A Structural Estimation on the Return to Public Infrastructure Investment in China*

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Abstract

The productivity effect of public infrastructure investment is controversial in the traditional literature using aggregate production function estimation, mainly due to reverse causality. This paper develops a new approach, using a structural model of endogenous productivity in a firm-level production function, and matching Chinese firm-level production data with province-level infrastructure data. The estimated rates of return are about 6% averaged from 1999 to 2007. The returns triple if national-level spillover effects are taken into account. Controlling the demand effect of public expenditure leads to lower but still positive returns. Firm-level evidences are consistent with a mechanism in which public infrastructure investment facilitates resource reallocation from less to more productive firms.

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Key Words: Public Infrastructure Investment, Endogenous Productivity, Demand Effect, Resource Reallocation

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1 Introduction

The effect of public infrastructure investment[1] on economic growth and development has been a subject of much controversy. On one hand, infrastructure investment has often been advocated as a precursor to economic development by many authorities and international institutions. The idea that public investment will boost economic growth becomes even more appealing when the global economy faces severe demand constraints and high unemployment. On the other hand, there is still a lack of convincing evidence that infrastructure investment in general does lead to a higher output and income in the long run (Warner, 2014). When the investment is financed by public debt, concerns on investment efficiency and financial stability, especially in China in recent years, often appear in academic papers and media reports (Ansar et al., 2016).

This paper investigates three questions.[2] First, what is the average rate of return of public infrastructure investment? A well-estimated overall return is at the centre of many policy debates. For example, if the investment earns a high enough return, it is actually possible to reduce debt burdens of future generations via debt-financed public investment.[3] The research question of estimating the return of public infrastructure investment differs from existing studies on the causal effects of a specific infrastructure investment, such as electricity, roads and railways, on a specific economic outcome, such as output, employment and trade. It focuses on the aggregate effect of general infrastructure thus requires a different model design and identification strategy.

Second, if public infrastructure investment does raise output and income, is it simply due to the demand effect of fiscal expansions or does it indeed enhance productivity of the supply side? Productivity gains are fundamental to long-term growth, because they typically translate into higher incomes, in turn boosting demand. The danger lies in debt-fueled investment that shifts future demand to the present, without stimulating productivity growth.[4] Meanwhile, despite the frequent use of public infrastructure investment as a form of fiscal stimulus, there is also little known about its short-run or

[1] Infrastructure investment, public investment and public infrastructure investment have often been used interchangeably in the literature, although their exact definitions are not always the same. This paper adopts the terminology "public infrastructure investment" to refer to those investment expenditures that are mainly financed by the government and have the nature of a public good.

[2] These questions are closely related with a poll on public infrastructure investment conducted by the Initiative on Global Markets Forum of the Booth Business School at the University of Chicago in 2014: http://www.igmchicago.org/surveys/economic-stimulus-revisited.

[3] Why public investment really is a free lunch? by Lawrence H. Summers on 6 October 2014 at *Financial Times*.

[4] Why public investment? by Michael Spence on 20 February 2015 at *Project Syndicate*.

immediate effectiveness. For many macroeconomists and policymakers the key issue is whether this form of spending quickly translates into higher output and economic activities or it affects the economy only slowly over time. [5]

Finally, if public infrastructure investment indeed promotes aggregate productivity in the long run, what are the underlying mechanisms for such investment to take effect? Understanding to this question is vital to the evaluation of existing projects, and to the planning of large scale infrastructure policies in the future.

To study whether public infrastructure investment enhances the output of the economy at the aggregate level, the traditional literature has mainly focused on cross-country or cross-state time series evidences.[6] Using an aggregate production function including public capital as an additional input, the average rate of return to the economy can be inferred by estimating the average relationship between public capital and GDP. In a seminal work, Aschauer (1989) estimates an output elasticity with respect to public capital to be from 0.38 to 0.56, which implies a rate of return more than 100% in the U.S. during 1949 to 1985. However, this finding has been extensively re-examined by many subsequent studies. In the survey of Bom and Ligthart (2014), they find remarkably little consensus has emerged in the literature. The estimated output elasticity varies widely, from -1.70 to 2.04. In between these extremes, a non-negligible share of the reported estimates of elasticity is statistically not different from zero. As pointed out by Banerjee et al. (2012), finding credible ways to estimate or even bound the social returns remains a very important next step in this research agenda.

The dispersed empirical findings in the existing literature could be the consequence of several methodological challenges, in particular, the reverse causality between output and infrastructure. Higher GDP may mean greater demand for the services provided by public infrastructure; higher GDP may also mean more income for expenditures on public infrastructure. The literature has tried various ways to deal with the reverse causality. The first candidate is the combination of disaggregated and aggregated data. Fernald (1999) explores the cross-industry variation in the productivity effect of infrastructure, by combining industry-level production data with national-level road stock data. He finds that when growth in roads changes, productivity growth

[5] Leduc and Wilson (2014) review the empirical findings on this question in the literature for the U.S. and other developed economies.

[6] For a specific public infrastructure investment project, for example, building an airport, it is straightforward to calculate its financial return, if the cash flows of the project are well recorded. However, such return may not fully reflect the social returns of the project if there are benefits and costs beyond the cash flows.

changes disproportionately in U.S. industries with more vehicles. The second option is the simultaneous-equation approach. For example, Röller and Waverman (2001) specify a micro-model of supply and demand for telecommunications investment, which is jointly estimated with an aggregate production function. However, their approach relies on detailed price information of telephone service, which is usually unavailable in other applications. The third methodology is to identify the effect of interest only from the exogenous movements in government spending, using institutional, political and bureaucratic designs, such as Blanchard and Perotti (2002) and Leduc and Wilson (2013). More recently, a growing literature that studies the effects of transport infrastructure on economic outcomes, has adopted various instrumental variables to control the endogenous placement of the transport infrastructure.[7] As commented by Redding and Turner (2015), these strategies are probably the best approaches currently available for estimating the causal effects of transport infrastructure. However, it is difficult to find valid instruments in the aggregate production function framework when estimating the return of general infrastructure.

This paper proposes a structural approach to estimate the effect of public infrastructure investment on productivity, and applies the approach to a panel of Chinese manufacturing firms matched with province-level infrastructure. Reverse causality could arise for two possible reasons under our context. First, firms choose their location. More productive firms are likely to self-select into more productive provinces, which in turn tend to have more infrastructure investment. Second, allocation of infrastructure might not be random. Instead, it could depend on the aggregate productivity of a province, the jurisdiction level at which the decision of most infrastructure investment is made in China. If public infrastructure investment depends on aggregate productivity, then firm-level productivity affects infrastructure investment by affecting the aggregate productivity.

To address these concerns, we first adopt an endogenous productivity process. It decomposes the actual firm-level productivity into the expected productivity and productivity shocks, and models the effect of infrastructure on the expected firm-level productivity through a first-order Markov process. As the endogenous productivity process allows for an arbitrary correlation between the lagged firm-level productivity and province-level infrastructure, it controls the reverse causality arising from the self-

[7] Some leading examples include, the planned route IV (Baum-Snow, 2007; Michaels et al., 2012; Donaldson, 2018), the historical route IV (Duranton and Turner, 2012; Baum-Snow et al., 2017; Hsu and Zhang, 2014) and the straight-line IV (Banerjee et al. 2012; Ghani et al., 2016; Faber, 2014).

selection mechanism. Second, to further control for the reverse causality arising from the correlation between the productivity shocks and infrastructure, we decompose the productivity shocks into a province-specific aggregate shock and a firm-specific idiosyncratic shock. After netting out the province-specific aggregate shock, the firm-specific idiosyncratic shock is assumed to be orthogonal to the province-level infrastructure investment, which provides the key identification condition. Thus, our identification strategy is based on an important feature that a province will not immediately adjust its infrastructure in light of a productivity shock to an individual firm, if this shock is uncorrelated with the shocks of all other firms in the province.

Besides mitigating the reverse causality, there are also two unique advantages of using firm-level data to address the second and third research questions. First, inspired by De Loecker (2011), we model the firm-specific demand shifter as a function of public infrastructure investment. This allows us to distinguish the revenue-based total factor productivity (TFPR) from the quantity-based total factor productivity (TFPQ). The effect estimated from a TFPR model includes both the demand effect and the productivity effect of public infrastructure, while the effect estimated from a TFPQ model only reflects the effect of public infrastructure on quantity productivity. Second, thanks to the flexibility of the endogenous productivity process, we allow an interaction term between firm-level productivity and province-level infrastructure in the process. The substantial heterogeneity in the estimated effects across firms allows us to investigate the underlying mechanism on why public infrastructure investment is productive at the aggregate level.

Here are the main empirical findings of this paper. First, during 1999 to 2007 there is a 6.2% annual real rate of return of public infrastructure investment in the TFPR model. Second, when we consider the spillover effects of public infrastructure investment across regions, in a specification where public infrastructure investment is allowed to have national-level spillover effects on firms locating outside of the province, the estimated rate of return triples. This implies that public infrastructure investment does have a positive causal effect on aggregate output. It offers a decent rate of return, especially when interregional spillover effects are taken into account.[8] Third, the returns estimated from the TFPQ models are 15% to 40% smaller than the corresponding TFPR models. This suggests a sizeable positive contribution of infrastructure on output is indeed via the demand effect. It thus confirms both the short-run stim-

[8] One way to evaluate these rates of return is to consider a common benchmark, the long-run annual real rate of return to capital investment in the U.S., which is about 4% to 6%.

ulus effect and the long-run productivity effect of public infrastructure. Finally, we examine how public infrastructure investment affects the exit probability and market share of firms with different productivity levels. The evidences are consistent with the hypothesis that public infrastructure investment plays a role as a catalyst for resource reallocation from less to more productive firms.

Our paper is closely related and complements to several strands of literature. First, the traditional literature on aggregate production function estimation provides a natural framework to estimate the rate of return. Our study shares the same core rationale but addresses the reverse causality problem in addition to a set of other identification issues, using a model of endogenous productivity process in a firm-level production function. Second, our key identification strategy shares the insight of Fernald (1999). Intuitively, by combining aggregate and disaggregate data, the endogeneity problem due to reverse causality can be characterized as an omitted aggregate productivity shock. By using a proxy for this omitted aggregate productivity shock, we thus mitigate the reverse causality. However, our fundamental source of identification is different. While the identification in Fernald (1999) lies in the variation of vehicle-intensity across different industries, our identification comes from the variation of infrastructure investment across different provinces, and from the variation of lagged productivity across different firms within the same provinces. Third, in the empirical literature on transport infrastructure, when investigating the mechanism of infrastructure, the state-of-the-art work, like Faber (2014), Ghani et al. (2016) and Baum-Snow et al. (2017), quantifies heterogeneity in effects for districts or industries. Our study utilizes the heterogeneity across firms and provides solid empirical evidence on how infrastructure investment affects firm performance along both the extensive and the intensive margins. This paper thus further contributes to the infrastructure literature by filling in a gap from microeconomic foundation to macroeconomic implications. Fourth, some recent literature, such as Holl (2016) and Li et al. (2017), also uses firm-level data to study the productivity effect of infrastructure. The estimated effects in the existing work, however, are under the standard exogenous productivity process assumption.[9] In this paper, we allow the infrastructure to impact the evolution of productivity and estimate the productivity process along with the production function itself. This endogenous productivity approach follows Aw et al. (2011), De Loecker (2013), and

[9] That is first to obtain an estimate of productivity without allowing infrastructure to affect productivity, and only in a second step to project the recovered productivity estimates against measure of infrastructure. See De Loecker (2011, 2013) for a discussion on this so-called two-stage approach.

Doraszelski and Jaumandreu (2013), which model and estimate the productivity effects of R&D investment and learning-by-exporting. While the R&D investment and exporting decisions are both at the firm-level, the infrastructure investment decision is made at the province level. Thus our paper extends the endogenous productivity approach to investigate the productivity gains from changes in firm's operating environment due to factors at a more aggregated level. Finally, our investigation on the mechanism highlights the importance of selection and market reallocation to aggregate productivity gains, a theme that has been emphasized by recent literature using firm-level data, such as Alfaro and Chen (2018) among many others. This paper therefore contributes to our understanding on the nature of aggregate productivity from the perspective of public infrastructure.

The rest of the paper is organized as follows. Section 2 describes the data and introduces the institutional background. Section 3 explains how to estimate the return of public infrastructure using our novel approach, after discussing the identification issues in the traditional literature. Section 4 distinguishes the productivity effect from the demand effect. The spillover effect is examined in Section 5. Section 6 presents evidences consistent with a mechanism of resource reallocation promoted by public infrastructure. Section 7 includes a set of specification tests and robustness checks. Finally, Section 8 summarizes the findings and discusses the limitations.

2 Data and Institutional Background

2.1 Firm-Level Production Data

The firm-level data come from the Annual Survey of Industrial Firms conducted by China's National Bureau of Statistics, covering years from 1998 to 2007. The data have been widely used in researches regarding the productivity of Chinese manufacturing firms, such as Song and Wu (2015) and Chen et al. (2018), among many others. The survey contains information on firm characteristics, output and input, and balance sheet variables, for all state-owned firms and non-state-owned firms with sales revenue above 5 million Chinese Yuan. In total these firms produce 80% value-added of China's industrial sector. Brandt et al. (2012) provide an excellent introduction and user manual to this dataset. We match the annual data into a panel and construct the real capital stock by the perpetuity inventory method strictly following their procedures. Both the output and input data are deflated using the 2-digit industry-wide price indices, which are aggregated over the 4-digit benchmark price indices constructed by Brandt et al. (2012).

