On the Reverse Causality between Output and Infrastructure: the Case of China *

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This version: Dec 31, 2017

Abstract

China has been considered as such a successful example of enhancing economic growth by massive infrastructure investments in the past decades. A recent paper by Shi and Huang (2014) indicates a very big positive return of public infrastructure in China during 1995-2011 using China’s provincial-level data. 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 discuss the institutional background on why upward bias is more likely to dominate in the case of China. Using provincial-level data over 1996-2015 and within the framework of an aggregate production function estimation, no strong evidence is found on the productivity effect of public infrastructure. This finding highlights the necessity of using alternative identification strategies or data types.

JEL Classification: C23, E22, H54, O40, O50

Key Words: Infrastructure, Productivity, Chinese Economy

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*We would like to thank Zhao Chen, Shigeyuki Hamori, Shaoqing Huang, Hao Shi, Guang-zhen Sun, Yi-Chan Tsai, and the audiences at TED conference 2015, Fudan University, the 1st Annual International Conference on Applied Econometrics in Hawaii 2015, and University of Macau for their constructive comments and suggestions. Zhifeng Wang provided excellent research assistance. Financial support from the MOE AcRF Tier 1 Grant M4011642 is gratefully acknowledged. Division of Economics, School of Social Sciences, Nanyang Technological University. Address: 14 Nanyang Drive, Singapore, 637332. Emails: qfeng@ntu.edu.sg (Q. Feng), guiying.wu@ntu.edu.sg (G. Wu).
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 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

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1 See the World Bank website https://data.worldbank.org/indicator/NE.GDI.TOTL.ZS?locations=CN-TH-VN-IN
2 This rate is calculated using the data from the website of National Bureau of Statistics of China. Also see Figure 14.3 of Naughton (2007) for the ratios of physical infrastructure investment to GDP during 1981-2004.
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 Lighthart (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 countercyclic tool to boost economic growth during economic recession.

In a recent study, 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, Caves and Frazer (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%.

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. Unlike Shi and Huang (2014), 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, no strong 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, Mansur and Wang (2015); Li, Wu and Chen (2017); and Wu, Feng and Wang (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 dis-
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., $A = A_0B^{\gamma_b}$, where $A_0$ is the component of TFP that is unrelated to public infrastructure. Thus, the aggregate production function becomes

$$Y = A_0B^{\gamma_b}K^{\gamma_k}L^{\gamma_l}. \quad (1)$$

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

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

and

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

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. $\delta_b$ and $\delta_k$ are depreciation rates of $B$ and $K$, respectively.

Under the assumption of constant returns to scale (CRS),\(^3\) $\gamma_b + \gamma_k + \gamma_l = 1$, 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

$$y = \gamma_0 + \gamma_bb + \gamma_kk,$$

where $y = \log(Y/L)$, $b = \log(B/L)$, $k = \log(K/L)$ and $\gamma_0 = \log(A_0)$. In this equation, $\gamma_b$ and $\gamma_k$ are the output of elasticities of public infrastructure and non-infrastructure

\(^3\)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.
capital. The economic return of public infrastructure, or the marginal output of public infrastructure, can be measured as

\[ \frac{\partial Y}{\partial B} = \frac{\gamma_b Y}{B}. \]

To estimate the coefficients \( \gamma_b, \gamma_k \), a panel data model based on the aggregate production function above is used

\[ y_{it} = \gamma_0 + \gamma_b b_{it} + \gamma_k k_{it} + \mu_i + T_t + \varepsilon_{it}, \]  

(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. \( \mu_i \) 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. \( \varepsilon_{it} \) denotes idiosyncratic shocks or measurement error in output. To deal with the non-stationarity in macroeconomic variables, first-differencing equation (4) gives our estimating equation:

\[ \Delta y_{it} = \gamma_b \Delta b_{it} + \gamma_k \Delta k_{it} + \Delta T_t + \Delta \varepsilon_{it}. \]  

(5)

