



DECOMPOSING PRODUCTIVITY GROWTH IN CHINESE MANUFACTURING

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Article History:

Received: 13-Jan-2017

Revised received: 03-Feb-2017

Accepted: 07-Feb-2017

Online available: 20-Feb-2017

Keywords:

Productivity,
Chinese Manufacturing,
Decomposition,
Translog

Abstract

In an increasingly globalized business environment, sustaining relatively high productivity growth is essential for maintaining an international competitive advantage. Economists typically identify manufacturing companies in China as prime examples of firms attaining cost competitiveness through productivity growth. This study contributes to the analysis of productivity growth in China by estimating unexplained technological change, scale and infrastructure investment's contribution to annual productivity growth for 27 manufacturing industries. A flexible form cost equation for manufacturing industries classified at the two-digit industry code level for the 1998-2005 sample period is used to investigate each factor's impact on productivity growth. The findings suggest that for all industries excluding furniture manufacturing, unexplained technological change contributes to productivity growth. Infrastructure investment and scale contribute to such growth for 16 and 5 of the 27 industries respectively.

1. INTRODUCTION

Productivity growth in China has greatly transformed its economy. Benefits from such growth include competitive cost advantage in a global economy, growing demand for jobs that pay well and improved standards of livings (see for example, [Lin, 2012](#)). While gains in the latter part of the 20th century and the beginning of the 21st century have far outpaced the global average, sustaining these gains may prove challenging in the longer term. A growing literature identifying sources of productivity has developed recently with the partial objective of providing a better understanding of the potential of sustained productivity growth in China.

Many researchers have studied productivity growth in the Chinese economy, with some focusing solely on its manufacturing sector ([Heytens & Zebregs, 2003](#); [Zheng et al., 2009](#)).

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These studies examine the impact of various factors, such as technology, foreign direct investment (FDI), and international trade on China's productivity growth. They all show significant annual productivity growth ranging from 1.4% to 4.5% (Hu & Khan, 1997; Zheng & Hu, 2006). Based on our understanding of China's institutional background and economic policies for the relevant time period (discussed below), we examine three factors: unexplained technological change, scale, and infrastructure investment to investigate productivity growth in the Chinese manufacturing sector. We decompose the annual productivity growth rate to identify each individual factor's contribution.

The empirical approach used to analyze productivity growth in Chinese manufacturing estimates a long-run cost function, which allows for taking advantage of an extensive panel data set covering an eight-year time span for 27 manufacturing industries in China's 31 provinces. We first estimate productivity growth with a flexible translog cost function. Estimated annual productivity growth is subsequently decomposed to isolate individual contribution from unexplained technological change, scale and infrastructure investment. The analysis enhances our understanding of the sources for China's manufacturing advantage and economic growth. It can also help in formulating economic policies to most efficiently use governmental and societal resources to maintain China's manufacturing competitiveness.

The remainder of this paper is organized as follows. Section 2 is a review of institutional factors that are beneficial for China's manufacturing productivity growth. Section 3 reviews relevant literature. Data and empirical approaches are explained in section 4. Section 5 discusses regression results from estimating the translog cost function and decomposing the annual productivity growth numbers. Section 6 provides concluding remarks.

2. GROWTH PROMOTING INSTITUTIONAL FACTORS

China's economic reform and opening-up policy¹ since 1978 has achieved phenomenal success. Among the many other contributing factors, the Chinese government's determination to upgrade its industrial technology by attracting FDI and promoting domestic research and development (R&D), to invest in infrastructure, and to develop its own large industrial firms greatly contributed to the impressive economic growth story.

One prominent policy enforced at the beginning of the economic reform was to attract FDI by establishing four Special Economic Zones (SEZs). Inside the SEZs, favorable policies and rules on tax, foreign exchange, international trade, labor, and other administrative measures were used to attract foreign investment. Taxes were generally much lower inside than outside the SEZs. In addition, firms received governmental financial assistance in obtaining land and other resources, such as lower rates on utility services. These policies produced remarkable outcomes: China has become an important destination for foreign business and has received huge amounts of incoming FDI. From the 1980s to late 1990s, contracted FDI into China grew from about \$1.5 billion to more than \$40 billion annually. The actual use of FDI grew from \$0.5 billion to more than \$40 billion a year during the same time period (Fung, 2002). Output growth and technological advances in the SEZs occurred very rapidly. The success in the SEZs encouraged the Chinese government to extend similar policies to 14 other large coastal cities in 1984. These policies were subsequently extended to even more cities. Many more new economic and technological development areas were established in these cities with a focus to attract FDI and improve technology to eventually boost economic growth and productivity.