<Insert Table 1 here>

Same as other literature using this dataset, our production function estimation focuses on the 29 industries in the manufacturing sector. Table 1 lists the industrial code and definition for these industries. Average annual number of observations for the corresponding industry is reported in column (1). On average there are more than 7,000 firms for each industry in every year. Column (2) reports the output deflators for each industry that have been employed to deflate the sales revenue data. Most industries have a very moderate ten-year deflator, which suggests this is a period of little inflation, consistent with the stylized fact on Chinese macroeconomy. Column (3) lists the median values of the markup by industry, where the markup is measured as the sales revenue to the total production cost.[10] Despite some variation across industries, on average the markup is 1.15 for the Chinese manufacturing sector. Column (4) presents the median values of the real annual growth rates of labor productivity by industry. Over our sample period the manufacturing sector has experienced a 6.9% annual growth in labor productivity.[11] The central theme of this paper is to investigate whether public infrastructure investment has a positive effect on productivity growth, and if so how large is the magnitude and through which mechanism.

2.2 Province-Level Infrastructure Data

The China Statistics Yearbooks and the China Fixed Investment Statistical Yearbooks report total investment in fixed assets by industry and by province. According to Aschauer (1989), the core infrastructure has the highest explanatory power for productivity, where the core infrastructure usually refers to highways, mass transit, airports, electrical and gas facilities, water and sewers in the traditional literature. The more recent literature, such as Czernich et al. (2011) and Commander et al. (2010),

[10] Using this dataset, the markups estimated following De Loecker and Warzynski (2012) and proxied by sales revenue to total production cost have very similar distribution. See Hsu et al. (2017) for a comparison.

[11] The industries 25 petroleum processing and coking and 33 smelting and pressing of nonferrous metals have witnessed much smaller growth rates. One possible reason is the great output price variation in these two industries over the sample period. As reported in column (2), while the average output deflator of the other 27 industries in 2007 is only around 109, the output prices of these two industries have doubled over the decade. In the following analyses, we thus drop the industries 25 and 33, to rule out the possible contamination from high inflation and large price volatility.

also finds the productivity effect of communication infrastructure in both developed and developing economies. Based on the data availability, in this paper we define infrastructure investment as total investment in fixed assets in the industries of (1) production and supply of electricity, gas and water; (2) transport, storage and post; and (3) information transmission, computer services and software. [12]

There are several implications under our definition of infrastructure that worth further discussion. First, we do not include those investment in urban environment as part of our infrastructure. This is because the focus of this paper is the productivity effect of infrastructure on firm production, although we recognize that direct, non-pecuniary, household benefits are a second avenue by which infrastructure may affect welfare. Second, we combine these three different types of infrastructure and ask their productivity effect as a whole package of public goods. This complements to a large literature listed in Section 6 which only studies the effect of one type of infrastructure. Third, we measure the infrastructure in terms of monetary value instead of physical units. This is driven by the fact that we have combined different types of infrastructure with different physical units together. This also implies that we only measure the quantity of infrastructure investment but are not able to observe the quality. However, the upside of using a monetary measure is to impose fewer assumptions or require less information in calculating the rate of return of infrastructure investment, the central theme of our research agenda.

Table 2 provides the overall pattern of the infrastructure investment in China from 1998 to 2007. The data are deflated by the price indices of investment in fixed assets by province and then summed up from province level to national level. According to Table 2, China's infrastructure investment has been steadily increasing during this period with a 11.9% average real annual growth rate. Although the absolute volume of investment substantially increased since year 2003,[13] the ratios of such investment to GDP have been rather stable across the decade, with an average value of 8.9%. Given

[12] Huang and Shi (2014) provide a comprehensive survey on the stylized facts of infrastructure investment in China. As argued by Feng and Wu (2018), this measure of infrastructure investment is also consistent with the description of physical infrastructure in Figure 14.3 of Naughton (2007) for China, and with the literature in general, e.g., Calderon et al. (2015). It is worth noting that infrastructure is not necessarily and exclusively funded by the government. The investments in sectors that may have spillover or network externalities are characterized as infrastructure, which include information transmission, computer services and software.

[13] There are two possible reasons to the sudden increase in infrastructure investment in year 2003. One is the substantial GDP growth since 2003 caused an increase in both the demand and the supply of infrastructure investment. Another explanation lies in a change in the statistical criteria on infrastructure investment. Before 2003, categories (2) and (3) were combined together as investment in transport, storage, post and telecommunication service, which were divided separately since 2003.

the growth and level documented in Table 2, understanding the efficiency of China's infrastructure investment is an important and pertinent research topic.

<Insert Table 2 here>

Table 3 describes the cross sectional pattern of infrastructure investment among the 30 provinces. The data are at the province level and averaged from 1998 to 2007. Values of three variables are listed in column (1) to (3) for each province: volume of infrastructure investment, its real annual growth rate and its ratio to province GDP. The averages and standard deviations of these variables are reported at the bottom of the table. According to Table 3, while our sample period witnesses a heavy investment in infrastructure at the national level, there is also substantial variation across provinces in infrastructure expenditure. For example, the province average volume of infrastructure investment is about 40 billion per year. Guangdong, a large and rich province, has invested more than 100 billion on average every year, while the number in Ningxia, a small and poor province, is less than 8 billion. Such variation provides an important though not exclusive source of identification in this paper.

<Insert Table 3 here>

2.3 Institutional Background

Bai and Qian (2010) provide a useful institutional background on China's infrastructure development, with a special emphasis on investment incentives.[14] Two stylized facts are most relevant for our identification strategy. First, most infrastructure investment are made by state-owned or state-controlled enterprises with funds from both the central government and the local governments. This is evident from Table A1 in the Appendix, which lists investment values and percentages by jurisdiction of management and by registration status. For example, across 2004 to 2006 and across three types of infrastructure – production and supply of power, road transport and railways, 90.4% of the investment is made by state enterprises, and the central and local governments contribute 42.7% and 57.3% of the funds, respectively.

Table A2 delivers a similar message by source of funds from 1998 to 2007. The self-raised funds by the local governments are the most important component and account for 50% of total infrastructure expenditure. Such funds include extra-budgetary

[14] This is in contrast to the institutional background of the U.S., for which Leduc and Wilson (2017) discuss the relationship between the federal and state governments and the investment incentives of the state governments.

funds for investment from central government ministries, local governments, as well as self-raised funds of enterprises and institutions. The 30% domestic loans follow behind, which refer to borrowing from banks and non-bank institutions backed by government guarantees, loans appropriated by higher responsible authorities, special loans by government and loans arranged by local government from special funds. A 10% of the funds are directly from state budget, which include capital construction fund from the budget of the central government, development fund for less developed areas, as well as local budgetary fund transferred from the central budget.

Second, among various jurisdiction levels the provincial government plays a key role in infrastructure investment decision. Take highways as an example. Based on numbers in 2005, 42% of the total spending on road development was funded by domestic and international bank loans backed by future toll revenues; 28% was funded directly by provincial government sources such as revenues from the annual road maintenance fees charged to vehicle owners (Qin, 2016). Among the 12 publicly listed expressway companies, 9 of them are controlled by a holding company wholly owned by a provincial government and 2 of them are jointly controlled by several provincial governments. To invest in a highway, the investors have to get project approval from a provincial government, follow the toll regulations set by a provincial government, negotiate with the Department of Finance of the province on tax and land concession, and get guarantees for bank loans and approvals for private placement or IPOs from a provincial government (Bai and Qian, 2010).

In the case of railway, there are three types of railway system in China. The first type is the urban mass transit railways, which is constructed mainly by city or metropolitan governments. The second type is the national high-speed railways, which is planned and led by the Ministry of Railways (MOR). The regional intercity rail system is the third type. It connects the nine mega-city regions that generate 70% of China's GDP. The Province-MOR Agreement is the most important financing scheme for the regional intercity rail system. The agreement defines the provincial share of the project capital in cash, which usually varies from 30% to 50%. Under such an agreement, the China Railway Investment Co., which is a subsidiary of the MOR, and the similar subsidiaries under the provincial governments, function as financial arms to issue bonds or borrow bank loans for railway development. Redemption and interest are guaranteed by the MOR or provincial governments (Wang et al., 2012).

There are several hypotheses on why the Chinese governments have a strong incentive in infrastructure investment. According to Démurger (2014), the rationale for the central government is twofold. First, infrastructure development is necessary to support the rapid economic growth of the country that fuels an ever-increasing demand for infrastructure services. Second, infrastructure development is needed to fight worsening regional inequality by promoting the catch-up of lagging inland provinces with coastal provinces. Two leading examples include the Western Development Strategy since 2000 and the Revitalization of the Northeast Strategy since 2004. The incentives for the local governments are more controversial. On one hand, public infrastructure investment has often been criticized as the hotbed of tunneling, bribery and corruption, from which government officials draw substantial personal gains.[15] On the other hand, a leading view, such as Li and Zhou (2005), Zhang et al. (2007) and Xu (2011) among many others, argues that 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.

3 Estimating Return of Public Infrastructure Investment

Before presenting our firm-level production function approach, we first discuss the identification challenges, had we used province-level aggregate data as in the traditional literature to estimate the return of infrastructure. The comparison illustrates first, how the approach proposed in this paper is connected with the traditional approach; and second, how the two important elements in our approach – an endogenous productivity process and the combination of aggregate and disaggregate data, are designed to address these identification challenges, in particular, the problem of reverse causality.

3.1 The Traditional Approach

Starting with Aschauer (1989), the traditional literature has assumed that the services provided by the public infrastructure capital contribute to the total factor productivity.

[15] "For example, since 1997, twenty director generals or deputy director generals of various provincial departments of transport have been convicted of bribery. In the case of Henan province, three consecutive director generals have been convicted of the crime one after the other in unrelated cases. Of these twenty cases, there are five death penalties. The temptation is so strong that even the risk of death penalty cannot deter corruption." (Bai and Qian, 2010)

This leads to an augmented aggregate production function in the logarithm form:

$$\ln Q_{jt} = \alpha_l \ln L_{jt} + \alpha_k \ln K_{jt} + \alpha_b \ln B_{jt} + \mu_j + v_{jt}, \tag{1}$$

where Q_{jt}, K_{jt}, L_{jt} and B_{jt} are the aggregate output, private capital, labor force and public infrastructure capital of province j and year t. There are two components in the error term, μ_j and v_{jt}, which respectively stand for those time-invariant and time-varying unobservable province-specific total factor productivity purged of the influence from infrastructure. The stock of public infrastructure capital, B_{jt}, evolves according to the law of motion:

$$B_{jt} = (1 - \delta_b)B_{jt-1} + G_{jt-1}, \tag{2}$$

where G_{jt} is the flow of investment in public infrastructure and δ_b is the depreciation rate of B. The output elasticity α_b is the key parameter of interest, as the economic return, or the marginal product of public infrastructure, can be inferred using the relationship:

$$r_t \equiv \frac{\partial Q_{jt}}{\partial B_{jt}} = \alpha_b \frac{Q_{jt}}{B_{jt}}. \tag{3}$$

Estimating α_b, however, involves a set of identification issues, as surveyed by Gramlich (1994) and Calderon et al. (2015). The first and also the main challenge is reverse causality, which is particularly relevant in China's context. To illustrate the nature of reverse causality, let the Solow residual ω_{jt} to measure the productivity of private inputs in production,

$$\begin{aligned} \omega_{jt} &\equiv \ln Q_{jt} - \alpha_l \ln L_{jt} - \alpha_k \ln K_{jt} \\ &= \alpha_b \ln B_{jt} + \mu_j + v_{jt}. \end{aligned} \tag{4}$$

Equation (4) or equivalently (1) aims to identify the causal effect of public infrastructure on productivity, but the causality could go from productivity to public infrastructure. This is because the allocation of infrastructure is seldom random. Instead, it is most likely dependent on the productivity itself.

First, all else being equal, μ_j, the permanent differences in productivity across provinces could simultaneously affect the infrastructure investment and determine the future productivity. On one hand, provinces with intrinsically higher productivity will on average have higher output. Higher output means higher income. Hence these provinces will demand more infrastructure. Higher output also implies higher fiscal revenue. Hence these provinces will be able to afford more infrastructure. On the other hand, the central government may assign infrastructure investment to provinces with intrinsically lower productivity in order to combat the diverging regional disparity. Both possibilities imply a potential correlation between μ_j and $\ln B_{jt}$. Thus, the OLS estimate for α_b is well-recognized to be biased and inconsistent.

Second, although the correlation between μ_j and $\ln B_{jt}$ equation (4) can be eliminated by first difference transformation or fixed effect estimation, reverse causality may still arise if policy makers have known v_{jt}, the latent productivity shock of each province. In this case, infrastructure may be placed by the central government into provinces that are expected to receive positive productivity shocks to accommodate the higher future demand for infrastructure. Furthermore, a province with better economic 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. Such possibilities suggest that, even the first-differenced or fixed-effect estimate for α_b could still suffer from simultaneity bias.

