A Structural Estimation of the Return to Infrastructure Investment in China*

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This version: April 2021

Abstract

The productivity effect of infrastructure investment is controversial in the traditional literature using aggregate production function estimation due to reverse causality. This paper develops a new approach, using a structural model of firm-level production function, and matching Chinese firm-level production data with province-level infrastructure data. The estimated rates of return are about 6 percent averaged from 1999 to 2007. The returns triple if national-level spillover effects are taken into account. Controlling for the demand effect of public expenditure leads to smaller but still positive returns. The effect of infrastructure investment on firm-level productivity is heterogenous. With an increase in infrastructure investment, lower productivity firms are more likely to exit and higher productivity firms gain more market share.

JEL Classification: O18, D24, E22, R53, H54

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

*We would like to thank the Co-Editor David Lagakos, two anonymous referees, and Abdul Abiad, Hanming Fang, Wen-Tai Hsu, Shaoqing Huang, Ruixue Jia, Jong-Wha Lee, Arthur Lewbel, Jing Li, Ming Lu, Yew-Kwang Ng, Albert Park, Yu Qin, Akshar Saxena, Hao Shi, Zheng Michael Song, Eik Swee, Matthew Turner, Ping Wang, Yong Wang, Shang-Jin Wei, Yanrui Wu, Chong Xiang and Xiaodong Zhu for their insights and suggestions, and valuable comments from audiences at various conferences, workshops and seminars, especially those from ABFER2017, AMES2017, CESI2017, CMES2018, NASM2018, SMU Urban and Regional Economics Conference 2018. Financial support from the MOE AcRF Tier 1 Grant M4011642 at Nanyang Technological University is gratefully acknowledged. Wu and Feng are from Nanyang Technological University, Singapore. Emails: guiying.wu@ntu.edu.sg (G. Wu), qfeng@ntu.edu.sg (Q. Feng). Wang is from Hunan University, China. Email: WANG0869@e.ntu.edu.sg (Z. Wang).

1 Introduction

Infrastructure investment[1] has often been advocated as a precursor to economic development by many authorities and international institutions. The idea that public investment in infrastructure will boost economic growth becomes even more appealing when the global economy faces severe demand constraints and high unemployment. However, there is lack of convincing evidence that infrastructure investment in general leads to a higher output and income in the long run (Warner, 2014). When the investment is financed by public debt, especially in China in recent years, there is additional concern on investment efficiency and financial stability (Ansar et al., 2016).

This paper investigates three questions. First, what is the average rate of return on 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.[2] Second, if infrastructure investment does raise output and income, is it due to the demand effect of fiscal expansions or the productivity gains on the supply side? Productivity gains are fundamental to long-term growth, because they typically translate into higher income, and in turn boost demand. However, the debt-fueled investment that shifts future demand to the present without stimulating productivity growth is detrimental to the economy.[3] Finally, if public infrastructure investment indeed promotes aggregate productivity, what are the underlying mechanisms for it 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 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. In a seminal work, Aschauer (1989) estimates an output elasticity with respect to infrastructure capital to be from 0.38 to 0.56, which implies a rate of return of more than 100 percent in the U.S. during 1949 to 1985. This finding has been extensively re-examined by many subsequent studies.

[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 uses "infrastructure investment" to refer to investment in those basic structures and facilities needed for the operation of a modern economy. Such investment expenditures are mainly although not exclusively financed by governments.

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

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

However, remarkably little consensus has emerged in the literature.[4] As pointed out by Banerjee et al. (2020), finding credible ways to estimate or even bound the social returns remains a very important next step in this research agenda.

The disparate empirical findings in the existing literature could be the consequence of several methodological challenges, in particular, the reverse causality between output and infrastructure. Various ways have been used to deal with the reverse causality. The first approach is the combination of disaggregated and aggregated data, such as Fernald (1999). The second method is the simultaneous-equation approach, such as Röller and Waverman (2001). The third identification strategy is to use exogenous changes 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 mainly adopted the instrumental variables approach.[5] 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 on general infrastructure.

This paper proposes a structural approach to estimate the effect of infrastructure investment on productivity, and applies the approach to a panel of Chinese manufacturing firms matched with province-level infrastructure. Reverse causality could arise due to endogenous location of firms and endogenous allocation of infrastructure. To address these concerns, we first model the firm-level productivity as the sum of a productivity shock and an expected productivity that is affected by infrastructure investment through a first-order Markov process. As this productivity process allows for an arbitrary correlation between the lagged firm-level productivity and province-level infrastructure, it controls for reverse causality arising from the self-selection of firms through space. Second, to further control for the reverse causality arising from the endogenous allocation of 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

[4] In a survey, Bom and Ligthart (2014) find that 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.

[5] 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).

is assumed to be orthogonal to the province-level infrastructure investment. This key identification condition is based on the assumption that policy makers will not adjust the infrastructure of a province, in light of an idiosyncratic firm-level productivity shock.

Besides mitigating the reverse causality, using firm-level data also makes it possible to control for the demand effect of infrastructure investment, the second research question of this paper. Inspired by De Loecker (2011), we model the firm-specific demand shifter as a function of 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 infrastructure, while the effect estimated from a TFPQ model only reflects the effect of infrastructure on quantity productivity.

Our main empirical findings are as follows. First, during 1999 to 2007 there is a 6.2 percent average annual real rate of return of infrastructure investment in the TFPR model. Second, when we consider the spillover effects of infrastructure investment across regions, in a specification where infrastructure investment has national-level spillover effects on firms locating outside of the province, the estimated rate of return triples. This implies that infrastructure investment does have a positive causal effect on aggregate output. Third, the returns estimated from the TFPQ models are 15 to 40 percent smaller than the corresponding TFPR models. This suggests a sizeable positive contribution of infrastructure on output is indeed via the demand effect. Thus, it confirms both the short-run stimulus effect and the long-run productivity effect of infrastructure. Finally, we present further firm-level evidence on heterogenous effect of infrastructure investment on productivity, depending on a firm's attained productivity and characteristics. We show that infrastructure investment is positively associated with the probability of exit of less productive firms and the market shares of more productive firms.

The rest of the paper is organized as follows. Section 2 discusses the identification challenges in the traditional approach and explains our novel approach to estimate the return of infrastructure. Section 3 describes the data and presents the baseline results. Section 4 studies two extensions: distinguishing productivity effect from demand effect and allowing for spillover effect. Section 5 presents further empirical evidence on mechanism. Section 6 summarizes the findings and discusses the limitations.