In addition to promoting FDI as a source of technological progress, the Chinese government also used direct funding and tax incentives to spur industrial R&D for both foreign and domestic

¹ In December 1978 the Third Plenary Session of the 11th Chinese Communist Party Central Committee decided to reform and open up its economy: reduced government planning and increased the role of markets and opened its economy for more international trade.

institutions. China also used technology policies to promote industrial development. Such incentives contributed to increased output and productivity (Zhu *et al.*, 2006, and Fan & Watanabe, 2006).

Past research shows that as the Chinese economy grew, especially with increases in international and domestic trade, the need for improved infrastructure grew, particularly in transportation facilities (Démurger, 2001). All levels of government have huge incentives to invest in infrastructure as they attract investments and commerce, thus creating jobs and economic growth. Much infrastructure is built at the regional (local and provincial) government level. With a decentralized fiscal structure, local governments are responsible for their finances. Thus investments in infrastructure exhibited large differences and created regional disparities in productivity, income, and other economic outcomes (Démurger, 2001).

In addition to regular budgetary revenue, local governments created various ways to finance their construction of public infrastructure (Herrmann-Pillath & Xingyuan, 2004), such as public-private cooperation in building highways, selling public land, and borrowing from local banks. Over the years resources devoted to public infrastructure have increased steadily in China. For example, revenues for urban infrastructure building increased from 2.7 billion *yuan* in 1980 to 198.9 billion *yuan* in 2000, and to 476.2 billion *yuan* in 2007 (Wang, 2011). Consequently China's overall infrastructure has improved tremendously and presents its manufacturing sector a significant cost advantage over many neighboring developing economies. However, the level of infrastructure in China is still below that in developed economies. Thus further improvement in infrastructure remains likely and consequent benefit to manufacturing productivities may continue.

The Chinese government, especially at local levels, played an important positive role in developing its industries and firms as well. Government owned firms, for example, State Owned Enterprises (SOEs), and Township and Village Enterprises (TVEs) dominated many industries. The fastest growth in output and productivity occurred in these firms (Walder, 1995). Zheng *et al.* (2003) show that considerable productivity growth was achieved through technological progress. They also find large SOEs were more likely to generate productivity growth than smaller ones. Based on such research evidence and their experience, the Chinese governments seem to lean toward making the strategic SOEs bigger to gain from larger scale. It is of practical importance to find out scale's impact on productivity growth.

In sum, the preceding review of growth and productivity promoting institutional factors suggests the Chinese government has implemented policies that encourage investment in technology in part through FDI, investment in infrastructure and in large SOE's. At issue is the effectiveness of such investment on productivity growth.

3. EMPIRICAL ANALYSIS OF DETERMINANTS OF PRODUCTIVITY GROWTH

The tremendous growth in China's economy and its manufacturing sector has prompted many researchers to investigate China's productivity growth. These studies show that annual productivity growth varied from a low of 1.4% to a high of 4.5% since China's economic reform policy was first introduced in 1978 (Maddison, 1998; World Bank, 1997; Hu & Khan, 1997; Young, 2003; Zheng & Hu, 2006, OECD, 2005). Empirical research on productivity growth include technology, economies of scale, and investment in infrastructure as influential determinants of such growth.

Economic theory suggests investment in technology enhances productivity. The intuition is that by introducing input-saving equipment and technology, such as the adoption of robotics and computers, and just-in-time inventory management in manufacturing, workers become more productive. For instance, existing literature of the effect of technology on productivity growth focuses heavily on potential gains arising from R&D, technology transfer, and FDI. Hu *et al.* (2005) show in-house R&D and technology transfers are significantly complementary in productivity growth. For

developing nations like China, productivity growth is also achieved through knowledge spillover effect, such as demonstration effect and labor mobility. Many local firms are started by the engineers who have worked for foreign invested companies and learned how to make similar products and compete with their former employers. Other local firms poach workers from foreign invested companies. [Caves \(2007\)](#) finds that it is difficult to prevent knowledge, which includes superior production technology, management practices or marketing information, to spill over and influence production efficiency of indigenous companies.

However, findings from [Fu \(2011\)](#) show that the technology spillover effect on the development of international competitiveness in indigenous firm is limited. Other studies show that the impacts of both domestic and foreign technology transfer on firm productivity are largely conditional on their interactions with in-house R&D ([Hu et al., 2005](#)). Technological investment may not always contribute to greater productivity growth for various reasons. For example, [Li \(2008\)](#) examines large and medium sized Chinese firms in 32 industries during the period of 1996 to 2003 and finds a negative rate-of-return from domestic R&D due to over-investment and soft budget constraints.