Besides reverse causality, the second challenge of the traditional approach lies in how to net out the demand effect of public expenditure. When researchers write down equation (1), the idea is to infer the contribution of public infrastructure to aggregate supply. But the observed Q_{jt} in this equation is the equilibrium aggregate output. When expenditure in public infrastructure increases, aggregate demand is what changes in the short run. Thus even if the true aggregate supply effect of public infrastructure were zero, a rise in such expenditure would raise aggregate demand and lead to a higher output in the short run. The estimated effect of public infrastructure using the equilibrium aggregate output therefore could mix both supply-side and demand-side contributions. This concern is also more relevant under China's GDP yardstick competition. Regardless whether infrastructure investment has any positive supply effect in the long run, province government officials may still invest heavily in infrastructure to stimulate short-run GDP growth by increasing aggregate demand.

Finally, equation (1) also shares some common econometric problems in estimating a production function. First, potential spurious correlation may arise due to the non-stationarity of aggregate variables. A common practice is to use some form of differencing. However, the literature that takes difference of equation (1) tend to get much lower estimates for α_b, often not even positive and always statistically insignificant. One possible explanation is due to the measurement errors in B_{jt}.[16] In

[16] If the serial correlation of the measurement errors is smaller than the serial correlation of the true unobserved explanatory variable, first differencing the data is bound to exacerbate the measurement errors and lead to more severe downward bias than OLS estimation of the levels equation.

order to construct B_{jt} using the perpetual inventory method, one needs information on the initial value and the whole history of the investment flow series and assumes a depreciation rate. This implies that the constructed stock data is very likely to be contaminated with measurement errors.

Second, besides reverse causality and the combined supply and demand effects, there is another form of simultaneity bias in equation (1), due to unobserved factors included in v_{jt}. For example, a technology shock or an institutional reform might simultaneously affect the province output and the private factor inputs. This would set up a correlation between the regressors and the errors, rending the OLS estimates biased and inconsistent.

3.2 Our Approach: The TFPR Model

To address the challenges in the traditional approach, this paper proposes a new approach with two key elements: first, an endogenous productivity process in a firm-level production function; and second, the combination of firm-level production data and province-level infrastructure data. For each industry, consider firm i in province j and year t, using the following sales revenue generating equation:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{ijt} + \epsilon_{it}, \tag{5}$$

where y_{it} is the real sales revenue, and k_{it}, l_{it}, and m_{it} are capital, labor and intermediate inputs, all in the logarithm form. An i.i.d. error term ϵ_{it} is included to capture the unanticipated shocks to firm's sales revenue or measurement errors in the revenue data. All these setups are standard in the production function estimation literature. What's new in equation (5) lies in ω_{ijt}, which represents an unobservable productivity and subsumes the constant term. The subscript ijt is adopted to highlight two facts. First, ω_{ijt} is a firm-specific productivity; and second, ω_{ijt} also has an aggregate component that is common across all the firms in province j and year t.

The effect of infrastructure investment on productivity is captured by an endogenous productivity process to model. It explicitly allows infrastructure investment to impact the evolution of productivity through a first-order Markov process:

$$\omega_{ijt} = h_t(\omega_{ijt-1}, g_{jt-1}) + v_{ijt}. \tag{6}$$

Equation (6) decomposes the actual productivity ω_{ijt} into the expected productivity $h_t(\omega_{ijt-1}, g_{jt-1})$ and the random shocks v_{ijt}. The nonparametric function $h_t(\omega_{ijt-1}, g_{jt-1})$

has two arguments. The first argument ω_{ijt-1} is the lagged or attained productivity of firm i. The second argument g_{jt-1} is the logarithm of G_{jt-1}, which is the public infrastructure investment flow in province j where firm i is located and in year $t-1$ when the investment is made. The time-to-build assumption implies that it takes time for the infrastructure investment to affect productivity.

The first-order Markov process assumption has three important attributes. First, the contribution of previous infrastructure investment flows to the current productivity ω_{ijt} has been absorbed by the lagged productivity ω_{ijt-1}. Thus we no longer require the whole historical information on the investment flows and impose any arbitrary depreciation rate. This helps us to avoid the classic measurement error problem in the literature.[17] Second, the current productivity ω_{ijt} has inherited those initial productivity differences across firms and across provinces from the lagged productivity ω_{ijt-1}.[18] Together, these two attributes imply that, the endogenous productivity process (6) can be regarded as a generalization of equation (4) but is presented in the form of firm-level productivity.

As the dependent variable y_{it} in the production function is a revenue-based output, following Foster et al. (2008), we refer the system of equations (5) and (6) to the TFPR model, and ω_{ijt} to the revenue-based productivity.

3.3 Identification

3.3.1 Endogenous Location of Firms

The setup in which the production decision is made at the firm-level and the infrastructure investment decision is made at the province-level has alleviated the reverse causality problem in the traditional approach to some extent. However, reverse causality may still arise under our context. The first source of reverse causality comes from the fact that firms choose their locations. With spatial sorting, more productive firms

[17] Our departure from the public infrastructure capital stock to the public infrastructure investment flow shares the same idea as in Doraszelski and Jaumandreu (2013). Rather than constructing a stock of knowledge capital from a firm's observed R&D expenditures, they consider productivity to be unobservable and model the impact of investment in knowledge on productivity through an endogenous productivity process.

[18] These two points are more evident once we rewrite ω_{ijt} in a recursive way:

$$\begin{aligned}\omega_{ijt} &= h_t(\omega_{ijt-1}, g_{jt-1}) + v_{ijt} \\ &= h_t(h_{t-1}(\omega_{ijt-2}, g_{jt-2}) + v_{ijt-1}, g_{jt-1}) + v_{ijt} \\ &= f\left(w_{ij1;}\, g_{j1,\dots}, g_{jt-1;}\, v_{ij2}, \cdots, v_{ijt}\right).\end{aligned}$$

tend to self-select into higher income provinces. Recall that a dominating component of province infrastructure investment comes from self-raised funds and government guaranteed bank loans. A province with more productive firms will be able to generate more self-raised funds and back up more bank loans. This implies a potentially positive correlation between firm-level productivity and province-level infrastructure. Therefore it is important to know whether the correlation is due to an underlying process whereby firms with exogenously high productivity locate in provinces with more public infrastructure investment; or whether the correlation is a consequence of infrastructure investment directly affecting productivity. The first possibility is a form of reverse causality arising from the self-selection mechanism.

We control for such possibility by including the lagged productivity using a first-order Markov process structure as in equation (6). Notice that the expected productivity $h_t(\omega_{ijt-1}, g_{jt-1})$ allows for arbitrary correlation between ω_{ijt-1} and g_{jt-1}. Such correlation implies it would be very difficult to identify the productivity effect of infrastructure from the level of productivity itself. However, under the assumption that ω_{ijt-1} has absorbed all the factors besides g_{jt-1} that will affect the expected productivity $h_t(\omega_{ijt-1}, g_{jt-1})$, we will still be able to identify the productivity effect of infrastructure, from the differences in the predicted current productivity ω_{ijt} between firms that locate in provinces with different infrastructure expenditure g_{jt-1}, conditional on the lagged productivity of these firms ω_{ijt-1}. Intuitively, including the lagged productivity in equation (6) allows us to mimic a randomized allocation and identify the causal effect of infrastructure from the differences in the change of productivity.

3.3.2 Endogenous Allocation of Infrastructure

There is another source of reverse causality: the allocation of infrastructure might not be random. If public infrastructure investment depends on aggregate output and hence aggregate productivity, then firm-level productivity shocks could affect public infrastructure investment by affecting the aggregate productivity shocks. This implies that there might still be a potential correlation between v_{ijt} and g_{jt-1} arising from endogenous placement of infrastructure. Thus, if the aggregate productivity process (4) suffers from reverse causality, so does the firm-level productivity process (6). To address this type of reverse causality, following Fernald (1999), we further decompose the firm-level productivity shocks v_{ijt} into two components:

$$v_{ijt} = \lambda v_{jt} + \varepsilon_{it}. \tag{7}$$

First, v_{jt}, is an unobservable province-specific innovation that is common across all the firms in province j. The loading parameter λ characterizes the relative importance of this common factor in the total random shocks. Second, ε_{it}, is an unobservable firm-specific innovation, which is orthogonal to the aggregate shock v_{jt}, and hence to the public infrastructure investment g_{jt-1}, assuming that g_{jt-1} is only affected by v_{jt}.

Substituting equation (7) into (6) leads to the decomposed endogenous productivity process:

$$\omega_{ijt} = h_t(\omega_{ijt-1}, g_{jt-1}) + \lambda v_{jt} + \varepsilon_{it}. \tag{8}$$

Equation (8) highlights the key identification assumption in our approach: the firm-level productivity shock is orthogonal to the province-level infrastructure investment, or formally,

$$E\left(\varepsilon_{it} | \omega_{ijt-1}, g_{jt-1}, v_{jt}\right) = 0. \tag{9}$$

The underlying rationale of this assumption is that, conditioning on the province-level aggregate productivity shock v_{jt}, the policy makers will not adjust the infrastructure of a province, in light of an idiosyncratic firm-level productivity shock ε_{it}.

Three empirical exercises are conducted to investigate the sensibility of this rationale. First, we count the number of firms in our dataset. Every year there are on average 6650 firms in each province. The large number of firms in a province implies that condition (9) is much more compelling in contrast to its counterpart in the traditional approach, which would require the orthogonality between v_{jt} and $\ln B_{jt}$. Second, we calculate the value-added of the top 1, 5 and 10 largest firms in each province as a share of the provincial GDP. The average ratio across provinces and across years are 1.6%, 3.8% and 4.9%. This implies that the firm-size distribution in our dataset also has a long right tail, a common finding in firm-level data. However, thanks to the large economy size of the Chinese provinces, even the largest firms do not dominate the aggregate output of a province. Finally, we drop the top 1% of the firms in each province and re-estimate the model in our robustness check. The estimated rates of return remain similar to those from the full sample.

3.3.3 Proxy for v_{jt}

The fact that the province-level aggregate productivity shock v_{jt} is not observable implies the importance of finding appropriate proxy for it. In our benchmark specifications, we infer v_{jt} directly from the starting point equation (1). Assume that the technology satisfies the restriction of constant return to scale. Then the aggregate production function can be written in intensive form:

$$\ln(Q_{jt}/L_{jt}) = \alpha_k \ln(K_{jt}/L_{jt}) + \alpha_b \ln(B_{jt}/L_{jt}) + \mu_j + v_{jt}.$$

Assume that the economy is on a balanced growth path so that the output per labor, private capital per labor and public capital per labor are all growing at a constant rate. Then the logarithm of output per labor can be modelled as a linear function of time t:

$$\ln(Q_{jt}/L_{jt}) = a_j + b_j t + v_{jt},$$

where a_j represents the initial differences in output per labor across the provinces and b_j stands for the province-specific growth rates of output per labor.

Assume that the values of a_j and b_j are known to the policy makers. With the ten-year data on province-level output per labor, we estimate a_j and b_j using OLS for each province j. This implies that expected output per labor of province j in year t is $\ln\left(\widehat{Q_{jt}/L_{jt}}\right) = \widehat{a}_j + \widehat{b}_j t$, so that the productivity shock can be inferred as $\widehat{v}_{jt} = \ln(Q_{jt}/L_{jt}) - \ln\left(\widehat{Q_{jt}/L_{jt}}\right)$. Table A3 reports the estimates for a_j and b_j.

In our robustness checks, we also experiment two alternative proxies for v_{jt}. Intuitively, with these two proxies, our estimation procedure will generate an upward biased and a downward biased estimate, respectively. Thus these two estimates provide a range of reference points for the true productivity effect of infrastructure investment. As expected, our benchmark estimates fall into the predicted range. Furthermore, compared with the wide range in the literature using the traditional approach, this range is also much tighter, highlighting the advantage of our identification strategy.

3.3.4 Firm-level Heterogeneity

Another issue in using matched firm-level and province-level data lies in that there might not be enough variation at the firm level regarding infrastructure. To address this concern, in addition to the lagged productivity ω_{ijt-1} and infrastructure investment g_{jt-1}, we also allow for their interaction term $\omega_{ijt-1} \cdot g_{jt-1}$ in the $h_t(\omega_{ijt-1}, g_{jt-1})$ function.

The rationale of this specification is that more productive firms tend to utilize the public infrastructure more frequently and more intensively. This is an analogy to the transport infrastructure literature, which measures a county's access to transport using distance; or to Fernald (1999), which measures an industry's reliance on road using vehicle-intensity. While the variation in such literature is at the county level or industry level, the variation in our specification is at the firm level. It implies that for firms that locate in the same province, the effect of public infrastructure could be different, depending on the attained productivity level of the firms. Our approach thus allows us to capture the heterogeneous effect of public infrastructure on firm's productivity. Such heterogeneity is crucial in exploring the mechanism of how infrastructure investment affects aggregate productivity and output.