2 Estimating Return of Infrastructure Investment

2.1 The Traditional Approach

Starting with Aschauer (1989), the traditional literature considers 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 stock, labor force and stock of infrastructure capital of province j and year t. The output elasticity with respect to infrastructure α_b is the key parameter of interest, as the economic return, or the marginal product of infrastructure, can be inferred using the relationship:[6]

$$r_t \equiv \frac{\partial Q_{jt}}{\partial B_{jt}} = \alpha_b \frac{Q_{jt}}{B_{jt}}. \tag{2}$$

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 foremost challenge is reverse causality, which is particularly relevant in China's context (Feng and Wu, 2018). To illustrate the nature of reverse causality, let the Solow residual ω_{jt} to measure the productivity of private inputs in production,

$$\omega_{jt} \equiv \ln Q_{jt} - \alpha_l \ln L_{jt} - \alpha_k \ln K_{jt} = \alpha_b \ln B_{jt} + \mu_j + v_{jt}. \tag{3}$$

Equation (3) or equivalently (1) aims to identify the causal effect of infrastructure on productivity, but the causality could go from productivity to 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. Second, reverse causality may also arise due to the correlation between v_{jt} and $\ln B_{jt}$ in equation (3) if policy makers can foresee v_{jt}, the latent productivity shock of each province.

Besides reverse causality, another challenge of the traditional approach lies in how to net out the demand effect of public expenditure. The observed Q_{jt} in equation (1)

[6] As Gramlich (1994) points out, "Because infrastructure capital is not paid for its services, interpretation of the productivity elasticities, α_l, α_k and α_b is tricky. If one assumes that private capital and labor are paid their marginal products and finds α_b to be positive, $\alpha_l + \alpha_k = 1$ and $\alpha_l + \alpha_k + \alpha_b > 1$ so that returns to scale are increasing." From the point of view of national income accounting, Cubas (2019) proposes that the income share of infrastructure capital equals to its elasticity divided by one plus its elasticity, under the assumption of constant rate to scale with respect to private capital and labor. This implies that from a social planner's perspective, if infrastructure capital was paid for its services, the rate of return would be adjusted as $r_t = \frac{\alpha_b}{1+\alpha_b} \frac{Q_{jt}}{B_{jt}}$.

is the equilibrium aggregate output. When expenditure in infrastructure increases, aggregate demand is what changes in the short run. Thus even if the true aggregate supply effect of 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 infrastructure using the equilibrium aggregate output therefore could mix both supply-side and demand-side contributions.

2.2 Our Approach: The TFPR Model

This paper proposes a new method to address the challenges one faces when using the traditional approach. For each industry, consider firm i in province j and year t, using the following sales revenue generating equation:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{ijt} + \epsilon_{it}, \tag{4}$$

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 error term ϵ_{it} is included to capture the unanticipated shocks to firm's sales revenue or measurement errors in the revenue data. These setups are standard in the production function estimation literature; instead, what is novel about equation (4) 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.

In this new approach, we capture the effect of infrastructure investment on productivity explicitly by allowing infrastructure investment to impact the evolution of productivity through a first-order Markov process:

$$\omega_{ijt} = h_t(\omega_{ijt-1}, g_{jt-1}) + v_{ijt}. \tag{5}$$

Equation (5) decomposes the actual productivity ω_{ijt} into an expected productivity term $h_t(\omega_{ijt-1}, g_{jt-1})$ and a random productivity shock v_{ijt}. The 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 infrastructure investment flow in province j where firm i is located and in year $t-1$ when the investment was 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 two important attributes. First, the contribution of previous infrastructure investment flows to ω_{ijt} is absorbed by its lag ω_{ijt-1}. Thus, we no longer require the entire history of investment flows nor do we need to impose arbitrary depreciation rates. This helps us circumvent the classic measurement error problem in the traditional literature that stems from the need to construct infrastructure capital stock.[7] Second, ω_{ijt} inherits initial productivity differences across firms and provinces from its lag ω_{ijt-1}.[8] Together, these two attributes imply that process (5) can be regarded as a generalization of equation (3) albeit presented in the form of firm-level productivity.

As y_{it} in the production function is a revenue-based output, following Foster et al. (2008), we refer to the system of equations (4) and (5) as the TFPR model, and ω_{ijt} as the revenue-based productivity.

2.3 Identification

Our approach using firm-level production function matched with province-level infrastructure investment alleviates the reverse causality problem in the traditional approach. However, reverse causality may still arise in our context.

2.3.1 Endogenous Location of Firms

The first source of reverse causality is endogenous location of firms. With spatial sorting, more productive firms tend to self-select into higher-income provinces. A province with more productive firms will be able to collect more tax revenue and finance more infrastructure. This implies a potentially positive correlation between firm-level productivity ω_{ijt-1} and province-level infrastructure g_{jt-1}.

We control for such a possibility by including the lagged productivity using a first-order Markov process structure as in equation (5). 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}, which, in turn, precludes the identification of the productivity effect of infrastructure from that of the firm. Nevertheless, under the structural assumption that ω_{ijt-1} has absorbed all

[7] Our departure from infrastructure capital stock to 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 a first-order Markov process.

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

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

the factors besides g_{jt-1} that will affect the expected productivity $h_t(\omega_{ijt-1}, g_{jt-1})$, we are still 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}.

2.3.2 Endogenous Allocation of Infrastructure

There is another source of reverse causality: non-random allocation of infrastructure. If infrastructure investment depends on aggregate output and hence aggregate productivity, then firm-level productivity shocks could affect infrastructure investment by affecting the aggregate productivity shocks. This implies that there might be a potential correlation between firm-level productivity shock v_{ijt} and province-level infrastructure g_{jt-1}. Thus, if the aggregate productivity process (3) suffers from reverse causality, so too does the firm-level productivity process (5). To address this type of reverse causality, following Fernald (1999), we further decompose the firm-level productivity shock v_{ijt} into two components:

$$v_{ijt} = \lambda v_{jt} + \varepsilon_{it}. \tag{6}$$

The first component, 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 across all random shocks. The second component, ε_{it}, is an unobservable firm-specific innovation, which is orthogonal to the aggregate shock v_{jt}, and hence to the infrastructure investment g_{jt-1}, assuming that g_{jt-1} is only affected by v_{jt}.

Substituting (6) into (5) leads to the decomposed productivity evolution process:

$$\omega_{ijt} = h_t(\omega_{ijt-1}, g_{jt-1}) + \lambda v_{jt} + \varepsilon_{it}. \tag{7}$$

Equation (7) highlights the key identification assumption in our approach, that the firm-level productivity shock is orthogonal to the province-level infrastructure investment:

$$E\left(\varepsilon_{it} | \omega_{ijt-1}, g_{jt-1}, v_{jt}\right) = 0. \tag{8}$$

The underlying rationale of this assumption is that, conditional on the province-level aggregate productivity shock v_{jt}, 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 data set. On average there are 6,650 firms in each province every year. The large number of firms in a province implies that condition (8) 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 ratios across provinces and across years are 1.6, 3.8 and 4.9 percent, respectively. This implies that the firm-size distribution in our data set also has a long right tail, a common finding in firm-level data. Thankfully, even the largest firms do not dominate the aggregate (provincial) output, due to the massive economic sizes of Chinese provinces. Finally, we conduct a couple of robustness checks in Appendix B to verify the validity of our assumption in equation (8). One is to drop the top 1 percent of the firms in each province and re-estimate the model. The other is to drop all the state-owned firms in our sample and re-estimate the model. The estimated rates of return for the TFPR model are relatively stable.

