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On the reverse causality between output and infrastructure: The case of China☆

Qu Feng *, Guiying Laura Wu

School of Social Sciences, Nanyang Technological University, Singapore

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ABSTRACT

After the 2008 global financial crisis, promoting public infrastructure investment as a growth engine has been revived by economists. China has been considered as such a successful example of enhancing economic growth by massive infrastructure investments in the past decades. However, the literature has provided conflicting empirical results on the productivity effect of public infrastructure using aggregate data, mainly due to reverse causality. Thus, the estimated productivity effect could be either upward or downward biased. In this paper we rely on the institutional background of infrastructure investment in China, and explore several alternative ways to mitigate the reverse causality. Using China's provincial-level data over 1996–2015 and within the framework of an aggregate production function estimation, we find that an upward bias dominates when estimating output elasticity of public infrastructure, and that weak evidence is found on the productivity effect of public infrastructure. This finding highlights the necessity of using alternative identification strategies or data types.

1. Introduction

After the 2008 global financial crisis, promoting public infrastructure investment as a growth engine has been revived by economists and policy makers. For example, a 4 trillion Chinese Yuan (equivalent to 600 billion US dollars) fiscal stimulus package was introduced by the Chinese government to invest mainly in the infrastructure in its western provinces in 2008 (Ouyang and Peng, 2015). Recently, as Chinese economy started to slow down in 2015, 1 trillion Chinese Yuan was further proposed to invest in infrastructure (*Financial Times*, August 5, 2015).

For a specific project on infrastructure investment, e.g., building an airport, it is straightforward to calculate its economic return if the benefits and costs of the project are well defined and recorded. However, its social return may not be fully captured in a financial evaluation framework. For a specific type of infrastructure, the literature has also developed various ways to identify its productivity effect, for example, Fernald (1999) for road in the US, Röller and Waverman (2001) for telecommunications infrastructure in OECD countries, and the recent works surveyed in Redding and Turner (2015) for transport infrastructure. In China, rates of return to railroad and road are found over 10% and 20%, respectively (Li and Li, 2013; Li and Chen, 2013).

To address whether public infrastructure investment as a whole enhances the growth of the whole economy, we take a macro view and focus on the productivity and return of the total public infrastructure investment. For this purpose, following the literature starting from Aschauer (1989), we estimate the output elasticity with respect to public infrastructure in an aggregate production function using China's provincial panel data over 1996–2015.

The importance of studying China's case is in two folds. First, it is well known that China is considered as an investment-driven economy with the investment-to-GDP ratio above 45% since 2009, far exceeding other developing countries and advanced economies.[1] As a major component of the total investment, public infrastructure investment

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* Corresponding author.

E-mail address: qfeng@ntu.edu.sg (Q. Feng).

[1] See the World Bank website https://data.worldbank.org/indicator/NE.GDI.TOTL.ZS?locations=CN-TH-VN-IN.

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accounts for an average rate of 9.3% of China's GDP during 1996-2015.[2] Thus, it is of policy significance to evaluate the productivity and return of public infrastructure investment in China. Second, China's institutional context may provide unique identification strategies for the endogeneity problem due to the reverse causality between output and public infrastructure when estimating its elasticity.

Using the framework of an aggregate production function estimation, the literature has provided conflicting empirical results, mainly due to reverse causality. As surveyed in Bom and Ligthart (2014), the output elasticity of public capital varies from the highest estimate of 2.04 for Australia in one research to the lowest one of −1.7 for New Zealand in another research. In between, many estimates are statistically not different from zero. The output elasticity of public infrastructure capital could be overestimated when a growth in output facilitates an increase in public infrastructure investment. That is, public infrastructure investment could be induced by economic growth, instead of driving economic growth. Alternatively, the output elasticity of public infrastructure capital could be underestimated when public infrastructure investment is used as a countercyclical tool to boost economic growth during economic recession.

In a recent study with a focus on the investment efficiency in China, Shi and Huang (2014) argue that a downward bias is more likely in China's case. This is because the Chinese government tends to use infrastructure investment as a choice for stimulating its economy when a negative productivity shock is expected. Consistent with this logic, they find that the output elasticity using a proxy approach developed by Ackerberg et al. (2015) is even larger than that from the OLS approach. Using China's provincial panels over 1995–2011, they obtain a big and positive output elasticity of public infrastructure, with a magnitude around 0.22 to 0.29. This implies a rate of return more than 50%.[3]

In this paper we rely on the institutional background of infrastructure investment in China, and explore several alternative ways to mitigate the reverse causality between aggregate output and public infrastructure. Using different approaches we find that an upward bias dominates when estimating output elasticity of public infrastructure using China's provincial-level data over 1996–2015. Within the framework of an aggregate production function estimation, weak evidence is found on the productivity effect of public infrastructure in China. This finding suggests the necessity of using alternative identification strategies or data types, e.g., a disaggregation approach using firm-level data, such as Fisher-Vanden et al. (2015); Li et al. (2017); and Wu et al. (2017).

The rest of the paper is organized as follows. Section 2 introduces a macroeconometric model using an aggregate production function, augmented with public infrastructure capital. Various strategies of dealing with the reverse causality are discussed in Section 3. Section 4 presents the data and reports the empirical findings. Section 5 concludes.

