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

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A B S T R A C T

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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[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., $A = A_0B^{\gamma_b}$, where A_0 is the component of TFP that is unrelated to public infrastructure. Thus, the aggregate production function becomes

$$Y = A_0B^{\gamma_b}K^{\gamma_k}L^{\gamma_l}. \tag{1}$$

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.