2.3.3 Proxy for v_{jt}

Since aggregate (provincial) productivity shocks v_{jt} are unobserved, it is important to find appropriate proxies for them. In our benchmark specifications, we infer v_{jt} directly from the starting point equation (1). Assuming that the technology satisfies the restriction of constant return to scale, the aggregate production function can then be written in intensive form:

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

Suppose that the economy is on a balanced growth path where 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 to be $\widehat{v}_{jt} = \ln(Q_{jt}/L_{jt}) - \ln\left(\widehat{Q_{jt}/L_{jt}}\right)$.

In our robustness checks in Appendix B, we also experiment with two alternative proxies for v_{jt}. Our two proxies, which generate positive and negative biases, thus provide upper and lower bounds for the true productivity effect of infrastructure investment. 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.

2.3.4 Firm-level Heterogeneity

One other issue in using matched firm-level and province-level data is a lack of variation in infrastructure as experienced by the firm. To address this concern, in addition to the lagged productivity and infrastructure investment, we also allow for the interaction of ω_{ijt-1} and g_{jt-1} in the $h_t(\omega_{ijt-1}, g_{jt-1})$ function.

The underlying rationale is that more productive firms tend to utilize the 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), who 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 infrastructure could be different, depending on the attained productivity level of the firms. Our approach thus allows us to capture the heterogeneous effect of infrastructure on firm's productivity. Such heterogeneity is crucial in exploring the mechanism of the productivity effect of infrastructure.

2.4 Output Elasticity of Infrastructure and Rate of Return

Our key parameter of interest is the firm-specific elasticity of output with respect to infrastructure investment, which can be translated into the rate of return to infrastructure investment at the aggregate level, the ultimate interest of this research. To take into account the potential differences in production technology and productivity process across industries, we estimate the TFPR model for each industry s separately, and then aggregate the firm-level elasticity into an aggregate-level elasticity. Since we estimate a three-factor revenue-based firm-level production function, we first use sales revenue as weights when aggregating the firm-level elasticity e_{ist} into the industry-level elasticity e_{st}. Since we use GDP, which is a value-added, in the final calculation of rate of return, we then use value-added as weights when aggregating the industry-level elasticity e_{st} into the aggregate-level elasticity e_t. At the industry-level, we adjust the sales-revenue-based elasticity into the value-added-based elasticity, using the relationship between sales revenue and value-added for each industry s.

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

$$e_{ist} = \frac{\partial y_{it}}{\partial g_{jt-1}} = \frac{\partial \omega_{ijt}}{\partial g_{jt-1}} = \frac{\partial h_{st}\left(\omega_{ijt-1}, g_{jt-1}\right)}{\partial g_{jt-1}}. \tag{9}$$

We then use sales revenue of each firm as the weight to aggregate these firm-level elasticities into an industry average,[9] and adjust the ratio between value-added and sales revenue:

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

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 $\frac{dz_s}{dy_s}$ is obtained by a fixed-effect regression of logarithm value-added on logarithm sales revenue for industry s. Finally, we use value-added of each industry as the weight to aggregate these industry-level elasticities into an average for the manufacturing sector:

$$e_t = \sum\nolimits_s e_{st} \frac{Z_{st}}{Z_t}, \tag{10}$$

where $\frac{Z_{st}}{Z_t}$ denotes industry s's value-added as a share of total value-added in the manufacturing sector in year t.[10]

Under the assumption that the output elasticity of infrastructure 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:[11]

$$r_t = e_t \frac{GDP_t}{G_{t-1}}. \tag{11}$$

[9] Since the infrastructure measure is province-specific, the alternative is to aggregate the output elasticity from the firm level to the industry-province level first before aggregating to the industry level. We conduct the robustness check in Appendix B and find the rates of return may decrease but only by a very small magnitude.

[10] Since sales revenue and value-added could be potentially endogenous, one refinement is to use their lagged values in constructing the weights. We do this as a robustness check in Appendix B and find very little change in the calcuated rates of return.

[11] To echo footenote 6, we find constant return to scale with respective to private inputs also holds for the majority of the manufacturing industries. Thus, we could also adjust the rate of return in our calculation into $r_t = \frac{e_t}{1+e_t} \frac{GDP_t}{G_{t-1}}$. As indicated in Table 3, since the 9-year average e_t in our application only varies between 0.004 to 0.016, the adjustment would only have a small impact on the reported rates of return.

Notice the similarity and difference between equation (11) and (2). While in the traditional approach the rate of return is inferred from output elasticity with respect to the stock of infrastructure, the return in our approach is based on the output elasticity with respect to the flow of infrastructure. Correspondingly, the two approaches also adjust GDP-to-capital stock and GDP-to-investment-flow to reach the final returns.

3 Data and Baseline Results

3.1 Data

3.1.1 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.[12] 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 percent value-added of China's industrial sector. Brandt et al. (2012) provide an excellent introduction and user manual to this data set. We match the annual data into a panel, construct the real capital stock by the perpetual inventory method, and deflate output and input data, strictly following their procedures and using their price indices.

Same as other literature using this data set, our production function estimation focuses on the 29 industries in the manufacturing sector. Table A1 in the Appendix reports the number of observations, output deflators, markups and labor productivity growth rates by industry. On average there are more than 7,000 firms in each industry-year. Most industries have a very moderate ten-year output deflator.[13] On average the markup is 1.15 for the Chinese manufacturing sector.[14] Over our sample period this sector has experienced a 6.9 percent annual growth in labor productivity. The central theme of this paper is to investigate whether infrastructure investment has a positive effect on productivity growth, and if so, how large and through which mechanism.

[12] The data have been widely used in researches regarding the productivity of Chinese manufacturing firms, such as Yu (2015), Wu (2018) and Chen et al. (2020), among many others.

[13] In sharp contrast, the output prices for industries 25 petroleum processing and coking and 33 smelting and pressing of nonferrous metals have doubled over the decade. In the following analyses, we drop these two industries to rule out the possible contamination from high inflation on productivity.

[14] 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. (2020) for a comparison. This markup information will allow us to infer the demand elasticity parameter σ in our extension for the TFPQ model in Section 4.1.