2. Empirical model

To model the general idea that public infrastructure investment promotes economic growth, following literature we introduce an aggregate production function:

$$Y = AK^{\gamma_k}L^{\gamma_l},$$

where Y is the total output; L is the total labor force; and K is the stock of non-infrastructure capital. The public infrastructure capital B, measuring the stock of public infrastructure investment, enters the production function as a contributing component to the total productivity factor (TFP) A, i.e., $A = A_0 B^{\gamma_b}$, where A_0 is the component of TFP that is unrelated to public infrastructure. Thus, the aggregate production function becomes

$$Y = A_0 B^{\gamma_b} K^{\gamma_k} L^{\gamma_l}. \tag{1}$$

The stock variables, B and K, accumulate according to the following laws of motion:

$$B_t = (1 - \delta_b)B_{t-1} + G_t \tag{2}$$

and

$$K_t = (1 - \delta_k)K_{t-1} + I_t. \tag{3}$$

Here G_t measures the infrastructure investment in industries with externalities, such as electricity, gas, water, transport, information transmission, and I_t is the investment in non-infrastructure sectors. δ_b and δ_k are depreciation rates of B and K, respectively.

Under the assumption of constant returns to scale (CRS),[4] $\gamma_b + \gamma_k + \gamma_l = 1$, so that (1) becomes $Y/L = A_0(B/L)^{\gamma_b}(K/L)^{\gamma_k}$. Thus the aggregate production function in the intensive form can be written as

$$y = \gamma_0 + \gamma_b b + \gamma_k k,$$

where $y = \log(Y/L)$, $b = \log(B/L)$, $k = \log(K/L)$ and $\gamma_0 = \log(A_0)$. In this equation, γ_b and γ_k are the output of elasticities of public infrastructure and non-infrastructure capital. The economic return of public infrastructure, or the marginal output of public infrastructure, can be measured as

$$\partial Y/\partial B = \gamma_b Y/B.$$

To estimate the coefficients γ_b, γ_k, a panel data model based on the aggregate production function above is used

$$y_{it} = \gamma_0 + \gamma_b b_{it} + \gamma_k k_{it} + \mu_i + T_t + \varepsilon_{it}, \tag{4}$$

where y_{it} is the logarithm of GDP per labor in province i in year t, and b_{it} is the logarithm of public infrastructure stock per labor, and k_{it} is the logarithm of non-infrastructure capital stock per labor. μ_i denotes province specific factors, such as different land area, location, weather, endowments of raw materials and myriad other factors. Time effects T_t can be used to control for national-level macro shocks, including business cycles and counter-cyclic policies. ε_{it} denotes idiosyncratic shocks or measurement error in output. To deal with the non-stationarity in macroeconomic variables, first-differencing Eq. (4) gives our estimating equation:

$$\Delta y_{it} = \gamma_b \Delta b_{it} + \gamma_k \Delta k_{it} + \Delta T_t + \Delta\varepsilon_{it}. \tag{5}$$

[2] This rate is calculated using the data from the website of National Bureau of Statistics of China. Also see Fig. 14.3 of Naughton (2007) for the ratios of physical infrastructure investment to GDP during 1981–2004.

[3] There are several other studies on China's infrastructure in the literature. Shi et al. (2017) incorporate a CES production function in Mankiw et al. (1992) model, and estimate the relationship between infrastructure and economic growth in a vector error correction model using a panel data set of China's 30 provinces over 1990–2013. Lin and Song (2002) obtain a significant OLS estimate of output elasticity of city infrastructure above 0.102 in a cross-section regression of the relationship between per capita GDP growth and investment, foreign direct investment, labor force growth, government expenditure and urban infrastructure using a data set of 189 large and medium-sized Chinese cities for the period 1991–1998. Ward and Zheng (2016) estimate the contribution of telecommunications services to economic growth using a panel data set of 31 Chinese provinces over the period from 1991 to 2010. To address the concern of reverse causality between telecommunications and per capita growth, system GMM estimators combined with external instruments are used in a dynamic panel data model. For a detailed survey on the effect of infrastructure on economic growth in China using aggregate level data, see Shi et al. (2017). Wu et al. (2017) also provide an extensive discussion on the literature on the relationship between public infrastructure and economic growth in China using disaggregate data.

[4] Results without the CRS restriction are not reported here for the sake of space but are available upon request. Despite the small variations in the output elasticities with and without the CRS restriction across various models, the main message obtained under the CRS restriction remains unchanged.

3. Dealing with reverse causality

When we write down Eq. (4) or (5), our aim is to identify the causal effect of public infrastructure on output. However, as pointed out, e.g., by Gramlich (1994), the causality could go from output to public infrastructure. Higher output may mean greater demand for the services from public infrastructure; higher output may also mean more income for expenditure on public infrastructure. Hence, a positive estimated elasticity could be mainly driven by this reverse causality. Thus, the OLS estimator of γ_b in (5) (i.e., the first difference (FD) estimator of (4)) could be biased upward. Alternatively, in the literature as summarized by Bom and Ligthart (2014), due to the Keynesian multiplier effect, public infrastructure investment is often used to boost economic growth during the period of economic recession. In this case, output and public infrastructure investment could be negatively correlated. Thus, the OLS estimator of γ_b in (5) (i.e., the first difference (FD) estimator of (4)) could be biased downward.