3 Dealing with reverse causality

When we write down equation (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 \( \gamma_b \) in (5) (i.e., the first-differenced (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 \( \gamma_b \) in (5) (i.e., the first-differenced (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 Roller and Waverman (2001) and Cadot, Roller and Stephan (2006). Another approach is to explore the heterogeneity of output effect from disaggregated data. A leading example is Fernald (1999). Recently, Calderon, Moral-Benito and Serven (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 $\Delta b_{it}$ and $\Delta \varepsilon_{it}$, where this correlation is dealt with by the proxy approach developed by Ackerberg, Caves and Frazer (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, Feng and Wang (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 $\mu_i$ in equation (4) and can be eliminated by first-differencing as in equation (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 $\Delta b_{it}$ and $\Delta \varepsilon_{it}$ in equation
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 to 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 $\Delta b_{it}$ and $\Delta \varepsilon_{it}$ in equation (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 cross-province variation 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 the equation (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 $b_i$ 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 zichang 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 zichang 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. 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.

We also make use of a measure of $b_{it}$ in the level equation (4) (or $\Delta b_{it}$ in the differenced equation (5)) that is less likely to be affected by $y_{it}$ (or $\Delta y_{it}$). A natural

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4NIFA 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.
candidate in the literature is the lagged value of \( b_{it} \) (or \( \Delta b_{it} \)). Different from \( b_{it} \) (or \( \Delta b_{it} \)), \( b_{it-1} \) (or \( \Delta b_{it-1} \)) is less likely to be affected by \( y_{it} \) (or \( \Delta y_{it} \)) 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 \( \gamma_b \). In this paper, three different sets of instruments are explored. First, as in Holtz-Eakin (1994), twice-lagged variables \( \Delta b_{it-2} \) and \( \Delta k_{it-2} \) are employed as internal instruments for \( \Delta b_{it} \) and \( \Delta k_{it} \) in equation (5). 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, Qian and Weingast, 2005; Wang, Zhang and Zhou, 2017). Under this scheme, local governments compete with each other on GDP growth, and their investment behavior could affect each other. Thus, \( \Delta b_{it} \) in neighboring regions (or provinces) can serve as an instrument for \( \Delta b_{it} \).

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. In this case, the ages of provincial governors and party leaders could be negatively correlated with public infrastructure investment.

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.

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5 \( \Delta b_{it-1} \) and \( \Delta k_{it-1} \) could be correlated with \( \Delta \varepsilon_{it} \). It is worth noting that this IV approach is different from using \( \Delta b_{it-1} \) and \( \Delta k_{it-1} \) as regressors in the FD regression above.

6 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.
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. I is defined as total investment minus G. Stock variables of B and K are constructed as in (2) and (3) using depreciation rates $\delta_b = \delta_k = 10\%$.

Table 1 reports the summary statistics for the variables used in the analysis. GDP, public infrastructure investment, non-infrastructure investment are deflated by the corresponding price indices. 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 $\gamma_b$ and $\gamma_k$ without dealing with reverse causality. Column (1) of Table 2 reports fixed-effects (FE) estimates of $\gamma_b$ and $\gamma_k$, which are 0.045 and 0.306, 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 0.117 and significant at 1% level. Considering that the return of public infrastructure capital is $\partial Y/\partial B = \gamma_b Y/B$ and $Y/B = 2.254$ averaging over 1996-2015 for depreciate rates $\delta_b = \delta_k = 10\%$

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7The definition of G here is consistent with the description of physical infrastructure in Figure 14.3 of Naughton (2007) for China, and the literature in general, e.g., Calderon, Moral-Benito and Serven (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.

8Clustered standard errors are reported in parenthesis below estimates, adjusted for 30 clusters in province.
in the sample, this elasticity indicates a return rate of 26.4%. 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), 0.137 and 0.070 for periods of 1996-2007 and 2008-2015, respectively. This implies rates of return to public infrastructure capital of \(0.137 \times 2.394 = 32.8\%\) and \(0.070 \times 2.043 = 14.3\%\), 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 \(\gamma_b\) becomes insignificant and falls markedly to 0.028 from 0.117 in column (2), with a rate of return of \(0.028 \times 3.707 = 10.4\%\). 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 in part driven 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 \(\gamma_b\) and \(\gamma_k\) are shown.