3.1.2 Definition of Infrastructure

The China Statistics Yearbooks and the China Fixed Investment Statistical Yearbooks report total investment in fixed assets by industry and by province. 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. Given that infrastructure is a broad subject and the concepts are evolving and context specific, there are several points that worth further discussion.

First, our definition of infrastructure in category (1) and (2) is very similar to the core infrastructure in the traditional literature. 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. As most core infrastructure is usually financed by government, the feature of public good property was a necessary condition to include a certain goods as public infrastructure. However, the productivity effect of the ICT (Information and Communications Technology) industries has becoming the focus of the more recent literature on infrastructure, such as telecommunication considered by Röller and Waverman (2001), computer services and software investigated by Commander et al. (2010), and internet and broadband studied in Czernich et al. (2011), Forman et al. (2012) and Akerman et al. (2015). Investment in such industries may not necessarily be public goods. However, they are still considered as infrastructure due to the positive externalities arising from network effects or as a general purpose technology. For this reason, we also include investment in category (3) as a component of infrastructure in this paper.

Second, in China's context, our three categories of infrastructure are consistent with the description of physical infrastructure in (i) electricity, (ii) transportation, and (iii) post and telecommunication in Berry Naughton's classic textbook on Chinese economy (2007).[15] A narrower definition could only include our category (1) and (2), such as in Bai and Qian (2010). A broader definition could also include the investment in the fourth category, that is (4) management of water conservancy, environment, and

[15] Our definition of infrastructure does not include the investment in court houses, public health, defense and security, which are crucially important for the daily operation of society. However, they are less likely to directly affect manufacturing firm's productivity. As found by Aschauer (1989), courthouses, hospitals, police and fire stations are considered as non-core infrastructure and have little impact on productivity.

public facilities, such as in Huang and Shi (2014). In a companion paper, Wang et al. (2020), we calculate how the production of the manufacturing industries in our data set relies on the infrastructure by category using the input-output table information. It turns out that on average the reliance is highest for our category (1) and (2), followed by category (3), and is virtually zero for category (4). This suggests our choice on the three categories of infrastructure is most appropriate for the purpose of this research.

Third, we combine these three different categories of infrastructure and ask their productivity effect and rate of return as a whole. This is partly to accommodate the complementarity among the effects of different infrastructure, and is also partly due to the data limitation.[16] Focusing on the combined effect and return allows us to address the long-standing controversy in macroeconomics literature since Aschauer (1989), and more recently in Warner (2014), on the investment efficiency of infrastructure at the aggregate level. It also complements to a large recent literature listed in Section 5.1 which only studies the effect of a specific type of infrastructure.

Finally, we measure the infrastructure in terms of monetary value instead of physical units. This is driven by the fact that we have combined different categories 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.

3.1.3 Province-Level Infrastructure Data

Bai and Qian (2010), Démurger (2014) and Qin (2016) provide some useful institutional background on China's infrastructure development, with a special emphasis on investment incentives.[17] 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. Second, among various jurisdiction levels, the provincial government plays a key role in infrastructure investment decision. This explains why we choose to match

[16] It is only starting from 2003 that investment in category (3) "information, transmission, computer service, and software" is reported separately in China's Fixed Asset Investment Statistics Yearbooks. Before 2003, investment in category (3) was reported as a combined term with category (2) as "transport, storage, post, transmission".

[17] 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.

the firm-level production data with the province-level infrastructure data.

Table A2 in the Appendix provides the overall pattern of the infrastructure investment in China from 1998 to 2007. It shows that China's infrastructure investment has been steadily increasing during this period with a 11.9 percent average real annual growth rate. Although the absolute volume of investment substantially increased since year 2003,[18] the ratios of such investment to GDP have been rather stable across the decade, with an average value of 8.9 percent. Table A3 in the Appendix describes the cross sectional pattern of infrastructure investment among the 30 provinces from 1998 to 2007. While our sample period witnesses a heavy investment at the national level, there is also substantial variation across provinces in infrastructure expenditure. Such variation provides an important though not exclusive source of identification in this paper.

3.2 Baseline Results

Following De Loecker (2011, 2013), we estimate the system of equation (4) and (7) simultaneously or in one-step.[19] The exact estimation procedure is explained in Appendix A. Table 1 reports the estimation results for the revenue production function (4) by industry. Column (1) of Table 2 presents the polynomial estimates of the productivity evolution process (7) 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.

<Insert Table 1 here>

There are a few important findings from our empirical exercises. First, the productivity process is highly non-linear. Second, both the infrastructure investment itself

[18] 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.

[19] 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. 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 the potential bias arising from this so-called two-stage approach.

and its interaction with the lagged productivity are highly significant. These two findings suggest that the productivity process would be misspecified by a simple linear model without the interaction term. 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 productivity, such as De Loecker (2013) for learning-by-exporting and Doraszelski and Jaumandreu (2013) for R&D investment. 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 2 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. Table 3 presents the average output elasticities of infrastructure and rates of return for 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 of infrastructure defined in equation (10) 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 (11). The 9-year average rate of return during our sample period is 6.2 percent. The yearly returns vary from 3.0 percent in 2006 and peak to 8.3 percent in 2003. This finding indicates that infrastructure investment does generate positive returns in China, at least during our sample period.

<Insert Table 3 here>

4 Extensions

4.1 Controlling For 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 infrastructure investment as an important extension. On the one hand, infrastructure investment enters the firm's 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 for the demand effect of infrastructure investment. In this sense, the effect estimated from a TFPR model includes both the demand effect and the productivity effect of infrastructure, while the effect estimated from a TFPQ model only reflects the effect of infrastructure on productivity.

4.1.1 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:

$$Q_{it} = K_{it}^{\gamma_k} L_{it}^{\gamma_l} M_{it}^{\gamma_m} \exp(\omega_{ijt}^q + \epsilon_{it}^q), \tag{12}$$

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 (7), the quantity-based productivity process ω_{ijt}^q follows a first-order Markov process:

$$\omega_{ijt}^q = h_t(\omega_{ijt-1}^q, g_{jt-1}) + \lambda v_{jt}^q + \varepsilon_{it}^q, \tag{13}$$

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.

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

$$P_{it} = Q_{it}^{-\frac{1}{\sigma}} \exp(\chi_{it}), \tag{14}$$

[20] Equation (14) has relaxed the constant elasticity of substitution (CES) restriction in De Loecker (2011) by considering a more general demand curve. The advantage of equation (14) over a CES structure lies in its flexibility, as there will be no restriction on the parameters in equation (16). 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 A1. Second, our estimation equation (16) 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 A1.

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:

$$\chi_{it} = \pi g_{jt} + \xi_{it}, \tag{15}$$

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 (13), equation (15) implies that the effect of infrastructure investment on demand is instantaneous.