In the literature, there are several ways to deal with this endogeneity issue due to reverse causality. The first and general approach is the instrumental variable (IV) estimation, e.g., Holtz-Eakin (1994), Baltagi and Pinnoi (1995) and the more recent literature surveyed in Redding and Turner (2015). An alternative way to address the reverse causality is the simultaneous-equations approach, explicitly modeling the relationship between y and b in an additional equation, such as Röller and Waverman (2001) and Cadot et al. (2006). Another approach is to explore the heterogeneity of output effect from disaggregated data. A leading example is Fernald (1999). Recently, Calderon et al. (2015) use a panel cointegration approach to deal with the nonstationarity and establish only one cointegrating relation to address concerns with reverse causality in a panel data set with a long span of time periods.

In the Chinese context, Shi and Huang (2014) claim that the reverse causality could lead to a negative correlation between output and public infrastructure since "Chinese government tends to use infrastructure investment as a choice for reviving its economy when it expects a large negative TFP shock", which will bias downward the estimated output elasticity of infrastructure. In their paper, the endogeneity due to reverse causality is interpreted as the negative correlation between Δb_{it} and $\Delta\varepsilon_{it}$, where this correlation is dealt with by the proxy approach developed by Ackerberg et al. (2015).

Different from Shi and Huang (2014), we argue that regarding the feedback effect of output on public infrastructure, a positive correlation is more likely to dominate in the case of China. Bai and Qian (2010) provide an interesting survey on the specific institutional background for infrastructure investment in China. Two stylized facts can be summarized from the survey. First, most infrastructure investment are made by state-owned enterprises with funds from both the central and the local governments. Second, among various jurisdiction levels, the provincial governments play a key role in infrastructure investment decision. Wu et al. (2017) survey several hypotheses on the investment incentives of the Chinese governments that have been discussed in the literature. In short, for the central government, first, infrastructure development is needed to fight against the worsening regional inequality by promoting the catch-up of lagging inland provinces with coastal provinces. This would imply a negative correlation between b_{it} and μ_i in Eq. (4) and can be eliminated by first differencing as in Eq. (5).[5] Second, infrastructure development is necessary to support the rapid economic growth of the country that fuels an ever-increasing demand for infrastructure services. This would imply a positive correlation between Δb_{it} and $\Delta\varepsilon_{it}$ in Eq. (5). Finally, for the provincial governments, under China's regionally decentralized authoritarian system, infrastructure investment has been adopted as the most effective instrument by the local governments as their response the GDP yardstick competition. Hence a province with better growth prospects could expect to produce higher output and collect more fiscal revenue in the future, which in turn may allow the province to invest more in current infrastructure via various financing schemes. This would also imply a positive correlation between Δb_{it} and $\Delta\varepsilon_{it}$ in Eq. (5).

It is a well-known fact that the 30 provinces in China are at different levels of economic development, varying substantially in GDP per capita, public facilities and fiscal budget (Naughton, 2007). Hence, over a relative long span of time, such positive correlation generated by financing abilities cross provinces could overpower the negative correlation between output and public infrastructure due to the short-run countercyclical story or national policies to reduce regional disparity. Therefore, after including time effects in Eq. (5) to mitigate the effect of national-level countercyclical policies, we conject that the upward bias due to the reverse causality is more likely when estimating output elasticity of public infrastructure γ_b in (5).

In this paper, we employ several ways to deal with or mitigate the endogeneity issue due to reverse causality. The first approach is to use an alternative measure of investment in fixed assets reported by the National Bureau of Statistics of China (NBS): Newly Increased Fixed Assets (NIFA hereafter) (*xinzeng guding zichan touzi* in Chinese). Different from the usual measure of investment to construct public infrastructure capital and non-infrastructure capital in (4), Total Investment in Fixed Assets (TIFA hereafter) (*quanshehui guding zichan touzi* in Chinese), which measures total *cost* spent on constructing and purchasing fixed assets, NIFA measures investment in fixed assets that have been *used* for production after the process of construction and purchase is completed.[6] Due to the time to build, NIFA is less likely to be affected by the current output. Thus, the reverse causality between output and public infrastructure (or non-infrastructure) capital is mitigated. [7]

We also make use of a measure of b_{it} in the level Eq. (4) (or Δb_{it} in the differenced Eq. (5)) that is less likely to be affected by y_{it} (or Δy_{it}). A natural candidate in the literature is the lagged value of b_{it} (or Δb_{it}). Different from b_{it} (or Δb_{it}), b_{it-1} (or Δb_{it-1}) is less likely to be affected by y_{it} (or Δy_{it}) under the assumption that the current output only affects the current and future, instead of the past, values of public infrastructure. As a stock variable accumulating all past public infrastructure investments, b_{it-1} still provides service to future production.