3.4 Estimation Procedure

The system of equations (5) and (8) leads to a standard endogenous firm-level production function considered by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). The OLS estimates of $(\beta_k, \beta_l, \beta_m)$ are known to be inconsistent due to the correlation between input factors (k_{it}, l_{it}, m_{it}) and ω_{ijt}. As the $h_t(\omega_{ijt-1}, g_{jt-1})$ function is estimated along with the parameters of the production function, any inconsistency in $(\beta_k, \beta_l, \beta_m)$ will lead to biased estimates on the productivity effect of infrastructure. We follow Ackerberg et al. (2015) to control this simultaneity bias by the proxy method. Our timing assumption for identifying $(\beta_k, \beta_l, \beta_m)$ is that decision on m_{it} is made at time t; decision on k_{it} is made at time $t-1$; and decision on l_{it} is made between $t-1$ and t. Profit maximization thus leads to an optimal intermediate inputs function:

$$m_{it} = m_t(k_{it}, l_{it}, \omega_{ijt}).$$

Assuming the strict monotonicity of m_{it} in ω_{ijt}, the unobservable ω_{ijt} can be proxied by observes in an inverse function:

$$\omega_{ijt} = \omega_t(k_{it}, l_{it}, m_{it}, j, t), \tag{10}$$

where we use j and t to denote those province-specific and year-specific aggregate components subsumed in ω_{ijt}, which are proxied by province dummy and year dummy.

Denote $\beta \equiv (\beta_k, \beta_l, \beta_m)'$ and $x_{it} \equiv (k_{it}, l_{it}, m_{it})'$. Inserting equation (10) into (5) yields a reduced-form equation:

$$y_{it} = x'_{it}\beta + \omega_{ijt} + \epsilon_{it} = \phi_t(x_{it}, j, t) + \epsilon_{it}, \tag{11}$$

where $\phi_t(x_{it}, j, t) = x'_{it}\beta + \omega_t(x_{it}, j, t)$. By construction ϵ_{it} has zero mean and is independent of any argument in $\phi_t(x_{it}, j, t)$. Thus, by proxying ω_{ijt} using equation (10), the reduced-form equation (11) can be consistently estimated by a nonparametric regression of y_{it} on (x_{it}, j, t). This process is called the first-stage regression, which provides a fitted value $\hat{\phi}_t(x_{it}, j, t)$ for y_{it}.

With this fitted value, the second-stage regression provides moment conditions to identify β, and simultaneously estimates the $h_t(\omega_{ijt-1}, g_{jt-1})$ function. To be specific, for a given value of β, the firm-specific productivity innovation ε_{it} can be obtained as the residual of a nonparametric regression of $\omega_{ijt}(\beta)$ on $\omega_{jit-1}(\beta)$, g_{jt-1} and v_{jt}:

$$\varepsilon_{it}(\beta) = \omega_{ijt}(\beta) - h_t(\omega_{ijt-1}(\beta), g_{jt-1}) - \lambda v_{jt}$$

where

$$\omega_{ijt}(\beta) = \hat{\phi}_t(x_{it}, j, t) - x'_{it}\beta. \tag{12}$$

The estimates of β can be obtained by the generalized method of moments estimation using the moment conditions:

$$E\left[(\varepsilon_{it}(\beta_k, \beta_l, \beta_m)) \otimes \begin{pmatrix} k_{it} \\ l_{it-1} \\ m_{it-1} \end{pmatrix} \right] = 0. \tag{13}$$

These moment conditions are based on our timing assumptions that capital is a dynamic input and intermediate input is a variable input, a typical assumption commonly made in the production function estimation literature. We experiment labor as a variable input and a dynamic input, and obtain very similar results.

3.5 Output Elasticity and Rate of Return

Our key parameter of interest is the firm-specific output elasticities with respect to infrastructure investment. To take into account the potential differences in production technology and productivity process across industries, we estimate the TFPR model for each of the 27 industries separately, and then aggregate the firm-level output elasticities into an aggregate-level output elasticity.

To be specific, for a firm i in industry s province j and year t, its output elasticity can be obtained as:

$$e_{ist} = \frac{\partial y_{it}}{\partial g_{jt-1}} = \frac{\partial \omega_{ijt}}{\partial g_{jt-1}} = \frac{\partial h_{st}\left(\omega_{ijt-1}, g_{jt-1}\right)}{\partial g_{jt-1}}. \tag{14}$$

We then use sales revenue of each firm as the weight to aggregate these firm-level output elasticities into an industry average, and adjust the ratio between value-added and sales revenue:

$$e_{st} = \left(\sum\nolimits_i e_{ist} \frac{Y_{ist}}{Y_{st}}\right) \frac{dv_s}{dy_s},$$

where $\frac{Y_{ist}}{Y_{st}}$ represents firm i's revenue as a share of total revenue in industry s and year t; the ratio $\frac{dv_s}{dy_s}$ is obtained by a fixed-effect regression of log value-added on log sales revenue for industry s. Finally, we use value-added of each industry as the weight to aggregate these industry-level output elasticities into an average for the manufacturing sector:

$$e_t = \sum\nolimits_s e_{st} \frac{V_{st}}{V_t}, \tag{15}$$

where $\frac{V_{st}}{V_t}$ denotes industry s's value-added as a share of total value-added in the manufacturing sector in year t.

Under the assumption that the output elasticity e_t calculated from manufacturing sector is representative for the whole economy, we then obtain the rate of return of infrastructure investment in year t, by multiplying e_t with the corresponding ratio between GDP and infrastructure:

$$r_t = e_t \frac{GDP_t}{G_{t-1}}. \tag{16}$$

Notice the similarity and difference between equation (16) and (3). While in the traditional approach the rate of return is inferred from output elasticity with respect to the stock of public infrastructure, the return in our approach is based on the output elasticity with respect to the flow of public infrastructure. Correspondingly, the two approaches also adjust the GDP-to-capital stock and GDP-to-investment-flow to reach the final rates of return.

3.6 Empirical Results

Table A4 reports the estimation results for the revenue production function (5). Column (1) of Table 4 presents the polynomial estimates of the endogenous productivity process (8) for the entire manufacturing sector. Standard errors are clustered at the province-industry level. It thus serves as a direct illustration for the average impact effect of the infrastructure investment on the revenue-based total factor productivity. First, the productivity process is highly non-linear. This suggests that the productivity process would be mis-specified by a simple linear model. Second, both the infrastructure investment itself and its interaction with the lagged productivity are highly significant. This implies that it is important to allow for an endogenous productivity process rather than assume it to be exogenous. Furthermore, the effect of infrastructure investment on productivity is firm-specific, depending on the firm's attained productivity level. Both the non-linearity of the productivity process and the significance of the attained productivity echo those findings in the recent literature on endogenous productivity, such as De Loecker (2013) and Doraszelski and Jaumandreu (2013). Finally, v_{jt} turns out to be highly significant, which confirms the importance to control for the aggregate productivity shocks in the productivity process.

<Insert Table 4 here>

Given the heterogeneous impact effect, we calculate the partial derivative of productivity with respect to infrastructure investment at the median value of lagged productivity. We obtain an elasticity of 0.013, suggesting that for a firm with median productivity level in the whole manufacturing sector, infrastructure investment does enhance its productivity. To further highlight the degree of heterogeneity, we also calculate the elasticities by industry and report their values at the 25^{th}, 50^{th} and 75^{th} percentiles of the productivity in Table 5. As expected, we see substantial variations along the productivity distribution within each industry, and also across different industries. For all industries, the effects of infrastructure investment on productivity increase with the initial productivity level. While firms at the higher quantiles of the productivity usually benefit from the infrastructure investment, firms at the lower quantiles of the productivity could in fact gain less or suffer from the infrastructure investment.

<Insert Table 5 here>

Table 6 presents the average output elasticities and rates of return for public infrastructure investment in China during 1999-2007. The top panel lists the ratios of GDP-to-infrastructure investment in every year. The sector-level output elasticities defined in equation (15) are reported in the middle panel. The multiplication of the top and middle panel yields the rates of return presented in the bottom panel, as defined in equation (16). The 9-year average rate of return during our sample period is 6.2%. The yearly returns vary from 3.0% in 2006 and peak to 8.3% in 2003. This finding indicates that public infrastructure investment does generate positive returns in China, at least during our sample period.

<Insert Table 6 here>

4 Controlling Demand Effect: The TFPQ Model

To answer the second research question of the paper, this section illustrates how to net out the demand effect from the estimated productivity effect of public infrastructure investment using a firm-level production function approach. One established finding in the productivity literature using firm-level data is that firm-level demand heterogeneity accounts for a sizeable variation in sales revenue and the measured productivity.[19] With firm-level data, on the one hand, public infrastructure investment enters the production function by enhancing productivity. On the other hand, one may explicitly write down a demand function where infrastructure investment shifts firm's demand. This allows us to distinguish the TFPQ from the TFPR by controlling the demand effect of public infrastructure investment. In this sense, the effect estimated from a TFPR model includes both the demand effect and the productivity effect of public infrastructure, while the effect estimated from a TFPQ model only reflects the effect of public infrastructure on productivity.

4.1 Production and Demand

Consider a firm i that actively produces and sells in province j and year t. It employs capital K_{it}, labor L_{it} and intermediate inputs M_{it} to produce physical output Q_{it} according to a Cobb-Douglas production technology:

$$Q_{it} = K_{it}^{\gamma_k} L_{it}^{\gamma_l} M_{it}^{\gamma_m} \exp(\omega_{ijt}^q + \epsilon_{it}^q), \tag{17}$$

where γ_k, γ_l and γ_m are the corresponding output elasticities. ω_{ijt}^q represents an unobservable firm-specific quantity-based productivity and subsumes the constant term. ϵ_{it}^q denotes a standard i.i.d. error term capturing unanticipated shocks to firm's physical output. Similar to the revenue-based productivity process (8), the quantity-based productivity process ω_{ijt}^q follows a first-order Markov process:

$$\omega_{ijt}^q = h_t(\omega_{ijt-1}^q, g_{jt-1}) + \lambda v_{jt}^q + \varepsilon_{it}^q, \tag{18}$$

where the expected productivity $h_t(\omega_{ijt-1}^q, g_{jt-1})$ is a nonparametric function of ω_{ijt-1}^q and g_{jt-1}, and the random shocks come from both an aggregate component v_{jt}^q and an idiosyncratic component ε_{it}^q.

[19] See Roberts et al. (2018) and the other empirical papers surveyed in their footnote 2.

Under the same spirit as De Loecker (2011), we explicitly model a downward sloping demand curve as following:[20]

$$P_{it} = Q_{it}^{-\frac{1}{\sigma}} \exp(\chi_{it}), \tag{19}$$

where P_{it} is the price of goods sold by firm i in year t. The parameter σ is the demand elasticity, where $1 < \sigma < \infty$. We use χ_{it} to denote a firm-specific demand shifter. To model the effect of infrastructure investment on demand, we decompose χ_{it} into two parts:

$$\chi_{it} = \pi g_{jt} + \xi_{it}, \tag{20}$$

where g_{jt} is the logarithm of province j's infrastructure investment in year t; and ξ_{it} denotes the unobservable firm-specific demand shocks. Different from the time-to-build assumption on the effect of infrastructure investment on productivity in equation (18), equation (20) implies that the effect of infrastructure investment on demand is instantaneous.

4.2 Estimation Equation

In most applications the firm-level physical output Q_{it} is not observed to econometricians. Sales revenue $P_{it}Q_{it}$ is usually taken as a proxy for output in practice. Under our specification (19), the logarithm of sales revenue is given by:

$$\ln P_{it}Q_{it} = \left(1 - \frac{1}{\sigma}\right) \ln Q_{it} + \chi_{it}$$

Substituting $\ln Q_{it}$ and χ_{it} using (17) and (20) yields the following equation:

$$\begin{aligned} \ln P_{it}Q_{it} \quad = \quad & \left(1 - \frac{1}{\sigma}\right) (\gamma_k k_{it} + \gamma_l l_{it} + \gamma_m m_{it}) \\ & + \left(1 - \frac{1}{\sigma}\right) \left(\omega_{ijt}^q + \epsilon_{it}^q\right) + (\pi g_{jt} + \xi_{it}) . \end{aligned}$$

[20] Equation (19) has relaxed the constant elasticity of substitution (CES) restriction in De Loecker (2011) by considering a more general demand curve. The advantage of equation (19) over a CES structure lies in its flexibility, as there will be no restriction on the parameters in equation (21). There are, however, two disadvantages, too. First, the demand elasticity σ cannot be estimated simultaneously with other structure parameters as in De Loecker (2011). Instead, we infer σ from the markup data of each industry as reported in Table 1. Second, our estimation equation (21) will not be able to control the omitted price variable bias as highlighted by De Loecker (2011). The omitted price variable bias arises from the discrepancy between firm-level price P_{it} and industry-level price P_{st}, which is often used to deflate firm-level revenue data. Nevertheless, this may not impose a major concern in our application, given that there is only very moderate price variation over our sample period as documented in Table 1.