4.1.2 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 (14), 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 (12) and (15) yields the following equation:

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

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

$$y_{it} = \beta^*_k k_{it} + \beta^*_l l_{it} + \beta^*_m m_{it} + \pi g_{jt} + \omega^*_{ijt} + \epsilon^*_{it}, \tag{16}$$

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 A1. The transformed productivity ω^*_{ijt}, is simply a linear scale of the original quantity-based productivity ω^q_{ijt}, that is

$$\omega^*_{ijt} = \left(1 - \frac{1}{\sigma}\right)\omega^q_{ijt}. \tag{17}$$

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

$$\epsilon^*_{it} = \left(1 - \frac{1}{\sigma}\right)\epsilon^q_{it} + \xi_{it}.$$

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

4.1.3 The TFPQ Model and Output Elasticities

It is useful to compare equation (16) with two other equations that appear in this paper. First, when we write down production function (12), our aim is to infer the impact of infrastructure investment on firm's supply through productivity process (13). 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:

$$e^q_{ist} = \frac{\partial \ln Q_{it}}{\partial g_{jt-1}} = \frac{\partial \omega^q_{ijt}}{\partial g_{jt-1}} = \frac{\partial h_{st}(\omega^q_{ijt-1}, g_{jt-1})}{\partial g_{jt-1}}. \tag{18}$$

However, the production function (12) is not estimable. Under our demand structure, we transform equation (12) into (16), which is estimable. Equation (17), that is the relationship between ω^q_{ijt} and ω^*_{ijt} implies that, estimating elasticity e^q_{ist} is equivalent to estimating equation (16) and obtaining a consistent estimator for ω^*_{ijt}. In this sense, we call the system of equations (16), (13) and (17) the TFPQ model, as they allow us to back out the effect of infrastructure investment on quantity productivity.

Second, compared with the revenue function (4), a specification widely adopted in empirical analyses, equation (16) includes an additional variable g_{jt} to capture the demand effect of infrastructure. Such comparison highlights the fact that the productivity ω_{ijt} in (4) 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 (9) are revenue-based, contrasting with the quantity-based elasticities and returns using (18).

4.1.4 Empirical Results

We explain how to estimate the TFPQ model in Appendix A. Table A4 reports the estimation results for the revenue generating equation (16). As expected, for almost all the industries the estimates for the parameter characterizing the demand effect are significantly positive. This suggests that increase in 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 2 reports the estimation for the productivity evolution process (13) 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, 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 2.4 to aggregate the firm-level output elasticities of infrastructure from the TFPQ model and calculate the rate of return in Table 3. The rate based on the quantity productivity is 5.3 percent, averaging across years 1999-2007. 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.[21]

4.2 Taking Into Account Spillover Effects

The baseline specifications in equation (7), (13) and (15) have explicitly assumed that the effects of infrastructure investment only take place on firms that locate within the province. However, firm i's productivity may benefit not only from those infrastructure in its location province j, but also from the infrastructure in the rest of the country. Similarly, firm i's demand may be shifted not only by those infrastructure in its location j, but also by the 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 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

[21] 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.

infrastructure investment.

4.2.1 Specifications for the Spillover Effects

To account for the spillover effects of infrastructure, we replace the province-level g_{jt-1} in (7), (13) and g_{jt} in (15) 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):

$$w_{jk} = \frac{\frac{1}{d_{jk}}}{\sum_{k \neq j} \frac{1}{d_{jk}}} \text{ for } k \neq j,\ w_{jj} = 0. \tag{19}$$

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 (19) indicates that the 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 estimated by Ma and Tang (2020) in the weighting matrix as a robustness check in Appendix B, 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 without spillover effects as the direct effect of infrastructure, and the estimates obtained in this extension as the total effects of infrastructure, with both direct and spillover effects.

4.2.2 Empirical Results

Column (3) of Table 2 reports the productivity evolution process for the TFPR model with national-level spillover effects. It can be considered as the counterpart of Column

(1), which assumes 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 of infrastructure inferred from the productivity processes, the 9-year average rate of return in the TFPR model now increases from 6.2 to 20.3 percent. Similarly, the 9-year average rate of return in the TFPQ model now increases from 5.3 to 12.1 percent.

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.

4.3 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.[22]

[22] The fall in return to investment after 2003 and the temporal rise after 2006 could be related to some national policy changes. Lu and Xiang (2016) find that the overall slowdown of economic

<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 percent 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.

5 Mechanisms

Understanding the specific links between 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 infrastructure could impact the distribution of economic activities. For example, Banerjee et al. (2020) 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 (NTHS) can lead to a reduction in industrial and total output growth among connected peripheral counties relative to non-connected ones.[23] Baum-Snow et al. (2017) study

efficiency in China after 2003 and link it to a clear policy turning point in the regional allocation of economic resources. The electricity reforms starting in December 2002 documented by Wu (2019) may explain the temporal increase in the return after 2006, as it could take a few years to materialize the effect of breaking monopoly and integrating market.

[23] Lu (2021) revisits the effects of NTHS using firm-level data and a time-varying instrument. It finds that the NTHS connection has led to faster growth in output and sales as well as labor productivity, due to a higher growth in intermediate inputs and capital.

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 by making good use of 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.

5.1 Heterogenous Effects

To first highlight the degree of heterogeneity in the productivity effect, we calculate the output elasticities by industry and report their values at the 25^{th}, 50^{th} and 75^{th} percentiles of the productivity in Table 4. As expected, there are 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 4 here>

Different from the perceived notion that all firms benefit from infrastructure investment, our finding that lower productivity firms could in fact suffer is new and interesting.[24] Since productivity is not directly observable, to further examine which firms are benefiting or benefiting more from infrastructure investment, we link the

[24] There could be many possible channels for this to take place. Infrastructure investment may reduce firm's costs, including production cost, management cost and trade cost. Infrastructure may also promote information dissemination, including information about goods market, capital market and labor market. However, the cost reduction and information dissemination effect could be heterogeneous, depending on firm characteristics and industry features. Consider Hopenhayn's (1992) dynamic industry model to monopolistic competition in a general equilibrium setting. With a lower cost and a better information, firms with different level of productivity could have different optimal choices in pricing, investing, hiring, exporting and innovation decision, which may lead to different impact on their subsequent productivity. One classic example is Melitz (2003), which illustrates how a reduction in trade cost leads to inter-firm reallocations towards more productive firms and forces less productive firms to exit.

firm-specific output elasticity, a measure on the impact effect of infrastructure investment on productivity, with observable firm characteristics. In Table 5, estimated output elasticities of infrastructure from various specifications are regressed on firm age, size, ownership, exporting status and geographic location. A systematic finding arises across all specifications: 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 tend to grow faster, this finding therefore suggests that infrastructure investment could be an important factor in promoting their growth.

