E., 2000. Does public infrastructure affect economic activity? Evidence from the rural interstate highway system. Reg. Sci. Urban Econ. 30, 457–490.

Cherniwcha, Jevan, 2017. Trade liberalization and the environment: evidence from NAFTA and U.S. manufacturing. J.f Int. Econ. 105, 130–149.

Datta, S., 2012. The impact of improved highways on Indian firms. J. Dev. Econ. 99, 46–57.

Démurger, S., 2001. Infrastructure development and economic growth: an explanation for regional disparities in China? J. Comp. Econ. 29 (1), 95–117.

De Loecker, J., 2011. Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity. Econometrica 79 (5), 1407–1451.

De Loecker, J., Warzynski, F., 2012. Markups and firm-level export status. Am. Econ. Rev. 102 (6), 2437–2471.

Donaldson, D., forthcoming. Railroads and the raj: estimating the impact of transport infrastructure. American Economic Review, forthcoming. 〈https://www.aeaweb.org/articles?Id=10.1257/aer.20101199 & & from=f〉.

Donaldson, D., Hornbeck R., 2013. . Railroads and American economic growth: A "Market Access' approach". NBER Working Paper No. 19213.

Dong, J., Cen, Y., 2011. Measurement of highway capital stock in China:1952- 2009. J. Transp. Syst. Eng. Inf. Technol. 11 (1), 20–23.

Duranton, G., Turner, M., 2011. The Fundamental Law of Road Congestion: evidence from US Cities. Am. Econ. Rev. 101 (6), 2616–2652.

Fernald, J.G., 1999. Roads to prosperity? Assessing the link between public capital and productivity. Am. Econ. Rev. 89 (3), 619–638.

Ghani, E., Goswami, A.G., Kerr, W.R., 2016. Highway to success: the impact of the golden quadrilateral project for the location and performance of Indian manufacturing. Econ. J. 126, 317–357.

Gillen, D.W., 1996. Transportation infrastructure and economic development - a review of recent literature. Logist. Transp. Rev. 3, 39–62.

Gollin D., Rogerson R., 2010. . Agriculture, roads, and economic development in Uganda, NBER Working Paper No. 15863.

Gordon, R.H., Li, W., 1995. The change in productivity of Chinese state enterprises, 1983–1987. J. Prod. Anal. 6 (1), 5–26.

Gramlich, E.M., 1994. Infrastructure investment: a review essay. J. Econ. Lit. 32 (3), 1176–1196.

Hsieh, C., Klenow, P., 2010. Development accounting. Am. Econ. J.: Macroecon. 2 (1), 207–223.

Holz, C.A., 2013. Chinese Statistics: Classification Systems and Data Sources. Stanford University, (SCID Working Paper 471).

Holtz-Eakin, D., Newey, W., Rosen, H.S., 1988. Estimating vector auto regressions with Panel Data. Econometrica 56 (6), 1371–1395.

Huang, Y., 2008. Capitalism with Chinese Characteristics: Entrepreneurship and the State. Cambridge University Press.

Jiang, B., 2001. A review of studies on the relationship between transport infrastructure investments and economic growth. Can. Transp. Act Rev. Panel.

Li, H., Li, Z., 2013. Road investment and inventory reduction: evidence from Chinese manufacturers. J. Urban Econ. 76, 43–52.

Li, Z., 2013. Transportation infrastructure investment and economic development. In: Lu Ming (Ed.), China's Regional Development: Review and Prospect. Routledge.

[18] The Highway Investment Plan (2013 – 2030) does not specify the target for total road length, but only establishes targets for national highways and expressways, which are to increase from 170,000km in 2011 to 401,000km by 2030 (http://zfxxgk.ndrc.gov.cn).

Li, Z., Chen, Y., 2013. Estimating the social return to transport infrastructure: a price-difference approach applied to a quasi-experiment. J. Comp. Econ. 41 (3), 669–683.
Li, Z., Yu, X., Zeng, Y., Holst, R., 2012. Estimating transport costs and trade barriers in China: direct evidence from Chinese agricultural traders. China Econ. Rev. 23 (4), 1003–1010.
Liu, B., Liu, Y., 2007. Estimation in China's cumulative amount of highway and waterway capital. J. Beijing Jiao Tong Univ. (Soc. Sci. Ed.), 44–48.
Lu, M., Chen, Z., 2006. Market Integration and Industry Agglomeration in Regional Economic Development in China. SDX Joint Publishing Company and Shanghai People's Publishing House.
Melo, P.C., Graham, D.J., Brage-Ardao, R., 2013. The productivity of transport infrastructure investment: a meta-analysis of empirical evidence. Reg. Sci. Urban Econ. 43, 695–706.
Michaels, G., 2008. The effect of trade on the demand for skill: evidence from the interstate highway system. Rev. Econ. Stat. 90 (4), 683–701.
Park, A., Jin, H., Rozelle, S., Huang, J., 2002. Market emergence and transition: arbitrage, transaction costs, and autarky in China's grain markets. Am. J. Agric. Econ. 84, 1.
Shirley, C., Winston, C., 2004. Firm inventory behavior and the returns from highway infrastructure investments. J. Urban Econ. 55 (2), 398–415.
Song, Z., Storesletten, K., Zilibotti, F., 2011. Growing like China. Am. Econ. Rev. 101 (1), 196–233.
Storeygard, A., 2013. . Farther on down the road: transport costs, trade and urban growth in Sub-Saharan Africa. World Bank Policy Research Working Paper 6444.
Verbeek, M., Nijman, T., 1992. Testing for selectivity bias in panel data models. Int. Econ. Rev. 33 (3), 681–703.
World Bank. China, 2005. Integration of National Product and Factor Markets−−Economic Benefits and Policy Recommendations. World Bank, Washington.
Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press.
Wooldridge, J.M., 2012. Introductory Econometrics: A Modern Approach 5th Ed.. CENGAGE Learning Custom Publishing.
Xing, Y., Wang, J., 2012. Evaluation of highway capital stock of China: 1952– 2010. J. Transp. Eng. Inf. 1 (10), 89–93.
Zhu, X., 2012. Understanding China's growth: past, present, and future. J. Econ. Perspect. 26 (4), 103–124.