As a general approach to deal with endogeneity, instrumental variable estimation is also used to consistently estimate γ_b. In this paper, three different sets of instruments are explored. First, as in Holtz-Eakin (1994), twice-lagged variables Δb_{it-2} and Δk_{it-2} are employed as internal instruments for Δb_{it} and Δk_{it} in Eq. (5).[8] Second, as widely documented in the literature one of distinctive institutional features of China's economic miracle is that under the so-called "GDP tournament" scheme local governments have been playing an active role in promoting economic growth, including investing in infrastructure (Li and Zhou, 2005; Jin et al., 2005; Wang et al., 2017). Under this scheme, local governments compete with each other on GDP growth, and their investment behavior could affect each other. Thus, Δb_{it} in neighboring

[5] When infrastructure investment is used to reduce regional inequality at the growth of output, instead of the level of output, Δb_{it} and $\Delta\varepsilon_{it}$ could be negatively correlated, as in Shi and Huang (2014).

[6] Ozyurt (2009) uses NIFA as a measure of effective investment in a study of estimating China's aggregate production function using time series data covering 1952–2005.

[7] NIFA is not a formal measure of investment reported by NBS. It is reported to show the extent of how investment process in fixed assets has been completed in some years and some sectors. Since the data on NIFA are not available before 2002, TIFA is used as a formal measure of investment throughout the paper. We construct the data of NIFA before 2002 by using the components of basic construction and renovations of NIFA and their ratios in provinces and industries in China Statistics Yearbooks.

[8] Δb_{it-1} and Δk_{it-1} could be correlated with $\Delta\varepsilon_{it}$. It is worth noting that this IV approach is different from using Δb_{it-1} and Δk_{it-1} as regressors in the FD regression above.

Table 1
Summary statistics of variables.

Symbol	Definition	Unit	Mean	Std. D.	Form in regression	Data sources
y	real output per labor	10,000 yuan	2.38	1.79	log	China NBS Website
b	real infrastructure capital per labor	10,000 yuan	1.17	0.92	log	China NBS Website
k	real non-infrastructure capital per labor	10,000 yuan	5.03	4.84	log	China NBS Website
newb	real infrastructure capital per labor based on NIFA	10,000 yuan	0.69	0.51	log	China NBS Website
nb	real infrastructure capital per labor in neighboring provinces		1.04	0.72	log	authors' calculation
G	infrastructure investment flow	100 million yuan	674	624		China NBS Website
L	number of labor force	10,000	3080	1847		China NBS Website
age 1	age of provincial governor		57.9	4.0	level	Wikipedia, baike.baidu.com
age 2	age of provincial party leader		59.7	4.1	level	Wikipedia, baike.baidu.com

Notes.

1. All variables are measured in provincial level.
2. Units and summary statistics of all variables are reported before taking log.

provinces, denoted as Δnb_{it}, can serve as an instrument for Δb_{it}.[9] A recent study by Zheng et al. (2015) finds that infrastructure spending in a province is positively correlated with infrastructure spending in its neighboring provinces. In addition, since Δy_{it} is only affected by Δb_{it} and Δk_{it} conditional on time dummies in Eq. (5), instruments of Δb_{it-2} and Δnb_{it} have no direct effect on Δy_{it}. They affect Δy_{it} only through Δb_{it}.

Third, we use the ages of provincial governors and party leaders as external instruments for public infrastructure in (5). In China's current political system, provincial governors and party leaders retire at an age of 65 if they are not promoted to top-level officials in Chinese central government. Given that GDP growth is the most important key performance indicator and that investment is one of the major contributing factors of GDP growth, provincial governors and party leaders are less motivated to invest when their ages are closer to 65.[10] In this case, the ages of provincial governors and party leaders could be negatively correlated with public infrastructure investment. In terms of exclusion restriction, like instruments of twice-lagged variables and neighboring public infrastructure, the ages of provincial governors and party leaders are considered to be irrelevant to output (or growth) in the aggregate production function (4) (or (5)).

The empirical results using the identification strategies above are reported in Section 4 below. Using a Chinese provincial panel data set during 1996–2015, we show that after dealing with the endogeneity issue due to reverse causality, the estimated output elasticities are notably smaller than the FD estimates, suggesting that an upward bias due to reverse causality is prevalent in China's case.

4. Data and empirical results

Data on GDP (Y) are obtained from the website of National Bureau of Statistics of China. We collect data for 30 provinces excluding Tibet over years 1996–2015. As in Shi and Huang (2014), the size of labor force (L) is calculated by number of residents multiplied by the ratio of age cohort of 16–65. For the key variables public infrastructure investment (G) and non-infrastructure investment (I), we collect data on the total investment in fixed assets (TIFA) from Statistical Yearbooks of The Chinese Investment in Fixed Assets and China Statistical Yearbooks. These two series of statistics yearbooks report total investment in fixed assets by industry and by province. Infrastructure investment G is measured by the sum of investments in the 3 industries: (1) production and supply of electricity, gas and water; (2) transport, storage and post; (3) information transmission, computer services and software.[11] I is defined as total investment minus G. Stock variables of B and K are constructed as in (2) and (3) using depreciation rates $\delta_b = \delta_k = 10\%$.[12]

Table 1 reports the summary statistics for the variables used in the analysis. GDP, public infrastructure investment, non-infrastructure investment are deflated by the province-specific price indices of investment in fixed assets.[13] The unit, mean and standard deviation for the real output per labor, real public infrastructure and non-infrastructure capital stocks per labor and other variables before taking logarithms are reported. These variables are used in the log form in regressions, so that the corresponding coefficients can be interpreted as elasticities.