<Insert Table 5 here>

5.2 Exit Probability and Market Share

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.

We present two additional empirical results from firm dynamics that are consistent with such a mechanism. First, all else being equal, infrastructure investment increases the probability of exit of the less productive firms. Second, 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 6 presents the Probit regressions of exit probability.[25] Standard errors are clustered at the province-industry level. A firm i is defined as exit in year $t+1$ if it is observed in year t but not in year $t+1$ in the dataset. On average, the exit probability is around 11 percent. In column (1) of the regressions, we start with a

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

baseline specification with productivity and capital stock only. Both coefficients are negative, significant and of a similar magnitude as that in Olley and Pakes (1996) and Pavcnik (2002). In column (2), the corresponding infrastructure investment measure is added in the regression in each model. Overall, infrastructure investment itself reduces the probability of exit. However, in column (3), we interact 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 infrastructure investment on firm's exit depends on firm's productivity. A low productivity firm is indeed more likely to exit with more infrastructure investment.

<Insert Table 6 here>

Table 7 has a similar structure as Table 6, replacing firm's exit with market share in year t as the dependent variable.[26] 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 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 infrastructure investment with a dummy variable for high productivity. Consistent with our expectation, this additional term is significantly positive, implying that the impact of infrastructure investment on firm's market share depends on firm's productivity. This suggests that infrastructure investment facilitates to reallocate market share towards more productive firms.

<Insert Table 7 here>

[26] There are more observations for regressions in Table 7 than in Table 6. 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.

6 Conclusion

This paper investigates three important and controversial research questions on the productivity effect of infrastructure investment. In contrast to the traditional literature, there are two novel features in our approach: a model of productivity evolution 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 infrastructure investment, which can be translated into a rate of return of 6 percent. Although a sizeable contribution of 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, the rate of return to infrastructure investment triples. The effect of infrastructure investment on firm-level productivity is heterogenous. With an increase in infrastructure investment, while higher productivity firms gain more market share, lower productivity firms are more likely to exit.

There are a few caveats and limitations that worth discussion for the external validity of our findings. First, our firm-level data only include all state-owned firms and non-state-owned firms with sales revenue above 5 million Chinese Yuan. It is less clear how infrastructure investment affects the productivity of small-size non-state-owned firms. Our infrastructure investment data excludes a wide category of infrastructure, e.g., investment in court houses, public health, defense and security. Second, the overall efficiency of 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. 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, 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. Finally, our analysis does not consider the financing issues behind infrastructure investment, which is itself an important topic for research.

7 Appendix

7.1 Appendix A: Estimation Procedure

In the TFPR model, the system of equations (4) and (7) 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 for 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:

$$\omega_{ijt} = \omega_t(k_{it}, l_{it}, m_{it}, j, t), \tag{20}$$

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 (20) into (4) yields a reduced-form equation:

$$y_{it} = x'_{it}\beta + \omega_{ijt} + \epsilon_{it} = \phi_t(x_{it}, j, t) + \epsilon_{it}, \tag{21}$$

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 (20), the reduced-form equation (21) 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

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

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

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

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.

To estimate the TFPQ model, same as estimating equation (4), we apply the proxy method by Ackerberg et al. (2015) to equation (16) 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},[27] where we make use of the linear relationship between ω^*_{ijt} and ω^q_{ijt} specified in equation (17). 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

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

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

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

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

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. The additional parameter π is identified by the assumption that the firm-level idiosyncratic shocks ε_{it}^q 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.[28] The ability to separately identify the demand from the productivity effect of 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.

7.2 Appendix B: Specification Tests and Robustness Checks

Table A5 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 (7) and (13), 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 (3), $\omega_{jt} - \mu_j = \alpha_b \ln B_{jt} + v_{jt}$. 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

[28] 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 $E\left(\varepsilon_{it}^q | \omega_{ijt-1}, g_{jt-1}\right) = 0$ and $Cov\left(\varepsilon_{it}^q, g_{jt}\right) = 0$.

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 percent higher than those benchmark returns. The estimated returns for spillover models in column (3) are 70 to 50 percent 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 a positive and moderate return.

In column (4) we omit the interaction term of $\omega_{ijt-1} \cdot g_{jt-1}$ (and $\omega^q_{ijt-1} \cdot g_{jt-1}$) 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 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 (8) present some robustness checks around our identification strategy. First, 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. In column (6) we drop all the firms that switched between provinces and obtain reassuring similar returns as in column (1). Second, 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. Therefore, in column (7) we drop the top 1 percent largest firms of each province and re-estimate the models. The returns in column (7) share the same pattern and have a similar magnitude as those in column (1). In column (8), we report results of a subsample by excluding all state-owned firms as an additional robustness check. Using the subsample of non-state-owned firms, we obtain similar magnitude of returns in the TFPR and TFPR-spillover models, but much smaller returns in the TFPQ and TFPQ-spillover models. However, one would be cautious to take the returns from this robustness check as a good estimate for the overall returns to infrastructure in China, because the non-state-owned firms subsample may not reflect the whole picture of the Chinese industrial firms. Thus, one way to read our results is to take the returns reported in column (8) as our most conservative estimates. The good news is that, even in this setup, the key message of our paper remains: i) positive returns in TFPR models; ii) big spillover effect; and iii) significant demand effect.

In column (9) and (10) we conduct two robustness checks for the spillover models. Column (9) presents the returns when we use travel cost instead of physical distance between capital cities of provinces to construct the weight matrix (Ma and Tang, 2020). The estimates in column (1) and (9) turn out to be very close to each other. In the benchmark case, we assume that the positive externality of public investment can spread across the whole nation. In column (10), we use a 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. If infrastructure 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 between column (1) and (10).

Finally, when we translate the firm-level output elasticity with respect to infrastructure investment into rate of return of infrastructure investment at the aggregate level, there are also two technical details worth a robustness check. First, to alleviate the potential concern of endogeneity using the current sales revenue and value-added variables in the weights, we use sales revenue and value-added from the previous year in constructing the weights. The results are reported in column (11), which are very close to the benchmark results in column (1). Second, since the infrastructure measure is province-specific, one could also aggregate the output elasticity from the firm level to the industry-province level first before aggregating to the industry level. We conduct this alternative in column (12). The resulting rates of return slightly decrease but only by a magnitude of 1 percent at the maximum.