Reparameterization leads to an estimation equation for the revenue generating production function:

$$y_{it} = \beta_k^* k_{it} + \beta_l^* l_{it} + \beta_m^* m_{it} + \pi g_{jt} + \omega_{ijt}^* + \epsilon_{it}^*, \tag{21}$$

where $\beta_n^* = \left(1 - \frac{1}{\sigma}\right)\gamma_n$ for $n = \{k, l, m\}$, represent the set of parameters, which can be used to recover the structural parameters $\{\gamma_k, \gamma_l, \gamma_m\}$ with an imposed value of σ inferred from the markup reported in Table 1. The transformed productivity ω_{ijt}^*, is simply a linear scale of the original quantity-based productivity ω_{ijt}^q, that is

$$\omega_{ijt}^* = \left(1 - \frac{1}{\sigma}\right)\omega_{ijt}^q. \tag{22}$$

The combined error term ϵ_{it}^* is a linear combination of those unobservable idiosyncratic shocks to production and demand, that is

$$\epsilon_{it}^* = \left(1 - \frac{1}{\sigma}\right)\epsilon_{it}^q + \xi_{it}.$$

Thus, by construction ϵ_{it}^* is uncorrelated with any of the regressors.

4.3 The TFPQ Model and Output Elasticities

It is useful to compare equation (21) with two other equations that appear in this paper. First, when we write down production function (17), our aim is to infer the impact of public infrastructure investment on firm's supply through productivity process (18). This can be measured by the elasticity of physical output with respect to infrastructure, for a firm i in industry s province j and year t:

$$e_{ist}^q = \frac{\partial \ln Q_{it}}{\partial g_{jt-1}} = \frac{\partial \omega_{ijt}^q}{\partial g_{jt-1}} = \frac{\partial h_{st}(\omega_{ijt-1}^q, g_{jt-1})}{\partial g_{jt-1}}. \tag{23}$$

However, the production function (17) is not estimable. Under our demand structure, we transform equation (17) into (21), which is estimable. Equation (22), that is the relationship between ω_{ijt}^q and ω_{ijt}^* implies that, estimating elasticity e_{ist}^q is equivalent to estimating equation (21) and obtaining a consistent estimator for ω_{ijt}^*. In this sense, we call the system of equations (21), (18) and (22) the TFPQ model, as they allow us to back out the effect of public infrastructure investment on quantity productivity.

Second, compared with the revenue function (5), a specification widely adopted in empirical analyses, equation (21) includes an additional variable g_{jt} to capture the demand effect of infrastructure. Such comparison highlights the fact that the productivity ω_{ijt} in (5) has also absorbed the demand effect of infrastructure, in addition to the supply effect. This distinguishes ω_{ijt} from ω^q_{ijt}, which only reflects the supply effect of infrastructure. That is why we refer ω_{ijt} to TFPR and ω^q_{ijt} to TFPQ. Consequently, the elasticities and returns calculated using (14) are revenue-based, contrasting with the quantity-based elasticities and returns using (23).

4.4 Estimation Procedure

Same as estimating equation (5), we apply the proxy method by Ackerberg et al. (2015) to equation (21) with one additional variable g_{jt}. Now in the first-stage regression, $\phi_t(x^*_{it}, j, t) = x^{*\prime}_{it}\beta^* + \omega_t(x^*_{it}, j, t)$, where $\beta^* \equiv (\beta^*_k, \beta^*_l, \beta^*_m, \pi)'$ and $x^*_{it} \equiv (k_{it}, l_{it}, m_{it}, g_{jt})$, so that $y_{it} = \phi_t(x^*_{it}, j, t) + \epsilon^*_{it}$. A nonparametric regression of y_{it} on (x^*_{it}, j, t) provides a fitted value $\hat{\phi}_t(x^*_{it}, j, t)$ for y_{it}.

In the second-stage regression, for a given value of β^*, the firm-level productivity innovation ε^q_{it} can be obtained as the residual of a nonparametric regression of $\omega^q_{ijt}(\beta^*)$ on $\omega^q_{ijt-1}(\beta^*)$ and g_{jt-1}, netting of v^q_{jt},[21] where we make use of the linear relationship between ω^*_{ijt} and ω^q_{ijt} specified in equation (22). That is

$$\varepsilon^q_{it}(\beta^*) = \frac{\sigma}{\sigma-1}\omega^*_{ijt}(\beta^*) - h_t\left(\frac{\sigma}{\sigma-1}\omega^*_{ijt-1}(\beta^*), g_{jt-1}\right) - \lambda v^q_{jt},$$

where

$$\omega^*_{ijt}(\beta^*) = \hat{\phi}_t(x^*_{it}, j, t) - x^{*\prime}_{it}\beta^*. \tag{24}$$

The moment conditions for identification in the second-stage now become

$$E\left[(\varepsilon^q_{it}(\beta^*_k, \beta^*_l, \beta^*_m, \pi)) \otimes \begin{pmatrix} k_{it} \\ l_{it-1} \\ m_{it-1} \\ g_{jt} \end{pmatrix}\right] = 0. \tag{25}$$

The identification of $(\beta^*_k, \beta^*_l, \beta^*_m)$ comes from the timing assumption on k, l and m, the same as in the TFPR model in Section 3. The additional parameter π is identified by the assumption that the firm-level idiosyncratic shocks ε^q_{it} are uncorrelated with the province-level infrastructure investment g_{jt}.

Notice that the productivity effect of infrastructure is identified from the productivity process while the demand effect of infrastructure is identified from the revenue function.[22] The ability to separately identify the demand from the productivity effect of

[21] The fact that the province-level revenue-based and quantity-based productivities are not distinguishable implies that $v^q_{jt} = v_{jt}$.

[22] To be specific, in the TFPR model, the identification only requires $E\left(\varepsilon_{it}|\omega_{ijt-1}, g_{jt-1}\right) = 0$. In the TFPQ model, the identification assumption is $E\left(\varepsilon^q_{it}|\omega_{ijt-1}, g_{jt-1}\right) = 0$ and $Cov\left(\varepsilon^q_{it}, g_{jt}\right) = 0$.

infrastructure is based on the assumption that public expenditure will instantaneously shift the demand of the firms, while the supply effect coming through productivity takes time to materialize.

4.5 Empirical Results

Table A5 reports the estimation results for the revenue generating equation (21). As expected, for almost all the industries the estimates for the parameter characterizing the demand effect are significantly positive. This suggests that increase in public infrastructure expenditure does shift the demand curve of individual firms upward and contributes to the increase in their output, even if it had no effect on productivity. Column (2) of Table 4 reports the estimation for the endogenous productivity process (18) for the quantity-based productivity. Similar to the patterns presented in Column (1), there are three important findings. First, this is a highly nonlinear productivity process. Second, public infrastructure investment has a significant and heterogeneous impact on firm-level productivity. Finally, the province-level aggregate shock also influences the quantity-based productivity.

We follow the procedure described in Section 3.5 to aggregate the firm-level output elasticities from the TFPQ model and calculate the rate of return in Table 6. The rate based on the quantity productivity is 5.3%, averaging across years from 1999 to 2007. It is about one percentage point smaller than that based on the revenue productivity. This indicates that first, some of the positive effect of infrastructure investment on output is indeed via the demand effect; and second, infrastructure investment also has a positive long-run supply effect on output through productivity.[23]

5 Taking Into Account Spillover Effects

The baseline specifications in equation (8), (18) and (20) have explicitly assumed that the effects of public infrastructure investment only take place on firms that locate within the province. However, firm i's productivity may benefit not only from those public infrastructure in its location province j, but also from the public infrastructure

[23] Despite using different research approaches, the gap of the returns inferred from the TFPQ and TFPR models in our paper delivers a similar message on the short-term and long-term effects of infrastructure on output as in Leduc and Wilson (2013). Using the institutional design of federal highway grants distribution among states, Leduc and Wilson (2013) find that changes in expectations of states future highway grants have large immediate impact effects on state GDP, with a short-run multiplier as high as 2.7 and a long-run multiplier even higher at 6.2.

in the rest of the country. Similarly, firm i's demand may be shifted not only by those public infrastructure in its location j, but also by the public infrastructure in the rest of the country.

To address the concern that interregional spillover effects cannot be fully captured by studies looking at small geographical units, the literature usually compares the effects inferred from geographical units at different levels. For example, Holtz-Eakin and Schwartz (1995), employ so-called "effective" public infrastructure, which includes the public infrastructure of neighboring regions in addition to the regional data. Pereira and Roca-Sagales (2003) use both regional and aggregated data from Spain, to infer the direct and spillover effects of public infrastructure.

Following this literature, we generalize our model by replacing the province-level infrastructure with a distance-weighted national-level of infrastructure. We also experiment by replacing the province-level data with the regional-level data of neighboring provinces for robustness check. These exercises turn out to be quantitatively important in inferring the return and qualitatively crucial in evaluating the efficiency of public infrastructure investment.

5.1 Specifications for the Spillover Effects

To account for the spillover effects of public infrastructure, we replace the province-level g_{jt-1} in (8), (18) and g_{jt} in (20) with an interregional measure of infrastructure investment $\overline{g}_{jt-1}$ and $\overline{g}_{jt}$ respectively, where

$$\overline{g}_{jt} = \ln(\overline{G}_{jt}),$$

and $\overline{G}_{jt}$ is the weighted average of G_{kt}:

$$\overline{G}_{jt} = G_{jt} + \sum\nolimits_{k \neq j} w_{jk} \cdot G_{kt}.$$

The weighting matrix w_{jk} is constructed and normalized following the spatial externality literature, such as in Ertur and Koch (2007):

$$w_{jk} = \frac{\frac{1}{d_{jk}}}{\sum_{k \neq j} \frac{1}{d_{jk}}} \text{ for } k \neq j,\ w_{jj} = 0. \tag{26}$$

Here, j is the province where the firm i locates. $k \neq j$ represents the rest of other provinces of the country, and d_{jk} is the exogenous geographic distance between capital cities of provinces j and k. Equation (26) indicates that the public infrastructure investment of a province also has an impact on those firms locating outside of the province, where the magnitude of the impact diminishes with the distance. Here the G_{kt} is approximated by a 'gravity' measure of G_{jt}, that is, an inverse physical distance weighted sum of province infrastructure investment. When we replace the physical distance with travel cost in the weighting matrix as a robustness check, we obtain very similar results.

Notice that the way we construct w_{jk} implies that when all the off-diagonal elements of w_{jk} are zero, $\overline{g}_{jt}$ is identical to g_{jt}. That is the specification in this section nests the non-spillover model as a special case. Therefore one may interpret the estimates obtained in Section 3 and 4 as the direct effect of infrastructure, and the estimates obtained in this section as the total effects of infrastructure, with both direct and spillover effects.

5.2 Empirical Results

Column (3) of Table 4 reports the endogenous productivity process for the TFPR model with national-level spillover effects. It can be considered as the counterpart of Column (1), which assumes public infrastructure only affects firms within the province where the investment takes place. Same comparison applies to column (2) and (4) for the TFPQ model. Although these columns display assuring patterns that are qualitatively similar, they also show a quantitatively important difference that highlights the significance of the spillover effects. Based on the output elasticities inferred from the productivity processes, the 9-year average rate of return in the TFPR model now increases from 6.2% to 20.3%. Similarly, the 9-year average rate of return in the TFPQ model now increases from 5.3% to 12.1%.

Our finding is therefore consistent with a general pattern documented in the literature, for example, the survey by Pereira and Andraz (2013), that the return rate of public investment at the regional level is usually smaller than the return at the national level. It also echoes the finding on the importance of spillover effects particularly in China. In Li and Li (2013), around two-thirds of all the inventory reduction due to road investment in China can be accounted by the spillover effect of road networks on firm in neighboring provinces. Note that in our empirical exercises, the returns obtained from a specification with weighted national-level infrastructure double or even triple those with province-level infrastructure. This suggests that the positive externality and the economy of scale from infrastructure investment might be more relevant in an economy with a large size and many provinces such as China.

5.3 A Summary on the Rates of Return

We use Figure 1 to visualize the returns from various models. Comparison across the four lines highlights three interesting patterns. First, the returns in the TFPR models are always larger than those in the TFPQ models. When we take into account the interregional spillover effects, the demand effect of public infrastructure is even more pronounced. Second, the returns double or even triple in models with spillover effects. This implies that evaluation for infrastructure investment could be misleading if one only considers small geographic units. Even when the province governments are making infrastructure investment decision, the spillover effects of such investment to other provinces may not be fully taken into account. Finally, over the time the rates of return from the four models all display an inverted-U shape which peaks around 2003. Hence the public infrastructure investment seems to be most productive in the middle of our sample period.

<Insert Figure 1 here>

Putting together, the average rates of return to public infrastructure investment during 1999 to 2007 are about 6%, 5%, 20% and 12% from four different models. When we compare this set of estimates with the vast estimates from the literature, we find positive and moderate returns to infrastructure investment. Even the highest returns from the TFPR model with spillover are much lower than those from the traditional literature such as Aschauer (1989) or from those using aggregate level data such as Shi and Huang (2014). Even the lowest returns from the TFPQ model without spillover verify the positive effect of infrastructure investment on productivity.