We first report estimation results on elasticities γ_b and γ_k without dealing with reverse causality. Column (1) of Table 2 reports fixed effects (FE) estimates of γ_b and γ_k, which are 0.057 and 0.303, respectively. To eliminate unit roots and common trends in the macro data, first-differencing is needed. Column (2) presents FD estimates, showing that the estimated elasticity of public infrastructure capital is 0.127 and significant at 1% level.[14] Considering that the return of public infras-

[9] We define a province as a neighboring province of i if it shares common border of province i. For examples, the neighboring provinces of Shanghai are Jiangsu and Zhejiang, and Jiangxi's neighbors are Zhejiang, Anhui, Hubei, Hunan, Fujian and Guangdong provinces. nb_{it} is defined as the log (sum of infrastructure stock in neighboring provinces/sum of labor in neighboring provinces). The instrument used is its first difference.

[10] A similar argument can be seen in Li and Zhou (2005), Wang et al. (2017), in which age is an important factor for the career concerns of provincial leaders.

[11] The definition of G here is consistent with the description of physical infrastructure in Fig. 14.3 of Naughton (2007) for China, and the literature in general, e.g., Calderon et al. (2015). Shi and Huang (2014) also include investment in management of water conservancy, environment, and public facilities as part of public infrastructure investment. When we broaden the definition of infrastructure as in Shi and Huang (2014) in robustness checks, we obtain similar findings as in our benchmark results.

[12] The choice of depreciation rate in the literature typically varies between 3% and 16%. Thus we set 10% as our benchmark depreciation rate and conducted robustness checks using other rates as alternatives. The main finding of our empirical exercise turns out to be not sensitive to the depreciation rate. To implement the perpetual inventory method, one has to start with an initial value for B_{it} and K_{it}. In our application, we assume that $B_{i1996} = G_{i1996}/(\delta_b + g)$ and $K_{i1996} = I_{i1996}/(\delta_k + g)$, where $g = 10\%$, the average long-run growth rate during our sample period. This assumption is based on the property of a balanced-growth-path model, in which new investment is made to compensate depreciation and guarantee a constant growth in capital stock.

[13] According to The Chinese Statistic Yearbook, the investment in fixed assets consists of three components, namely the investment in construction and installation, the investment in purchases of equipment and instrument, and the investment in other items. Price indices of investment in fixed assets are calculated as the weighted arithmetic mean of the price indices of the three components of investment in fixed assets. Under our definition, both infrastructure and non-infrastructure investment contain investment in all three components. Without knowing the exact proportion of each component, we apply the price indices of investment in fixed assets to both infrastructure and non-infrastructure investment.

[14] Clustered standard errors are reported in parenthesis below estimates, adjusted for 30 clusters in province.

Table 2
Output elasticities: Fixed-effects and first-differenced estimates.

Dependent variable: Output per labor									
Independent variables:	FE	FD			FDnew			FDlag	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Infrastructure capital per labor	0.057	0.127***	0.144***	0.088**	0.037*	0.033	0.035	0.005	−0.030
	(0.07)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)
Non-infrastructure capital per labor	0.303***	0.324***	0.340***	0.315***	0.228***	0.250***	0.210***	0.215***	0.402***
	−0.04	−0.03	−0.04	−0.02	−0.02	−0.03	−0.02	−0.04	−0.03
Periods	All	All	1996–2007	2008–2015	All	1996–2007	2008–2015	All	All
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.84	0.73	0.76	0.67	0.60	0.63	0.54	0.45	0.71
No. of observations	599	569	329	240	569	329	240	539	539

Notes.

1. FE and FD in columns (1)–(4) denote fixed effects regression and first difference regression, respectively.
2. FDnew in columns (5)–(7) refer to the first-difference estimates using data based on *newly increased fixed asset investment*.
3. FDlag in columns (8) refer to the first difference estimates using the lags of both public infrastructure and non-infrastructure capital. In column (9) only the lagged value of public infrastructure capital is used.
4. Standard errors are reported in parentheses. The stars, *, ** and *** indicate the significance level at 10%, 5% and 1%, respectively.
5. Standard errors are adjusted for 30 clusters in province.
6. Depreciation rate 10% is used to calculate public infrastructure and non-infrastructure capital stocks.
7. For the definition, unit of variables and data sources, please refer to Table 1.

Table 3
Output elasticities: Instrumental variable estimates.

Independent variables:	FD IV1			FD IV2	FD IV3	
	(1)	(2)	(3)	(4)	(5)	(6)
Infrastructure capital per labor	−0.095	−0.050	−0.063	−0.098	0.059	0.140
	(0.09)	(0.14)	(0.10)	(0.19)	(0.21)	(0.15)
Non-infrastructure capital per labor	0.332***	0.210***	0.370***	0.333***	0.258***	0.220***
	(0.04)	(0.08)	(0.05)	(0.11)	(0.09)	(0.06)
Periods	All	1996–2007	2008–2015	All	All	All
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.62	0.60	0.63	0.62	0.70	0.71
No. of observations	509	269	240	509	509	509
Instruments	Δb_{t-2}, Δk_{t-2}			Δnb_t, Δk_{t-2}	age1, Δk_{t-2}	age1, age2, Δk_{t-2}
1st-stage regression coefficient	0.337	0.356	0.345	0.272	−0.001	−0.001
1st-stage *t*-ratio	(6.94)	(4.93)	(5.36)	(3.67)	(-2.25)	(-2.11)
Sargan test (p-value)						0.46

Notes.