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Table1 Estimates for the sales revenue equation in the TFPR model

industry code	industry name	β_l	$s.e.(\beta_l)$	β_k	$s.e.(\beta_k)$	β_m	$s.e.(\beta_m)$
13	Food processing	0.051	0.017	0.036	0.005	0.901	0.013
14	Food manufacturing	0.024	0.021	0.049	0.006	0.924	0.012
15	Beverage	0.180	0.028	0.019	0.026	0.852	0.031
16	Tobacco	0.665	0.325	0.251	0.116	0.521	0.205
17	Textile	0.008	0.045	0.011	0.010	0.982	0.062
18	Garments and fiber	0.079	0.083	0.006	0.007	0.929	0.075
19	Leather, furs	0.080	0.029	0.016	0.011	0.918	0.041
20	Timber, bamboo	0.004	0.083	0.072	0.064	0.833	0.090
21	Furniture	0.117	0.045	-0.001	0.033	0.936	0.045
22	Papermaking and paper	0.065	0.027	0.095	0.025	0.784	0.036
23	Printing	0.310	0.097	0.115	0.041	0.646	0.090
24	Cultural, educational	0.086	0.053	0.044	0.017	0.865	0.074
26	Raw chemical materials	0.012	0.048	0.026	0.006	0.953	0.040
27	Medical and pharmaceutical	0.104	0.022	0.145	0.021	0.729	0.031
28	Chemical fiber	0.018	0.013	0.022	0.008	0.946	0.014
29	Rubber	0.096	0.080	0.021	0.042	0.895	0.106
30	Plastic	0.066	0.009	0.066	0.014	0.848	0.016
31	Nonmetal mineral	0.120	0.009	0.006	0.030	0.846	0.007
32	Ferrous metals	0.055	0.014	0.012	0.009	0.946	0.013
34	Metal products	0.133	0.047	0.018	0.011	0.890	0.033
35	Ordinary machinery	-0.004	0.008	0.039	0.005	0.944	0.011
36	Special purpose equipment	0.098	0.049	0.062	0.051	0.810	0.063
37	Transport	0.193	0.046	-0.025	0.046	0.895	0.037
39	Electric	0.044	0.008	0.028	0.004	0.924	0.008
40	Electronic and telecom	0.108	0.016	0.126	0.015	0.771	0.019
41	Instruments, meters	0.103	0.043	0.046	0.044	0.852	0.070
42	Other manufacturing	0.091	0.057	0.035	0.007	0.874	0.058

Note: All standard errors are bootstrapped using 1000 replications.

Table 2 Regressions for the productivity evolution processes

Depedent variable: current productivity in respective model

Model	(1) TFPR		(2) TFPQ		(3) TFPR-spillover		(4) 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***
		(0.136)		(0.044)		(0.221)		(0.016)
	$\omega^{2}_{ij,t-1}$	-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***
		(0.004)		(0.001)		(0.005)		(0.001)
	$\omega_{ij,t-1}*g_{j,t-1}$	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***
		(0.007)		(0.002)		(0.011)		(0.000)
	v_{jt}	0.420***	v^{q}_{jt}	0.511***	v_{jt}	0.249***	v^{q}_{jt}	0.383***
		(0.022)		(0.033)		(0.015)		(0.024)
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

Notes:

1. Industrial dummies are included.
2. Standard errors are reported in parentheses.
3. *** p<0.01, ** p<0.05, * p<0.1

Table 3 Output elasticities of infrastructure 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

Notes:

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 4 Output elasticities of infrastructure by productivity percentile: TFPR model

industry code	industry name	25th percentile	50th percentile	75th percentile
13	Food processing	0.0053	0.0059	0.0063
14	Food manufacturing	0.0124	0.0181	0.0236
15	Beverage	-0.0002	0.0092	0.0193
16	Tobacco	0.0265	0.0297	0.0318
17	Textile	-0.0065	-0.0003	0.0073
18	Garments and fiber	0.0018	0.0094	0.0189
19	Leather, furs	-0.0038	0.0007	0.0066
20	Timber, bamboo	0.0026	0.0112	0.0195
21	Furniture	-0.0190	-0.0033	0.0140
22	Papermaking and paper	0.0186	0.0206	0.0227
23	Printing	0.0346	0.0369	0.0393
24	Cultural, educational	-0.0003	0.0117	0.0245
26	Raw chemical materials	-0.0062	-0.0046	-0.0029
27	Medical and pharmaceutical	0.0191	0.0236	0.0282
28	Chemical fiber	-0.0003	0.0094	0.0194
29	Rubber	-0.0220	0.0014	0.0162
30	Plastic	-0.0054	0.0014	0.0045
31	Nonmetal mineral	0.0064	0.0128	0.0217
32	Ferrous metals	0.0008	0.0032	0.0058
34	Metal products	-0.0107	-0.0099	-0.0091
35	Ordinary machinery	0.0008	0.0061	0.0099
36	Special purpose equipment	-0.0006	0.0081	0.0151
37	Transport	-0.0011	0.0032	0.0075
39	Electric	-0.0263	-0.0263	-0.0263
40	Electronic and telecom	0.0124	0.0151	0.0183
41	Instruments, meters	-0.0216	-0.0116	0.0028
42	Other manufacturing	-0.0103	-0.0076	-0.0043
average*		0.0003	0.0065	0.0126

Note:

* unweighted simple average

Table 5 Linking output elasticity of infrastructure 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

Notes:

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 6 Probit regressions of exit probability

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

model	TFPR			TFPR-spillover		
	(1)	(2)	(3)	(1)	(2)	(3)
Productivity	-0.154***	-0.151***	-0.105***	-0.147***	-0.144***	-0.097***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Capital	-0.136***	-0.135***	-0.136***	-0.137***	-0.136***	-0.137***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Infrastructure		-0.087***	-0.091***		-0.171***	-0.176***
		(0.010)	(0.010)		(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			TFPQ-spillover		
	(1)	(2)	(3)	(1)	(2)	(3)
Productivity	-0.143***	-0.145***	-0.100***	-0.125***	-0.131***	-0.085***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Capital	-0.137***	-0.137***	-0.138***	-0.137***	-0.136***	-0.138***
	(0.002)	(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 7 Regressions of market share