6 Mechanism

Understanding the specific links between public infrastructure and economic performance is equally pertinent as estimating the returns. One trend of recent works has made substantial progress in characterizing how a specific type of infrastructure affects certain economic outcome. For example, electricity constraints may increase firm's production cost and distort firm's technology choice (Fisher-Vanden, et al. 2015; Abeberese, 2016); railways and highways may enhance a region's access to goods market and labor market (Donaldson, 2018; Donaldson and Hornbeck, 2016; Duranton and Turner, 2012); road construction may reduce transportation costs for both internal and international trade (Coşar and Demir, 2016; Jedwab and Moradi, 2016);

and communication infrastructure may facilitate knowledge spillover and complement skilled workers (Bernstain, 2000; Akerman et al. 2015).

Another trend of recent researches on transport infrastructure in China emphasizes that public infrastructure could impact the distribution of economic activities. For example, Banerjee et al. (2012) find that proximity to transportation networks has a moderately positive causal effect on per capita GDP levels across sectors, but it has no effect on per capita GDP growth. Faber (2014) shows that the National Trunk Highway System can lead to a reduction in industrial and total output growth among connected peripheral counties relative to non-connected ones. Baum-Snow et al. (2017) study the impact of roads and railways on the decentralization of Chinese cities in terms of population and industrial GDP.

This section studies how the general infrastructure as a whole may lead to aggregate productivity gains using firm-level data. It complements the existing literature in the following sense. First, we offer a new mechanism from the perspective of resource reallocation that has not been fully-captured in the first trend of literature. Second, we also emphasize the heterogeneous impact effects of infrastructure as does the second trend of literature. However, we move one more step forward by providing firm-level evidences.

6.1 A Possible Channel: Resource Reallocation

Two important findings can be established from our empirical exercises so far. First, at the aggregate level, public infrastructure investment contributes to the productivity positively, both in the TFPR and TFPQ models and both with and without the spillover effects. Second, and probably more interesting, at the firm-level, public infrastructure investment has a heterogeneous effect across different firms, depending on the attained productivity level of the firm. The findings of an aggregate positive effect and a heterogeneous individual effect are consistent with the theme advocated by a recent literature on misallocation and productivity, see, for example, the survey by Restuccia and Rogerson (2013). In an economy with heterogeneous firms, when resources are reallocated from less productive firms to more productive ones, the aggregate productivity of the economy increases.

The public infrastructure may play an important role as the catalyst in facilitating such resource reallocation, especially during the decade of trade liberalization of our sample period. It is well known that before the 2000s China has been largely excluded from the international goods market and subject to widespread local protectionism (Young, 2000; Bai et al., 2004). Tombe and Zhu (2018), who recently study on how misallocation due to goods- and labor-market frictions affects aggregate productivity in China, find that reductions in international and in particular internal trade costs account for two-fifths of aggregate productivity growth in China between 2000 and 2005. Besides various policy and institutional reforms, one particular contribution to the reduction in the trade costs could come from the public infrastructure investment.

6.2 Linking Output Elasticity with Firm Characteristics

To examine this possible channel, we first provide some evidence on which firms are benefiting or benefiting more from public infrastructure investment. Since both productivity and elasticity are not directly observable, Table 7 links output elasticity, the impact of infrastructure investment on productivity, with observable firm characteristics. Estimated output elasticities from various specifications in Section 3, 4 and 5 are regressed on firm age, size, ownership, exporting status and geographic location.

<Insert Table 7 here>

A common finding arises across all specifications, that all else being equal, a firm that is younger, smaller, non-state-owned, exporting and locating in the eastern region has a larger output elasticity than its counterpart. Since firms with such characteristics are well-known to be more productive firms in China, this finding therefore suggests that infrastructure investment tends to benefit firms with high productivity more than those with low productivity, consistent with the resource reallocation mechanism.

6.3 Testing the Hypothesis

To test the hypothesis that public infrastructure investment facilities resource reallocation by reducing trade costs and increasing firm's exposure to trade, we now examine two specific predictions. First, all else being equal, public infrastructure investment increases the probability of exit of the less productive firms. Second, public infrastructure investment increases the market shares of the more productive firms. Following the literature, such as Olley and Pakes (1996), Pavcnik (2002) and De Loecker (2011), we use the Solow residual as a productivity measure in these exercises.

Table 8 presents the Probit regressions of exit probability.[24] Standard errors are clustered at the province-industry level. A firm i is defined as exit in year $t+1$ if it is

[24] To be more accurate, exit here means exit from our dataset.

observed in year t but not in year $t+1$ in the dataset. On average, the exit probability is around 11%. In column (1) of the regressions, we start with a baseline specification with productivity and capital stock only. Both are negative, significant and of a similar magnitude as that in Olley and Pakes (1996) and Pavcnik (2002). In column (2), the corresponding public infrastructure investment measure is added in the regression in each model. Overall, public infrastructure investment itself reduces the probability of exit. However, in column (3), we interact public infrastructure investment with a dummy variable, which has a value one if a firm's productivity in year t is below the median value of productivity. This interaction term is significantly positive, implying that the impact of public infrastructure investment on firm's exit depends on firm's productivity. A low productivity firm is indeed more likely to exit with more public infrastructure investment.

<Insert Table 8 here>

Table 9 has a similar structure as Table 8, replacing firm's exit with market share in year t as the dependent variable.[25] In column (1), productivity and capital stock have positive and significant prediction power on the market share of a firm in the next year. When public infrastructure investment is added into the regressions as in column (2), it also contributes positively and significantly to firm's market share. What is the most relevant is again column (3), where we interact public infrastructure investment with a dummy variable for high productivity. Consistent with our expectation, this additional term is significantly positive, implying that the impact of public infrastructure investment on firm's market share depends on firm's productivity. This verifies the hypothesis that public infrastructure investment facilitates to reallocate the market share towards more productive firms.

<Insert Table 9 here>

The empirical evidences, from both the extensive and intensive margins are consistent with our hypothesis on resource reallocation. This finding echoes the recent literature on how transport infrastructure affects the distribution of economic activities, and also challenges one of the original intentions of public infrastructure investment in reducing regional disparity.

[25] There are more observations for regressions in Table 9 than in Table 8. This is because we cannot apply the exit model to observations in year 2007, as we do not know whether a firm existed in 2007 has exited or not in 2008.

7 Specification Tests and Robustness Checks

Table 10 lists the rates of return from a set of specification tests and robustness checks, where the returns from our benchmark models are listed in the first column. Recall that these benchmark estimates use a proxy for v_{jt} (and v_{jt}^q) in the productivity process (8) and (18), where the proxy is obtained based on the assumption of constant return to scale and balanced growth path. Therefore it is important to investigate the possible range of the returns had we not adopted this specific proxy.

In column (2), we estimate our models without including any province-specific productivity shock at all. In column (3), we proxy v_{jt} (and v_{jt}^q) using $\left(\omega_{jt} - \mu_j\right)$. The province-level Solow residual ω_{jt} is backed from a growth accounting framework, using information on province-level GDP Q_{jt}, labor force L_{jt}, private capital stock K_{jt} and labor income share α_l and assuming $\alpha_k = 1 - \alpha_l$. Then we regress ω_{jt} over province dummies to purge the effect of μ_j. According to equation (4), $\omega_{jt} - \mu_j = \alpha_b \ln B_{jt} + v_{jt}$. Thus this proxy for v_{jt} (and v_{jt}^q) contains the impact of $\ln B_{jt}$ by construction.

Under China's institutional background, the correlation between v_{jt} (and v_{jt}^q) and g_{jt-1} is most likely to be positive. By definition, $\ln B_{jt}$ and g_{jt-1} are also positively correlated. Therefore, the estimates in column (2) are most likely to be upward biased for the true values as such estimates suffer from an omitted variable bias and the omitted variable v_{jt} (and v_{jt}^q) is positively correlated with the regressor g_{jt-1}. In contrast, the estimates in column (3) are most likely to be downward biased for the true values as the effect of the regressor g_{jt-1} is now absorbed by $\ln B_{jt}$ which is positively correlated with the regressor g_{jt-1}. Thus the true value of the productivity effect should be covered by the range bounded by these two estimates.

Consistent with our expectation, the estimates from column (2) are 20% to 40% higher than those benchmark returns. The estimated returns for spillover models in column (3) are 70% to 50% lower than those benchmark returns and the returns without spillover effect are just marginally negative. It is therefore an assuring evidence that the estimates from our benchmark models fall in between those from column (2) and (3). It is also an assuring evidence that the range between column (2) and (3) is tight enough for us to conclude on positive and moderate returns to public infrastructure investment.

<Insert Table 10 here>

In column (4) we omit the interaction term of $\omega_{ijt-1} \cdot g_{jt-1}$ (and $\omega_{ijt-1}^q \cdot g_{jt-1}$) from the productivity processes. Although this imposes a homogeneous effect of infrastructure investment on different firms, the average rates of return are very close to those in column (1). This suggests that the productivity effect of public infrastructure investment we obtained in the benchmark model is not driven by the fact that we have allowed for the heterogeneity in the effect. In column (5), we experiment by assuming the productivity processes is cubic in the lagged productivity ω_{ijt-1} (and ω^q_{ijt-1}), which delivers similar returns to the benchmark results. In contrast, if we only allow for a linear specification for the lagged productivity, it will lead to vast different results. This once again highlights the importance of the nonlinearity of the productivity process.

Column (6) and (7) present some robustness checks around our identification strategy. First, our identification requires the orthogonality between firm-specific productivity shock and province-level infrastructure. However, in theory there could be some firms that are big enough to influence the infrastructure investment decision of a province, which would invalidate our identification assumption. Second, we use lagged firm-level productivity to control for the self-selection of more productive firms into move productive province. However, in reality some firms could move across provinces. This may question the sufficiency of our conditioning strategy. Therefore, in column (6) we drop the top 1% largest firms of each province; and in column (7) we drop all the firms that switched between provinces. The fact that returns in column (6) and (7) share the same pattern and magnitude as those in column (1) implies the robustness of our results to these two concerns.

In column (8) and (9) we test the robustness of the spillover models. Column (8) presents the returns when we use travel cost instead of physical distance between capital cities of provinces to construct the weight matrix. The estimates in column (1) and (8) turn out to be very close to each other. Finally, in the benchmark case, we assume that the positive externality of public investment can spread across the whole nation. In column (9), we consider a more conservative assumption that the public investment of a province only affects the productivity and demand of firms locating within this province and its neighboring provinces. This is another common practice in the literature studying the interregional effect of infrastructure investment. If public investment does have a positive spillover effect, and if such effect does go beyond the neighboring provinces, we should expect the returns from this setup to be larger than those without spillover effect but smaller than those with national-level spillover effect. This is indeed the pattern we observe across column (1) and (9).

8 Conclusion

This paper investigates three important and controversial research questions on the productivity effect of public infrastructure investment. In contrast to the traditional literature, there are two novel features in our approach: a model of endogenous productivity process and the combination of firm-level production data and province-level infrastructure investment data. When we apply this approach to China, we find robust evidences on the productivity effect of public infrastructure investment. Although a sizeable contribution of public infrastructure investment to output is via the short-run demand effect, the long-run quantity-based total factor productivity also benefits from such investment. When interregional spillover effects are taken into account, infrastructure investment offers a respectable rate of return. An important mechanism of the productivity effect comes from the role of infrastructure in facilitating resource reallocation from less to more productive firms.

The answers to these research questions clearly have significant policy implications. There are, however, also some other questions that go beyond the limit of this paper. First, the overall efficiency of public infrastructure investment does not rule out the possibility that some type of infrastructure investment could be unproductive or inefficient in some industries and in some regions, even during our sample period. Second, beyond our sample period, we have to be very cautious on concluding whether China has over-invested or under-invested in infrastructure investment. On one hand, the rates of return of infrastructure investment seem to peak during 2003 and 2004, a period when China just completed the reforms of state-owned firms and entered the WTO so that the catalyst role of infrastructure investment in resource reallocation is maximized. Further investment could be subject to the diminishing returns to capital. On the other hand, spatial spillover and network externalities do not rule out the possibility of economy of scale and increasing returns. Infrastructure investment could also affect productivity via other mechanisms that are not captured by our research design. Finally, what has been identified in this paper can be regarded as the benefits of public infrastructure investment. A more complete evaluation requires studies on the schemes and designs of public finance, and on the institutions and incentives from a perspective of political economy.