1. FD IV denotes first difference instrumental variable regression.
2. Depreciation rate 10% is used to calculate the capital stocks.
3. Standard errors are reported in parentheses. The stars, *, ** and *** indicate the significance level at 10%, 5% and 1%, respectively.
4. Standard errors are adjusted for 30 clusters in province in columns (1)–(6).

tructure capital is $\partial Y/\partial B = \gamma_b Y/B$ and $Y/B = 2.254$ averaging over 1996–2015 for depreciate rates $\delta_b = \delta_k = 10\%$ in the sample, this elasticity indicates a return rate of 28.6%. This means that investment in public sectors is very productive and profitable. To examine the change of return over time, FD estimates using subsamples are also reported in columns (3) and (4), 0.144 and 0.088 for periods of 1996–2007 and 2008–2015, respectively. This implies rates of return to public infrastructure capital of $0.144 \times 2.394 = 34.5\%$ and $0.088 \times 2.043 = 18.0\%$, respectively.

However, due to the reverse causality discussed above, FD estimates could be upward or downward biased. To mitigate this issue, first, we use an alternative measure of public infrastructure capital based on NIFA, which is less likely affected by y. Column (5) of Table 2 displays the FD estimates using this new measure, labelled by FDnew. Consistent with the discussion above, after weakening the positive linkage from y to b (and k), the estimated elasticity of public infrastructure capital of γ_b becomes less significant and falls markedly to 0.037 from 0.127 in column (2), with a rate of return of $0.037 \times 3.707 = 13.7\%$. Such a big drop in estimated output elasticity of infrastructure suggests that an upward bias is more likely than a downward bias in the FD estimate in column (2), and that a positive productivity effect of public infrastructure capital could be driven in part by the positive feedback effect of output on public infrastructure. In the subsample estimates of columns (6) and (7) of Table 2, similar estimated elasticities γ_b and γ_k are shown.

We also use the lagged values of Δb_{it} (and Δk_{it}), instead of the current values, to reduce the feedback effect of y on b. The resulting FD estimates using the lagged values of Δb_{it} and Δk_{it}, labelled by FDlag, are reported in column (8) of Table 2. Completely different from FD estimate of γ_b in column (2), after mitigating reverse causality, the FDlag estimate of γ_b drops to 0.005 and insignificant. Though using the lagged value may weaken the direct impact of infrastructure on output, the sharp difference in estimated γ_b between columns (2) and (8) suggests that the big positive elasticity of public infrastructure capital in column (2) could be overestimated due to the positive feedback effect of output on public infrastructure. By contrast, the FDlag estimate

Table 4
Output elasticities: Robustness checks.

Dependent variable: Output per labor															
Independent variables:	A: Depreciation rates $\delta_b = 4\%$, $\delta_k = 10\%$					B: year-end employment					C: FE on Differenced data				
	FD (1)	FDnew (2)	FDlag (3)	FDIV1 (4)	FDIV2 (5)	FD (6)	FDnew (7)	FDlag (8)	FDIV1 (9)	FDIV2 (10)	FE (11)	FEnew (12)	FElag (13)	FE IV1 (14)	FE IV2 (15)
Infrastructure capital	0.182***	0.075**	−0.003	−0.089	−0.144	0.156***	0.047*	0.051	0.096	−0.242	0.167***	0.039*	−0.009	−0.227	0.228
per labor	(0.031)	(0.030)	(0.046)	(0.10)	(0.22)	(0.04)	(0.03)	(0.05)	(0.08)	(0.41)	(0.02)	(0.02)	(0.02)	(0.14)	(0.18)
Non-infrastructure	0.301***	0.211***	0.219***	0.326***	0.351***	0.357***	0.257***	0.175***	0.252***	0.399*	0.378***	0.238***	0.137***	0.245***	0.188***
capital per labor	(0.028)	(0.024)	(0.035)	(0.04)	(0.12)	(0.05)	(0.04)	(0.03)	(0.04)	(0.20)	(0.04)	(0.03)	(0.04)	(0.07)	(0.06)
Regions	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
Periods	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Overall R^2	0.74	0.61	0.45	0.63	0.60	0.69	0.55	0.40	0.68	0.43	0.72	0.60	0.43	0.35	0.69
No. of observations	569	569	539	509	509	569	569	539	509	509	569	569	539	509	509
Instruments				$\Delta b_{t-2}, \Delta k_{t-2}$	$\Delta nb_t, \Delta k_{t-2}$				$\Delta b_{t-2}, \Delta k_{t-2}$	$\Delta nb_t, \Delta k_{t-2}$				$\Delta b_{t-2}, \Delta k_{t-2}$	$\Delta nb_t, \Delta k_{t-2}$
1st-stage regression coefficient				0.360	0.274				0.397	0.193				0.202	0.210
1st-stage t-ratio				(7.14)	(3.81)				(8.47)	(2.70)				(4.08)	(2.42)

Notes.