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

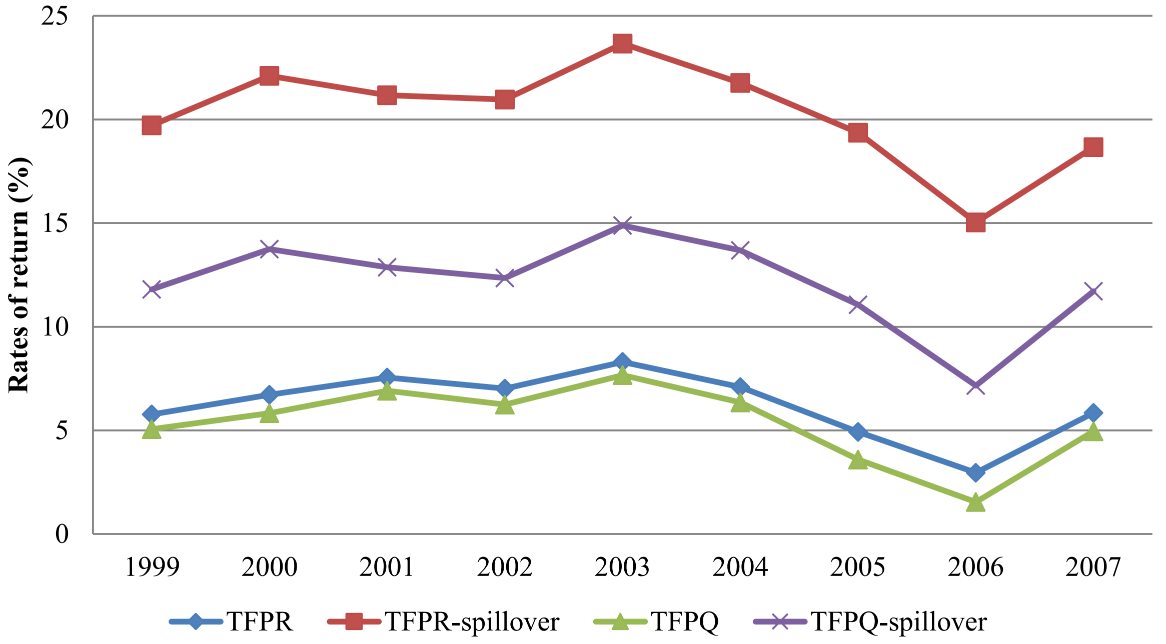
model	TFPR			TFPR-spillover		
	(1)	(2)	(3)	(1)	(2)	(3)
Productivity	0.563***	0.563***	0.394***	0.535***	0.537***	0.359***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Capital	0.561***	0.562***	0.562***	0.563***	0.564***	0.566***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infrastructure		0.311***	0.308***		0.601***	0.604***
		(0.002)	(0.002)		(0.003)	(0.003)
Infrastructure*HIGH			0.014***			0.015***
			(0.000)			(0.000)
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***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Capital	0.565***	0.565***	0.567***	0.563***	0.565***	0.566***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infrastructure		0.345***	0.360***		0.680***	0.736***
		(0.002)	(0.002)		(0.003)	(0.004)
Infrastructure*HIGH			0.016***			0.015***
			(0.000)			(0.000)
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

Notes:

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 parenthese.
5. *** p<0.01, ** p<0.05, * p<0.1

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 A1 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
	sector average	7,388	108.80	1.15	6.9

Notes:

(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

(5): sector average excluding industry 25 and 33

Table A2 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

Notes:
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 A3 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

Notes:

(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 A4 Estimates for the sales revenue equation in the TFPQ model

industry code	industry name	β_l*	*s.e.* (β_l*)	β_k*	*s.e.* (β_k*)	β_m*	*s.e.* (β_m*)	π*	*s.e.* (π*)
13	Food processing	0.071	0.022	0.036	0.005	0.886	0.017	0.145	0.005
14	Food manufacturing	0.030	0.020	0.050	0.006	0.918	0.012	0.088	0.010
15	Beverage	0.175	0.029	0.029	0.031	0.845	0.037	0.070	0.009
16	Tobacco	0.643	0.343	0.252	0.112	0.530	0.214	0.065	0.075
17	Textile	0.008	0.076	0.011	0.019	0.982	0.112	-0.002	0.004
18	Garments and fiber	0.077	0.084	0.009	0.007	0.925	0.076	0.080	0.009
19	Leather, furs	0.078	0.028	0.017	0.012	0.916	0.042	0.029	0.006
20	Timber, bamboo	-0.118	0.063	0.168	0.049	0.709	0.094	0.233	0.018
21	Furniture	0.082	0.038	0.027	0.029	0.900	0.037	0.105	0.015
22	Papermaking and paper	0.065	0.028	0.091	0.025	0.792	0.035	0.067	0.006
23	Printing	0.328	0.101	0.115	0.038	0.630	0.089	0.072	0.019
24	Cultural, educational	0.087	0.053	0.046	0.015	0.858	0.072	0.031	0.012
26	Raw chemical materials	0.015	0.079	0.026	0.014	0.950	0.076	0.028	0.006
27	Medical and pharmaceutical	0.107	0.045	0.139	0.053	0.731	0.068	0.076	0.012
28	Chemical fiber	0.017	0.014	0.022	0.008	0.947	0.015	-0.036	0.019
29	Rubber	0.141	0.077	0.067	0.044	0.782	0.101	0.067	0.019
30	Plastic	0.064	0.010	0.060	0.016	0.856	0.019	0.091	0.005
31	Nonmetal mineral	0.101	0.006	0.080	0.025	0.836	0.007	0.101	0.003
32	Ferrous metals	0.053	0.014	0.011	0.009	0.948	0.013	-0.035	0.011
34	Metal products	0.131	0.041	0.020	0.010	0.888	0.030	0.007	0.005
35	Ordinary machinery	0.000	0.007	0.039	0.005	0.941	0.011	0.045	0.007
36	Special purpose equipment	0.093	0.044	0.056	0.047	0.830	0.060	0.043	0.006
37	Transport	0.176	0.039	-0.015	0.035	0.891	0.028	0.032	0.005
39	Electric	0.045	0.008	0.029	0.004	0.923	0.008	0.022	0.007
40	Electronic and telecom	0.115	0.016	0.121	0.014	0.774	0.019	0.103	0.007
41	Instruments, meters	0.077	0.045	0.123	0.049	0.732	0.077	0.057	0.021
42	Other manufacturing	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.

Table A5 Rates of return from specification tests and robustness checks (%)

model	**(1)**	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TFPR	**6.2**	8.7	-0.2	5.1	6.6	5.6	6.7	5.5	6.2	6.2	6.2	5.5
TFPQ	**5.3**	7.5	-1.0	3.4	2.5	5.1	2.8	-0.7	5.3	5.3	5.3	4.4
TFPR-spillover	**20.3**	24.6	9.8	22.4	21.1	17.7	24.9	24.0	19.9	9.0	20.1	18.9
TFPQ-spillover	**12.1**	16.4	3.8	12.0	9.7	15.2	10.3	4.4	12.2	6.5	11.9	11.2

Notes:

(1): benchmark estimates

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

(3): downward biased estimates - including $\omega_{jt} - \mu_{jt}$ 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 those firms that switched province

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

(8): dropping all state-owned firms

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

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

(11): using sales revenue and value-added from the previous year in constructing the weights

(12): aggregating output elasticity from the firm level to the industry-province level first before aggregating to the industry level