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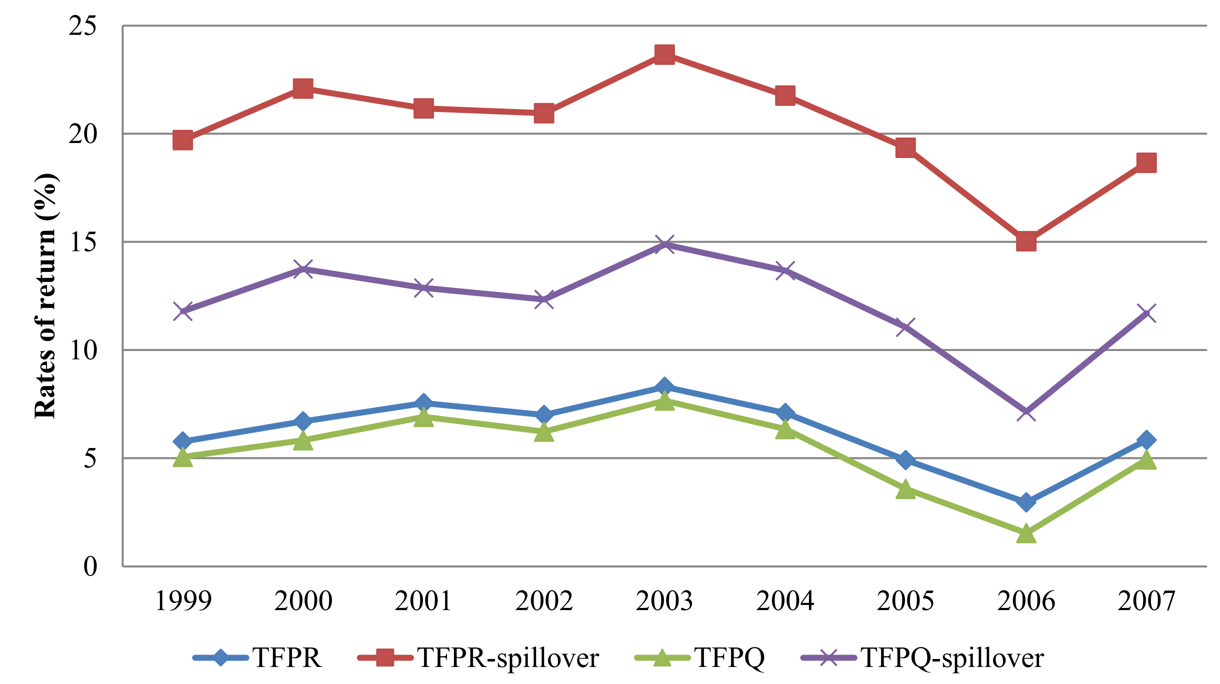
Figure 1 Estimated returns of public infrastructure investment



Note:
This figure reports the returns of public infrastructure investment over 1999-2007 in 4 models: TFPR, TFPR with spillover effects, TFPQ and TFPQ with spillover effects, respectively.

Table 1 Firm-level data description

industry	definition	(1)	(2)	(3)	(4)
13	Food processing	13,029	126.72	1.19	6.9
14	Food manufacturing	5,246	106.94	1.15	6.7
15	Beverage manufacturing	3,590	102.26	1.20	8.2
16	Tobacco processing	264	121.75	1.54	6.4
17	Textile industry	17,562	109.13	1.13	7.0
18	Garments & other fiber products	9,725	103.03	1.10	5.6
19	Leather, furs, down & related products	4,861	109.42	1.11	6.7
20	Timber processing, bamboo, cane, palm fiber	4,453	108.26	1.17	11.0
21	Furniture manufacturing	2,365	104.87	1.14	7.2
22	Papermaking & paper products	6,124	105.03	1.14	7.4
23	Printing industry	4,361	93.40	1.13	4.5
24	Cultural, educational & sports goods	2,658	107.00	1.10	4.8
25	*Petroleum processing & coking*	*1,802*	*201.03*	*1.20*	*1.6*
26	Raw chemical materials & chemical products	14,970	122.16	1.17	7.5
27	Medical & pharmaceutical products	4,303	96.49	1.15	8.4
28	Chemical fiber	1,031	122.58	1.14	6.6
29	Rubber products	2,427	111.31	1.14	7.3
30	Plastic products	9,446	114.49	1.14	5.4
31	Nonmetal mineral products	17,594	106.08	1.15	10.3
32	Smelting & pressing of ferrous metals	4,948	133.74	1.16	8.8
33	*Smelting & pressing of nonferrous metals*	*3,643*	*196.66*	*1.16*	*1.8*
34	Metal products	11,018	114.41	1.13	6.1
35	Ordinary machinery	15,358	105.55	1.13	8.7
36	Special purpose equipment	8,606	106.39	1.13	7.2
37	Transport equipment	9,896	96.11	1.13	7.4
39	Electric equipment & machinery	12,025	117.62	1.13	4.7
40	Electronic & telecommunications equipment	6,766	83.49	1.12	7.5
41	Instruments, meters, cultural & office equipment	2,907	92.19	1.12	6.3
42	Other manufacturing	3,952	117.17	1.11	2.4
	average*	7,388	108.80	1.15	6.9

Note:
(1): number of observations per year: (number of total firms for each industry during 1998-2007)/10
(2): output deflator of 2007 (1998 = 100): from Brandt et al. (2012)
(3): markup: median value of sales/total cost of production
(4): labor productivity growth (%): median value of real growth rate of value-added/employees
* industry average excluding industry 25 and 33

Table 2 Data description on infrastructure investment -- national level

	average	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
volume (billion Yuan, 1998 price)	1184.1	729.4	778.0	845.9	884.6	891.9	1058.9	1284.6	1559.1	1847.6	1961.5
real growth rate (%)	11.9	NA	6.7	8.7	4.6	0.8	18.7	21.3	21.4	18.5	6.2
investment/GDP (%)	8.9	8.6	8.5	8.5	8.2	7.6	8.2	9.1	9.9	10.4	9.7

Note:

1. Data are from China Statistics Yearbooks and China Fixed Investment Statistical Yearbooks.
2. Infrastructure investment data are deflated by the price indices of investment in fixed assets by province.
3. GDP data are deflated by the national level GDP deflator.

Table 3 Data description on infrastructure investment -- by province

	(1) volume (billion Yuan)	(2) real growth rate (%)	(3) investment/GDP (%)
Beijing	34.9	12.0	7.7
Tianjing	20.0	14.5	7.5
Hebei	60.8	10.0	8.3
Shanxi	35.2	12.8	12.4
Inner Mongolia	44.2	29.1	15.1
Liaoning	43.7	12.2	6.4
Jilin	20.0	13.9	7.4
Helongjiang	32.8	8.9	7.0
Shanghai	50.4	14.1	7.0
Jiangsu	81.4	7.1	6.3
Zhejiang	88.9	11.7	9.6
Anhui	33.2	15.7	7.6
Fujian	48.8	9.8	8.9
Jiangxi	30.8	12.3	10.4
Shandong	65.4	7.3	5.4
Henan	60.6	12.5	8.1
Hubei	55.1	8.6	10.9
Hunan	38.0	11.6	7.6
Guangdong	112.3	9.7	7.1
Guangxi	33.2	13.5	10.3
Hainan	7.6	8.9	10.6
Chongqing	27.0	13.9	9.8
Sichuan	57.1	8.1	9.9
Guizhou	27.8	16.9	19.2
Yunnan	42.9	15.6	14.3
Shaanxi	31.6	12.4	12.2
Gansu	18.2	10.9	12.4
Qinghai	8.8	15.1	22.7
Ningxia	7.8	12.8	18.3
Xinjiang	20.6	7.5	11.6
average	41.3	12.3	10.4
standard deviation	24.2	4.1	4.1

Note:

(1): annual investment volumn averaged from 1998 to 2007, billion Yuan, 1998 price

(2): real annual growth rate of investment, geometric average from 1998 to 2007

(3): investment to GDP ratio average from 1998 to 2007

1. Data are from China Statistics Yearbooks and China Fixed Investment Statistical Yearbooks.
2. Infrastructure data are deflated by the price indices of investment in fixed assets by province.
3. GDP data are deflated by the GDP deflator by province.

Table 4 Endogenous productivity processes in various models

Depedent variable: current productivity in respective model

Model	TFPR		TFPQ		TFPR-spillover		TFPQ-spillover	
	$\omega_{ij,t-1}$	-0.719***	$\omega^{q}_{ij,t-1}$	0.540***	$\omega_{ij,t-1}$	-1.572***	$\omega^{q}_{ij,t-1}$	0.532***
		(0.181)		(0.070)		(0.287)		(0.036)
	$\omega^{2}_{ij,t-1}$	-0.023***	$\omega^{q\,2}_{ij,t-1}$	-0.023***	$\omega^{2}_{ij,t-1}$	-0.023***	$\omega^{q\,2}_{ij,t-1}$	-0.017***
		(0.005)		(0.005)		(0.005)		(0.002)
	$\omega^{3}_{ij,t-1}$	0.000***	$\omega^{q\,3}_{ij,t-1}$	0.000***	$\omega^{3}_{ij,t-1}$	0.000**	$\omega^{q\,3}_{ij,t-1}$	0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
	$\omega^{4}_{ij,t-1}$	0.000***	$\omega^{q\,4}_{ij,t-1}$	0.000***	$\omega^{4}_{ij,t-1}$	0.000***	$\omega^{q\,4}_{ij,t-1}$	0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
	$g_{j,t-1}$	-0.036***	$g_{j,t-1}$	0.015***	$\bar{g}_{j,t-1}$	-0.026***	$\bar{g}_{j,t-1}$	0.022***
		(0.006)		(0.003)		(0.009)		(0.006)
	$\omega_{ij,t-1}*g_{j,t-1}$	0.084***	$\omega^{q}_{ij,t-1}*g_{j,t-1}$	0.009***	$\omega_{ij,t-1}*\bar{g}_{j,t-1}$	0.125***	$\omega^{q}_{ij,t-1}*\bar{g}_{j,t-1}$	0.001
		(0.009)		(0.004)		(0.015)		(0.002)
	v_{jt}	0.420***	v^{q}_{jt}	0.511***	v_{jt}	0.249***	v^{q}_{jt}	0.383***
		(0.048)		(0.060)		(0.044)		(0.054)
median elasticity		0.013		0.014		0.046		0.020
number of obs.		1,347,547		1,347,547		1,347,547		1,347,547
R-squared		0.861		0.953		0.827		0.995

Note:

1. Industrial dummies are included.

2. Clustered standard errors at the province-industry level are reported in parentheses.

3. *** p<0.01, ** p<0.05, * p<0.1

Table 5 Output elasticities by productivity percentile: TFPR model

industry	25th percentile	50th percentile	75th percentile
13	0.005	0.006	0.006
14	0.012	0.018	0.024
15	0.000	0.009	0.019
16	0.027	0.030	0.032
17	-0.006	0.000	0.007
18	0.002	0.009	0.019
19	-0.004	0.001	0.007
20	0.003	0.011	0.019
21	-0.019	-0.003	0.014
22	0.019	0.021	0.023
23	0.035	0.037	0.039
24	0.000	0.012	0.024
26	-0.006	-0.005	-0.003
27	0.019	0.024	0.028
28	0.000	0.009	0.019
29	-0.022	0.001	0.016
30	-0.005	0.001	0.004
31	0.006	0.013	0.022
32	0.001	0.003	0.006
34	-0.011	-0.010	-0.009
35	0.001	0.006	0.010
36	-0.001	0.008	0.015
37	-0.001	0.003	0.007
39	-0.026	-0.026	-0.026
40	0.012	0.015	0.018
41	-0.022	-0.012	0.003
42	-0.010	-0.008	-0.004
average*	0.000	0.006	0.013

Note:

* unweighted simple average

Table 6 Output elasticities and rates of return

	9-year average	1999	2000	2001	2002	2003	2004	2005	2006	2007
GDP/G	12.630	12.525	12.733	12.682	13.229	14.437	13.385	12.285	11.406	10.992
average output elasticity										
TFPR	0.005	0.005	0.005	0.006	0.005	0.006	0.005	0.004	0.003	0.005
TFPQ	0.004	0.004	0.005	0.005	0.005	0.005	0.005	0.003	0.001	0.005
TFPR-spillover	0.016	0.016	0.017	0.017	0.016	0.016	0.016	0.016	0.013	0.017
TFPQ-spillover	0.010	0.009	0.011	0.010	0.009	0.010	0.010	0.009	0.006	0.011
rate of return (%)										
TFPR	6.2	5.8	6.7	7.6	7.0	8.3	7.1	4.9	3.0	5.8
TFPQ	5.3	5.1	5.8	6.9	6.2	7.7	6.3	3.6	1.5	4.9
TFPR-spillover	20.3	19.7	22.1	21.2	21.0	23.7	21.8	19.4	15.0	18.7
TFPQ-spillover	12.1	11.8	13.7	12.9	12.3	14.9	13.7	11.1	7.2	11.7

Note:

1. Average output elasticity denotes the value-added-weighted average elasticity of the manufacturing sector.
2. Rate of return is the product of average output elasticity and total GDP/G.