We also use the lagged values of \(\Delta b_{it}\) (and \(\Delta k_{it}\)), instead of the current values, to reduce the feedback effect of \(y\) on \(b\). The resulting FD estimates using the lagged values of \(\Delta b_{it}\) and \(\Delta k_{it}\), labelled by FDlag, are reported in column (8) of Table 2. Completely different from FD estimate of \(\gamma_b\) in column (2), after mitigating reverse causality, the FDlag estimate of \(\gamma_b\) drops to −0.004 and insignificant. Though using the lagged value may weaken the direct impact of infrastructure on output, the sharp difference in estimated \(\gamma_b\) 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 of non-infrastructure capital elasticity \(\gamma_k\) is still of a big magnitude of 0.221 and significant, though decreasing from 0.327 in column (2). To further confirm the effect of reverse causality on estimating \(\gamma_b\), Column (9) gives FD estimates using the lagged value of \(\Delta b_{it}\) and current value of \(\Delta k_{it}\). Same pattern remains as in column (8).

Table 3 reports IV estimates of elasticities using instruments of twice-lagged vari-
ables (FDIV1), neighboring public infrastructure (FDIV2) and the ages of provincial governors and party leaders (FDIV3), respectively. non-infrastructure capital $\Delta k_{it}$ is also considered as endogenous and instrumented by $\Delta k_{it-2}$. The estimates of public capital elasticity using the full sample are $-0.115$ and $-0.129$ 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 exception is that the FD IV estimate of $\gamma_b$ using external instruments of the ages of provincial governors and party leaders is 0.134, but insignificant, in column (5). Columns (2)-(3) also give FDIV1 estimates using subsamples in the periods of 1996-2007 and 2008-2015. The estimates of $\gamma_b$ are small and negative, and both are insignificant.

Unlike $\gamma_b$, the respective estimates of $\gamma_k$ in columns (1), (4) and (5) in Table 3, 0.343, 0.350 and 0.222, are still positive and significant, and are comparable with the FD estimates in Table 2.\(^9\) Thus, the difference between $\gamma_b$ and $\gamma_k$ 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 $\delta_b = \delta_k = 15\%$ in panel A, 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 each panel, we report 4 estimates using NIFA, lagged variables and two internal instruments $\Delta b_{it-2}$ and $\Delta b_{it}$ in neighboring provinces, corresponding to columns (5), (8) of Table 2 and columns (1), (4) of Table 3, respectively. Consistent with the message delivered by Tables 2 and 3, no big positive and significant estimates of $\gamma_b$ are found in various cases, sharply contrasted with the estimates of $\gamma_k$.\(^{10}\)

\(^9\)The mean value for the ratio $Y/K$ is 0.611 during our sample period. Thus the output elasticities of non-infrastructure capital from Table 2 and 3 indicate a rate of return around 20%. This number is close to the results reported by Bai and Zhang (2014).

\(^{10}\)As in Tables 2 and 3, the FD estimates of $\gamma_b$ and $\gamma_k$ in Panel A and Panel B, and FE estimates of of $\gamma_b$ and $\gamma_k$ in Panel C, which are not reported here, are consistently great than 0.100 and 0.300, significantly at the 1% significance level. We also conduct robustness checks using other different depreciate rates and the same definition of infrastructure investment as Shi and Huang (2014), and same results remain.
5 Conclusion

This paper aims to answer the question whether infrastructure investment contributes to productivity gains and long-run 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, there is no strong evidence of a big positive productivity effect of public infrastructure.