1. Panel A: depreciation rates of 4% and 10% are used to construct the capital stocks. Definitions of FD, FDnew, FDlag, FDIV1 and FDIV2 remain as in Tables 2 and 3
2. Panel B: year-end employment is used to measure the labor force. Depreciate rates of 10% remain as in Tables 2 and 3
3. Panel C: FE, FEnew, FElag, FEIV1 and FEIV2 refer to fixed effects estimates using differenced data and those using newly increased fixed asset investment, lags of public infrastructure and private capital stocks, instruments of lagged values and neighboring public infrastructure, respectively.
4. Standard errors are reported in parentheses. The stars, *, ** and *** indicate the significance level at 10%, 5% and 1%, respectively.
5. Standard errors are adjusted for 30 clusters in province in columns (1)–(15).

Table 5
Output elasticities: Additional robustness checks.

Dependent variable: Output per labor											
Independent variables:	D: Alternative IV2	E: Broad Definition of Infrastrstructure					F: Subsample of Eastern Region				
	FD IV2	FD	FDnew	FDlag	FDIV1	FDIV2	FD	FDnew	FDlag	FDIV1	FDIV2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Infrastructure capital	0.077	0.140***	0.058**	0.03	−0.055	−0.160	0.107**	0.034	−0.021	−0.409	−0.125
per labor	(0.15)	(0.03)	(0.02)	(0.04)	(0.08)	(0.46)	(0.038)	(0.031)	(0.053)	(0.27)	(0.31)
Non-infrastructure	0.250***	0.306***	0.208***	0.201***	0.337***	0.412	0.321***	0.215***	0.261***	0.500***	0.363*
capital per labor	(0.08)	(0.03)	(0.02)	(0.04)	(0.05)	(0.33)	(0.033)	(0.027)	(0.033)	(0.12)	(0.17)
Regions	All	All	All	All	All	All	Eastern	Eastern	Easter	Eastern	Eastern
Periods	Yes	All	All	All	All	All	All	All	All	All	All
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.70	0.73	0.60	0.45	0.66	0.59	0.76	0.64	0.52	0.34	0.67
No. of observations	509	569	569	539	509	509	209	209	198	187	187
Instruments	$\Delta nb_t,\Delta k_{t-2}$				$\Delta b_{t-2},\Delta k_{t-2}$	$\Delta nb_t,\Delta k_{t-2}$				$\Delta b_{t-2},\Delta k_{t-2}$	$\Delta nb_t,\Delta k_{t-2}$
1st-stage regression coefficient	0.256				0.381	0.185				0.182	0.287
1st-stage t-ratio	(4.61)				(7.30)	(2.54)				(2.18)	(2.40)

Notes.

1. Panel D: an instrument based on a new measure of infrastructure investments in neighboring provinces, defined as their GDP competitors instead of their geographic neighbors.
2. Panel E: an alternative definition of infrastructure by including investments in industries related to management of water conservancy, environment, and public facilities.
3. Panel F: subsample of eastern region is used.
4. Definitions of FD, FDnew, FDlag, FDIV1 and FDIV2 remain as in Tables 2–4
5. Standard errors are reported in parentheses. The stars, *, ** and *** indicate the significance level at 10%, 5% and 1%, respectively.
6. Standard errors are adjusted for 30 clusters in province in columns (1)–(6). Robust standard errors are used in columns (7)–(11).

of non-infrastructure capital elasticity γ_k is still of a big magnitude of 0.215 and significant, though decreasing from 0.324 in column (2). To further confirm the effect of reverse causality on estimating γ_b, Column (9) gives FD estimates using the lagged value of Δb_{it} and current value of Δk_{it}. Same pattern remains as in column (8).

Table 3 reports IV estimates of elasticities using instruments of twice-lagged variables (FDIV1), neighboring public infrastructure (FDIV2) and the ages of provincial governors and party leaders (FDIV3), respectively. Non-infrastructure capital Δk_{it} is also considered as endogenous and instrumented by Δk_{it-2}. The estimates of public capital elasticity using the full sample are −0.095 and −0.098 in columns (1) and (4), respectively. Similar to FDnew and FDlag estimates Table 2, after dealing with the reverse causality between y and b (and k), the FD IV estimates of output elasticity public infrastructure drop to small negative numbers, and are no longer statistically significant from 0. The FD IV estimates of γ_b using external instruments of the ages of provincial governors alone and both ages of provincial governors and party leaders are 0.059 and 0.140 in columns (5) and (6), respectively. Both are positive and of a big magnitude, but statistically insignificant.[15] Columns (2)–(3) also give FDIV1 estimates using subsamples in the periods of 1996–2007 and 2008–2015.[16] The estimates of γ_b are small, negative, and insignificant.

Unlike γ_b, the corresponding estimates of γ_k in columns (1), (4) and (5) in Table 3, 0.332, 0.333 and 0.258, are still positive and significant, and are comparable with the FD estimates in Table 2.[17] Thus, the difference between γ_b and γ_k indicates the different roles that the public infrastructure and non-infrastructure capital play in the aggregate production function. Public infrastructure is more likely positively affected by the output than non-infrastructure capital.