Table 7 Linking output elasticity with firm characteristics

Dependant variable: output elasticity*1000

model	TFPR	TFPQ	TFPR-spillover	TFPQ-spillover
age	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
lnemp	-0.200***	-0.560***	-0.876***	-0.762***
	(0.016)	(0.020)	(0.037)	(0.044)
NSOE	1.426***	1.984***	0.519***	0.505***
	(0.061)	(0.073)	(0.145)	(0.175)
EXPORT	0.816***	1.087***	1.168***	1.607***
	(0.024)	(0.028)	(0.050)	(0.060)
EASTERN	0.241***	0.336***	0.356***	0.853***
	(0.026)	(0.036)	(0.058)	(0.069)
number of obs.	1,346,897	1,346,897	1,346,897	1,346,897
R-squared	0.502	0.603	0.454	0.554

Note:

1. age: firm's age
2. lnemp: log of number of employees
3. NSOE: non-SOE dummy, non-SOEs = 1, SOEs = 0
4. EXPORT: exporter dummy, exporters = 1, nonexporters = 0
5. EASTERN: location dummy, eastern provinces = 1, noneastern provinces = 0
6. Industry dummies and year dummies are included in all regressions.
7. Robust standard errors are reported in parentheses.
8. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8 Probit regressions of exit probability

Dependent variable: firm *i*'s exit in year *t*+1

model	TFPR (1)	TFPR (2)	TFPR (3)	TFPR-spillover (1)	TFPR-spillover (2)	TFPR-spillover (3)
Productivity	-0.154***	-0.151***	-0.105***	-0.147***	-0.144***	-0.097***
	(0.009)	(0.008)	(0.023)	(0.008)	(0.008)	(0.009)
Capital	-0.136***	-0.135***	-0.136***	-0.137***	-0.136***	-0.137***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
Infrastructure		-0.087***	-0.091***		-0.171***	-0.176***
		(0.010)	(0.028)		(0.019)	(0.020)
Infrastructure*LOW			0.005***			0.005***
			(0.001)			(0.000)
number of obs.	1,106,116	1,106,116	1,106,116	1,106,116	1,106,116	1,106,116
predicted prob	0.121	0.121	0.121	0.121	0.121	0.121

model	TFPQ (1)	TFPQ (2)	TFPQ (3)	TFPQ-spillover (1)	TFPQ-spillover (2)	TFPQ-spillover (3)
Productivity	-0.143***	-0.145***	-0.100***	-0.125***	-0.131***	-0.085***
	(0.019)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Capital	-0.137***	-0.137***	-0.138***	-0.137***	-0.136***	-0.138***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Infrastructure		-0.096***	-0.107***		-0.194***	-0.219***
		(0.010)	(0.009)		(0.019)	(0.018)
Infrastructure*LOW			0.006***			0.005***
			(0.001)			(0.000)
number of obs.	1,106,116	1,106,116	1,106,116	1,106,116	1,106,116	1,106,116
predicted prob	0.121	0.121	0.121	0.121	0.121	0.121

Note:

1. Industry dummiess and year dummies are included in all regressions.
2. LOW: dummy variable, LOW_{it} = 1 (0) if productivity is below (above) the median.
3. Clustered standard errors at the province-industry level are reported in parentheses.
4. *** p<0.01, ** p<0.05, * p<0.1

Table 9 Regressions of market share

Dependent variable: firm *i* 's market share in year *t* +1

model	TFPR			TFPR-spillover		
	(1)	(2)	(3)	(1)	(2)	(3)
Productivity	0.563***	0.563***	0.394***	0.535***	0.537***	0.359***
	(0.022)	(0.021)	(0.018)	(0.019)	(0.018)	(0.016)
Capital	0.561***	0.562***	0.562***	0.563***	0.564***	0.566***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Infrastructure		0.311***	0.308***		0.601***	0.604***
		(0.016)	(0.016)		(0.031)	(0.031)
Infrastructure*HIGH			0.014***			0.015***
			(0.001)			(0.001)
number of obs.	1,346,842	1,346,842	1,346,842	1,346,842	1,346,842	1,346,842
R-squared	0.556	0.567	0.572	0.554	0.565	0.571

model	TFPQ			TFPQ-spillover		
	(1)	(2)	(3)	(1)	(2)	(3)
Productivity	0.504***	0.532***	0.369***	0.417***	0.461***	0.299***
	(0.019)	(0.019)	(0.016)	(0.015)	(0.015)	(0.014)
Capital	0.565***	0.565***	0.567***	0.563***	0.565***	0.566***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Infrastructure		0.345***	0.360***		0.680***	0.736***
		(0.017)	(0.017)		(0.033)	(0.034)
Infrastructure*HIGH			0.016***			0.015***
			(0.001)			(0.001)
number of obs.	1,346,842	1,346,842	1,346,842	1,346,842	1,346,842	1,346,842
R-squared	0.557	0.571	0.577	0.549	0.564	0.570

Note:

1. Industry dummies and year dummies are included in all regressions.
2. HIGH: dummy variable, $HIGH_{it-1}$ = 1 (0) if productivity is above (below) the median.
3. Lagged values of explanatory variables are used in regressions.
4. Clustered standard errors at the province-industry level are reported in parentheses.
5. *** p<0.01, ** p<0.05, * p<0.1

Table 10 Rates of return from specification tests and robustness checks (%)

model	**(1)**	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TFPR	**6.2**	8.7	-0.2	5.1	6.6	6.7	5.6	N.A.	N.A.
TFPQ	**5.3**	7.5	-1.0	3.4	2.5	2.8	5.1	N.A.	N.A.
TFPR-spillover	**20.3**	24.6	9.8	22.4	21.1	24.9	17.7	19.9	9.0
TFPQ-spillover	**12.1**	16.4	3.8	12.0	9.7	10.3	15.2	12.2	6.5

Note:

(1): benchmark estimates

(2): upward biased estimates - not including any proxy for v_{jt} in the productivity process

(3): downward biased estimates - including ω_{jt} - μ_{jt} as a proxy for v_{jt} in the productivity process

(4): omitting the interaction between lagged productivity and infrastructure

(5): assuming third instead of fourth-order polynominal for the productivity process

(6): dropping the top 1% largest firms in each province

(7): dropping those firms that switched province

(8): using travel cost to construct the weighting matrix for spillover effects

(9): assuming spillover effects only apply to neighboring provinces

Table A1 Infrastructure investment in urban area by jurisdiction of management and by registration status

Infrastructure type	Year	Total[1]	By jurisdiction (%)		By registration status (%)		
			Central	Local	State	Collective	Private
Power	2004	485.4	35.0	65.0	80.8	1.3	1.8
	2005	650.3	33.7	66.3	78.1	0.9	1.8
	2006	727.4	36.6	63.4	78.6	5.8	11.0
Road transport	2004	466.6	4.3	95.7	95.2	0.7	0.4
	2005	558.1	5.1	94.9	93.2	0.8	0.8
	2006	648.2	2.5	97.5	93.2	2.3	3.8
Railways	2004	84.6	88.9	11.1	99.0	0.5	0.0
	2005	126.8	88.5	11.5	98.2	0.8	0.0
	2006	196.7	89.8	10.2	97.5	1.8	0.6
		average	42.7	57.3	90.4	1.7	2.3

Note:
1. investment volumn, billion Yuan, current price
2. Source of data: Table 2, Table 4 and Table 6 from Bai and Qian (2010)

Table A2 Infrastructure investment in urban area by source of funds (%)

Year	State budget	Domestic loans	Foreign investment	Self-raised funds	Others
1998	8.8	24.2	12.4	41.9	12.6
1999	12.5	25.1	9.0	41.0	12.4
2000	12.6	28.3	6.7	41.3	11.0
2001	14.4	25.5	6.3	43.7	10.1
2002	14.7	25.6	6.0	44.5	9.2
2003	9.2	26.9	5.4	49.3	9.1
2004	9.1	32.3	2.4	49.7	6.6
2005	9.4	31.8	2.0	50.3	6.4
2006	9.7	30.7	1.8	50.2	7.6
2007	10.7	29.0	1.4	51.2	7.7

Note:
Source of data: Figure 2.1 and Table 2.1 from Huang and Shi (2014)

Table A3 Regression of province-level productivity

Dependent variable: log real GDP per capita ω_{jt}

	a_j	b_j
Beijing	-152.53	0.08
Tianjing	-215.06	0.11
Hebei	-193.46	0.10
Shanxi	-209.16	0.11
Inner Mongolia	-283.33	0.15
Liaoning	-195.91	0.10
Jilin	-192.32	0.10
Helongjiang	-185.93	0.10
Shanghai	-158.78	0.08
Jiangsu	-217.90	0.11
Zhejiang	-203.72	0.11
Anhui	-190.12	0.10
Fujian	-180.23	0.09
Jiangxi	-190.94	0.10
Shandong	-220.94	0.12
Henan	-207.02	0.11
Hubei	-191.63	0.10
Hunan	-195.47	0.10
Guangdong	-196.03	0.10
Guangxi	-183.91	0.10
Hainan	-161.60	0.09
Chongqing	-193.51	0.10
Sichuan	-196.08	0.10
Guizhou	-174.23	0.09
Yunnan	-148.77	0.08
Shaanxi	-195.27	0.10
Gansu	-189.69	0.10
Qinghai	-188.89	0.10
Ningxia	-169.40	0.09
Xinjiang	-149.47	0.08

Note:

1. OLS estimates for model $\omega_{jt} = a_j + b_j \cdot t + v_{jt}$
2. All the estimates are significant at the 1% confidence level.

Table A4 Estimates for the sales revenue equation in the TFPR model

industry	β_l	$s.e.(\beta_l)$	β_k	$s.e.(\beta_k)$	β_m	$s.e.(\beta_m)$
13	0.051	0.017	0.036	0.005	0.901	0.013
14	0.024	0.021	0.049	0.006	0.924	0.012
15	0.180	0.028	0.019	0.026	0.852	0.031
16	0.665	0.325	0.251	0.116	0.521	0.205
17	0.008	0.045	0.011	0.010	0.982	0.062
18	0.079	0.083	0.006	0.007	0.929	0.075
19	0.080	0.029	0.016	0.011	0.918	0.041
20	0.004	0.083	0.072	0.064	0.833	0.090
21	0.117	0.045	-0.001	0.033	0.936	0.045
22	0.065	0.027	0.095	0.025	0.784	0.036
23	0.310	0.097	0.115	0.041	0.646	0.090
24	0.086	0.053	0.044	0.017	0.865	0.074
26	0.012	0.048	0.026	0.006	0.953	0.040
27	0.104	0.022	0.145	0.021	0.729	0.031
28	0.018	0.013	0.022	0.008	0.946	0.014
29	0.096	0.080	0.021	0.042	0.895	0.106
30	0.066	0.009	0.066	0.014	0.848	0.016
31	0.120	0.009	0.006	0.030	0.846	0.007
32	0.055	0.014	0.012	0.009	0.946	0.013
34	0.133	0.047	0.018	0.011	0.890	0.033
35	-0.004	0.008	0.039	0.005	0.944	0.011
36	0.098	0.049	0.062	0.051	0.810	0.063
37	0.193	0.046	-0.025	0.046	0.895	0.037
39	0.044	0.008	0.028	0.004	0.924	0.008
40	0.108	0.016	0.126	0.015	0.771	0.019
41	0.103	0.043	0.046	0.044	0.852	0.070
42	0.091	0.057	0.035	0.007	0.874	0.058

Note: All standard errors are bootstrapped using 1000 replications.

Table A5 Estimates for the sales revenue equation in the TFPQ model

industry	β_l*	*s.e.* (β_l*)	β_k*	*s.e.* (β_k*)	β_m*	*s.e.* (β_m*)	π*	*s.e.* (π*)
13	0.071	0.022	0.036	0.005	0.886	0.017	0.145	0.005
14	0.030	0.020	0.050	0.006	0.918	0.012	0.088	0.010
15	0.175	0.029	0.029	0.031	0.845	0.037	0.070	0.009
16	0.643	0.343	0.252	0.112	0.530	0.214	0.065	0.075
17	0.008	0.076	0.011	0.019	0.982	0.112	-0.002	0.004
18	0.077	0.084	0.009	0.007	0.925	0.076	0.080	0.009
19	0.078	0.028	0.017	0.012	0.916	0.042	0.029	0.006
20	-0.118	0.063	0.168	0.049	0.709	0.094	0.233	0.018
21	0.082	0.038	0.027	0.029	0.900	0.037	0.105	0.015
22	0.065	0.028	0.091	0.025	0.792	0.035	0.067	0.006
23	0.328	0.101	0.115	0.038	0.630	0.089	0.072	0.019
24	0.087	0.053	0.046	0.015	0.858	0.072	0.031	0.012
26	0.015	0.079	0.026	0.014	0.950	0.076	0.028	0.006
27	0.107	0.045	0.139	0.053	0.731	0.068	0.076	0.012
28	0.017	0.014	0.022	0.008	0.947	0.015	-0.036	0.019
29	0.141	0.077	0.067	0.044	0.782	0.101	0.067	0.019
30	0.064	0.010	0.060	0.016	0.856	0.019	0.091	0.005
31	0.101	0.006	0.080	0.025	0.836	0.007	0.101	0.003
32	0.053	0.014	0.011	0.009	0.948	0.013	-0.035	0.011
34	0.131	0.041	0.020	0.010	0.888	0.030	0.007	0.005
35	0.000	0.007	0.039	0.005	0.941	0.011	0.045	0.007
36	0.093	0.044	0.056	0.047	0.830	0.060	0.043	0.006
37	0.176	0.039	-0.015	0.035	0.891	0.028	0.032	0.005
39	0.045	0.008	0.029	0.004	0.923	0.008	0.022	0.007
40	0.115	0.016	0.121	0.014	0.774	0.019	0.103	0.007
41	0.077	0.045	0.123	0.049	0.732	0.077	0.057	0.021
42	0.086	0.055	0.035	0.007	0.877	0.056	0.019	0.007

Note: All standard errors are bootstrapped using 1000 replications.