This, of course, does not deny the possibility that public infrastructure investment may play an important role in economic growth and development. Instead, what we want to highlight in this note 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, Mansur and Wang (2015); Li, Wu and Chen (2017); and Wu, Feng and Wang (2017).
References


<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. D.</th>
<th>Form in regression</th>
<th>Data sources</th>
</tr>
</thead>
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<td>$y$</td>
<td>real output per labor</td>
<td>10,000 yuan</td>
<td>2.38</td>
<td>1.79</td>
<td>log</td>
<td>China NBS Website</td>
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<tr>
<td>$b$</td>
<td>real infrastructure capital per labor</td>
<td>10,000 yuan</td>
<td>1.17</td>
<td>0.92</td>
<td>log</td>
<td>China NBS Website</td>
</tr>
<tr>
<td>$k$</td>
<td>real non-infrastructure capital per labor</td>
<td>10,000 yuan</td>
<td>5.21</td>
<td>5.05</td>
<td>log</td>
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<tr>
<td>newb</td>
<td>real infrastructure capital per labor based on NIFA</td>
<td>10,000 yuan</td>
<td>0.69</td>
<td>0.51</td>
<td>log</td>
<td>China NBS Website</td>
</tr>
<tr>
<td>nb</td>
<td>real infrastructure capital per labor in neighboring provinces</td>
<td>10,000 yuan</td>
<td>1.04</td>
<td>0.72</td>
<td>log</td>
<td>authors' calculation</td>
</tr>
<tr>
<td>$G$</td>
<td>infrastructure investment flow</td>
<td>100 million yuan</td>
<td>674</td>
<td>624</td>
<td></td>
<td>China NBS Website</td>
</tr>
<tr>
<td>$L$</td>
<td>number of labor force</td>
<td>10,000</td>
<td>3080</td>
<td>1847</td>
<td>level</td>
<td>China NBS Website</td>
</tr>
<tr>
<td>$age_1$</td>
<td>age of provincial governor</td>
<td></td>
<td>57.9</td>
<td>4.0</td>
<td>level</td>
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<tr>
<td>$age_2$</td>
<td>age of provincial party leader</td>
<td></td>
<td>59.7</td>
<td>4.1</td>
<td>level</td>
<td>Wikipedia</td>
</tr>
</tbody>
</table>

Notes:
1. All variables are measured in provincial level.
2. Units and summary statistics of all variables are reported before taking log.
### Table 2 Output Elasticities: Fixed-Effects and First-Differenced Estimates

<table>
<thead>
<tr>
<th>Independent variables:</th>
<th>FE (1)</th>
<th>FD (2)</th>
<th>FDlag (9)</th>
<th>FDnew (5)</th>
<th>FDnew (6)</th>
<th>FDnew (7)</th>
<th>FDlag (9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infrastructure capital per labor</td>
<td>0.045</td>
<td>0.117***</td>
<td>0.137***</td>
<td>0.070**</td>
<td>0.028</td>
<td>0.027</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.025)</td>
<td>(0.032)</td>
<td>(0.037)</td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Non-infrastructure capital per labor</td>
<td>0.306***</td>
<td>0.327***</td>
<td>0.336***</td>
<td>0.327***</td>
<td>0.233***</td>
<td>0.251***</td>
<td>0.219***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.028)</td>
<td>(0.040)</td>
<td>(0.026)</td>
<td>(0.024)</td>
<td>(0.031)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Year effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Overall $R^2$</td>
<td>0.83</td>
<td>0.72</td>
<td>0.75</td>
<td>0.67</td>
<td>0.60</td>
<td>0.63</td>
<td>0.54</td>
</tr>
<tr>
<td>No. of observations</td>
<td>599</td>
<td>569</td>
<td>329</td>
<td>240</td>
<td>569</td>
<td>329</td>
<td>240</td>
</tr>
</tbody>
</table>

**Notes:**
1. FE and FD in columns (1)-(4) denote fixed-effects regression and first-difference regression, respectively.
2. FDnew in columns (5)-(9) 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