Three robustness checks are reported in Table 4: using depreciate rates $\delta_b = 4\%$, $\delta_k = 10\%$ in panel A,[18] replacing calculated labor force with year-end employment reported by NBS in panel B, and running fixed effects estimation on differenced data instead of pooled OLS in panel C. In panels A and B, we report FD and 4 estimates using NIFA (FDnew), lagged variables (FDlag) and two internal instruments Δb_{it-2}, Δk_{it-2}(FDIV1) and Δb_{it} in neighboring provinces (FDIV2), corresponding to columns (5), (8) of Table 2 and columns (1), (4) of Table 3, respectively. In panel C, FE and FE estimates using NIFA (FEnew), lagged variables (FElag) and 2 sets of instruments (FEIV1, FEIV2) are presented in columns (11)–(15), respectively. Consistent with the message delivered by Tables 2 and 3, estimates of γ_b in columns (2)–(5), (7)–(10), (12)–(14) decrease substantially after reverse causality is taken into consideration. In column (15), using differenced data the fixed effects IV estimate of γ_b is 0.228 but insignificant. No robust pattern of a big positive and significant estimates of γ_b are found in various cases, sharply constrasted with the estimates of γ_k.

Table 5 shows the results of three additional robustness checks. First,

[15] The first-stage regression results of regressing instruments for Δb on exogenous variables in Eq. (5) are reported in the last three rows in Tables 3 and 4 For instruments of instruments of twice-lagged variables and neighboring public infrastructure, both are very informative. The magnitude of instrument of age of provincial governors (age1) is small but still statistically significant. Sargan test for overidentification is conducted in column (6) of Table 3. No evidence shows that instruments of age1 and age2 are invalid.

[16] The year of 2008 as the cutoff point is used because a 4 trillion Chinese Yuan fiscal stimulus package was introduced by the Chinese government to invest mainly in the infrastructure in its western provinces in 2008. This event could lead to different output elasticities of infrastructure before and after 2008.

[17] The mean value for the ratio Y/K is 0.624 during our sample period. Thus the output elasticities of non-infrastructure capital from Tables 2 and 3 indicate a rate of return around 20%. This number is close to the results reported by Bai and Zhang (2014).

[18] We also conduct robustness checks using other different depreciate rates, including combinations of i) $\delta_b = 5\%$, $\delta_k = 10\%$; ii) $\delta_b = 15\%$, $\delta_k = 15\%$; iii) $\delta_b = 10\%$, $\delta_k = 15\%$; iv) $\delta_b = 15\%$, $\delta_k = 10\%$. Main results remain.

panel D employs an alternative measure of infrastructure investments in neighboring provinces, defined as their GDP competitors instead of their geographic neighbors used in column (4) of Table 3.[19] The estimated output elasticity of infrastructure becomes 0.077 and statistically insignificant. Second, in Panel E we consider an alternative definition of infrastructure by including investments in industries related to management of water conservancy, environment, and public facilities, i.e., the fourth category of infrastructure investment considered in Shi and Huang (2014). As in Table 4, FD, FDnew, FDlag, FDIV1 and FDIV2 estimates are reported in columns (2)–(6). Third, considering China's geographic heterogeneity and different economic development across regions, we split the sample into 3 groups: eastern, central and western regions. Panel F presents 5 estimates as in panel E. As in Table 4, the same pattern emerges. Once the reverse causality between the output and infrastructure is mitigated, the estimates of γ_b decrease remarkably and become statistically insignificantly in most cases. This evidence suggests that the reverse causality may lead to an upward bias.

5. Conclusion

This paper is motivated by the question whether infrastructure investment contributes to productivity gains and economic growth in China. We address this issue in the framework of an aggregate production function, in which public infrastructure capital is modelled as a contributing factor of TFP, and a panel data set of 30 Chinese provinces during 1996–2015 is used to estimate the output elasticities of public infrastructure and non-infrastructure capital stocks. In such a framework, the main identification problem is the reverse causality between the output and public infrastructure investment, which could lead to an upward or downward bias.

In this empirical study, we proposed several different ways to mitigate the reverse causality. Unlike Shi and Huang (2014), we find that an upward bias dominates when estimating output elasticity of public infrastructure in China's context. After controlling for the reverse causality between the GDP growth and public investment, we find weak evidence of a big positive productivity effect of public infrastructure within the framework of an aggregate production function.

This, of course, does not deny the possibility that public infrastructure investment may play an important role in economic growth and development. As surveyed by Gramlich (1994), Shi and Huang (2014) and Calderon et al. (2015), there are other econometric issues that are not discussed in the short note. Instead, what we want to highlight here is the challenge of identifying the productivity effect of public infrastructure investment in the aggregate production function estimation framework. Dealing with reverse causality is of the first order importance, and it is difficult to find good external instruments due the nature of aggregate data. This difficulty suggests the unique value of using alternative identification strategies or data types, e.g., a disaggregation approach using firm-level data such as Fisher-Vanden et al. (2015); Li et al. (2017); and Wu et al. (2017).

[19] For example, the neighbors of Jiangsu, the ranked 2nd in 2016, are Guangdong and Shandong. The information on Chinese provinces GDP ranking 2016 is from Wikipedia: https://en.wikipedia.org/wiki/List_of_Chinese_administrative_divisions_by_GDP

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.econmod.2018.05.006.

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