<table>
<thead>
<tr>
<th>Independent variables:</th>
<th>FD IV1</th>
<th>FD IV2</th>
<th>FD IV3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infrastructure capital per labor</td>
<td>-0.115 (0.10)</td>
<td>-0.064 (0.15)</td>
<td>-0.078 (0.10)</td>
</tr>
<tr>
<td>Non-infrastructure capital per labor</td>
<td>0.343*** (0.05)</td>
<td>0.214*** (0.08)</td>
<td>0.385*** (0.05)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Periods</th>
<th>All</th>
<th>1996-2007</th>
<th>2008-2015</th>
<th>All</th>
<th>All</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Year effects</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Overall $R^2$</th>
<th>0.62</th>
<th>0.59</th>
<th>0.63</th>
<th>0.60</th>
<th>0.71</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of observations</td>
<td>509</td>
<td>269</td>
<td>240</td>
<td>509</td>
<td>509</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instruments</th>
<th>$\Delta b_{t-2}$, $\Delta k_{t-2}$</th>
<th>$\Delta n b_{t-2}$, $\Delta k_{t-2}$</th>
<th>age1, age2, $\Delta k_{t-2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st-stage regression</td>
<td>0.328 (6.63)</td>
<td>0.351 (4.78)</td>
<td>0.330 (3.55)</td>
</tr>
<tr>
<td>1st-stage t-ratio</td>
<td>(5.04)</td>
<td>(4.78)</td>
<td>(5.04)</td>
</tr>
</tbody>
</table>

**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)-(5).
<table>
<thead>
<tr>
<th>Independent variables:</th>
<th>A: Depreciation rates $\delta_b=\delta_k=15%$</th>
<th>B: year-end employment</th>
<th>C: FE on Differenced data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infrastructure capital per labor</td>
<td>0.018 (0.02)</td>
<td>0.038 (0.03)</td>
<td>0.030 (0.02)</td>
</tr>
<tr>
<td></td>
<td>0.003 (0.03)</td>
<td>0.045 (0.05)</td>
<td>-0.021 (0.02)</td>
</tr>
<tr>
<td></td>
<td>-0.128 (0.10)</td>
<td>0.086 (0.09)</td>
<td>-0.243* (0.14)</td>
</tr>
<tr>
<td></td>
<td>-0.102 (0.18)</td>
<td>-0.296 (0.47)</td>
<td>0.227 (0.18)</td>
</tr>
<tr>
<td>Non-infrastructure capital per labor</td>
<td>0.207*** (0.02)</td>
<td>0.262*** (0.04)</td>
<td>0.245*** (0.03)</td>
</tr>
<tr>
<td></td>
<td>0.204*** (0.03)</td>
<td>0.178*** (0.03)</td>
<td>0.111*** (0.03)</td>
</tr>
<tr>
<td></td>
<td>0.340*** (0.05)</td>
<td>0.255*** (0.04)</td>
<td>0.261*** (0.08)</td>
</tr>
<tr>
<td></td>
<td>0.327*** (0.11)</td>
<td>0.427* (0.23)</td>
<td>0.192*** (0.06)</td>
</tr>
<tr>
<td>Regions</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Periods</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Year effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Overall $R^2$</td>
<td>0.58</td>
<td>0.55</td>
<td>0.60</td>
</tr>
<tr>
<td>No. of observations</td>
<td>569</td>
<td>569</td>
<td>569</td>
</tr>
<tr>
<td>Instruments</td>
<td>$\Delta b_{t-2}$</td>
<td>$\Delta nb_t$</td>
<td>$\Delta b_{t-2}$</td>
</tr>
<tr>
<td>1st-stage regression</td>
<td>0.297</td>
<td>0.297</td>
<td>0.203</td>
</tr>
<tr>
<td>1st-stage t-ratio</td>
<td>(6.15)</td>
<td>(8.21)</td>
<td>(4.03)</td>
</tr>
</tbody>
</table>

Notes:
1. Panel A: depreciation rates of 15% are used to construct the capital stocks. Definitions of 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 1-3.
3. Panel C: FEon Differenced data using newly increased fixed asset investment, lags of public infrastructure and private capital stocks, instruments of lagged values and neighboring public infrastructure, respectively.
4. In columns (3)-(4), (7)-(8), (11)-(12), non-infrastructure capital is assumed endogenous and its lagged value is used as its instruments as in Table 3.
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)-(12).