As is the case for technological investment, traditional economic theory does not offer an obvious prediction of the effect of industry scale on productivity. On the one hand, by increasing the size of operations, companies can take advantage of the gains from specialization of workers and division of labor, thus lowering average variable costs. It is well known that economies of scale also occur as a result of lowering per unit fixed costs, such as machinery and plants, by increasing output levels. Furthermore, it is easier to innovate when production is increased. For instance, [Jacobs \(1969\)](#) and [Glaeser et al. \(1992\)](#) show that new firms, especially technology-oriented firms, benefit from urbanization economies, which arise from the scale and diversity of urban industrial activities.² On the other hand, large operations may experience diseconomies of scale. For instance, large operations may be plagued by loss of management efficiency. The complexity associated with managing large operations with many layers of bureaucracy creates a challenge for managers maintaining internal efficiency ([Carlton & Perloff, 2005](#)).

Analyses of infrastructure investment's influence on productivity suggest that such investment has the potential to enhance productivity growth but such results are not guaranteed. Typically using a Cobb-Douglas production or cost function for empirical analysis, past research identifies over investment in new projects rather than upgrading existing infrastructure projects as a common planning mistake that impedes productivity growth ([Fernald, 1999](#)). Empirical analysis of infrastructure investment and productivity supports Fernald's observation by revealing mixed results for the infrastructure-productivity association. For instance, with national and regional public infrastructure data, [Aschauer \(1989\)](#) and [Munnell \(1990\)](#) show that output elasticity with respect to public infrastructure is between 0.30 and 0.40 in the U.S. In addition, [Ford and Poret \(1991\)](#) show average elasticity of total factor productivity (TFP) with respect to changes in infrastructure to be about 0.45 when they use data from nine OECD countries.³ However, estimates from [Eberts \(1986\)](#) and [Garcia-Milà and McGuire \(1992\)](#) show much lower elasticity, between 0.040 and 0.045. Furthermore, [Hulten and Schwab \(1991\)](#) and [Holtz-Eakin \(1994\)](#) find no statistically significant relationship between the growth of TFP and the growth of public capital when observing productivity trends at the regional level.

These conflicting results lead to doubts over the validity of using the Cobb-Douglas production function framework to assess the effects of investment in public infrastructure on output and productivity. In addition, empirical results from using aggregate national level data are criticized as "too good to be true" ([World Bank, 1994](#)). These differences between estimates based on aggregate

² Standard economic theory suggests gains associated with scale arise in part from the benefits of specialization and the ability to lower unit cost due to high fixed costs at least in the short-run.

³ Total-factor productivity, is a measurement variable that accounts for effects in total output not caused by traditionally measured inputs of labor and capital.

data and state level data may reflect the impossibility of capturing all the payoffs to public sector capital formation at the lower regional levels (Nadiri & Mamuneas, 1991). Moreover, the Cobb-Douglas production function is inherently limited to a constant technology and ignores the role of input prices in the decision-making process by individual firms. A flexible cost function can measure the effects of infrastructure investment on productivity by examining savings from various production costs. The estimates of this cost saving on productivity effect are shown to be smaller (Paul *et al.*, 2004). With a cost-function approach, Shah (1992) reports that the output elasticity of public infrastructure for the Mexican manufacturing sector is 0.5. Morrison and Schwartz (1996) use a generalized Leontief cost function with non-constant returns to scale to analyze cost-benefits. Their results show that the benefits of additional infrastructure investment for manufacturing firms are lower than the social price of the investment. Sturm (1998) uses a generalized McFadden cost function to estimate the cost elasticity of public infrastructure investment for the aggregated, the sheltered, and the exposed sectors in the Netherlands. He finds the three elasticities are respectively -0.31, -0.28 and -0.2. Nadiri and Mamuneas (1991) use the seemingly unrelated regression technique to estimate a translog cost function and input share equations simultaneously with data providing information at a much more disaggregated industry level than the data used by Sturm. Their estimates of cost saving effect on productivity suggest cost-saving effect is in the range of 0-0.2 percent annually at the two-digit census observation level for manufacturing industries. Such small savings hardly support the notion that infrastructure investment promotes substantial productivity gains.

In sum, this brief overview of past empirical analysis of the determinants of productivity growth reveals that while investment in technology, production scale, and investment in infrastructure are key to promoting such growth, their effects are not obvious *a priori*. In addition, empirical analysis reveals the importance of using a flexible form cost function when examining productivity trends. This study contributes to the understanding of productivity growth in China by empirically decomposing the overall productivity growth into individual components to see how unexplained technological change, scale, and infrastructure investment contribute to such growth in Chinese manufacturing.

4. DATA AND EMPIRICAL APPROACH

4.1. Data

Individual firm-level output, input and other accounting information is used to examine productivity growth in major Chinese manufacturing industries. The Chinese National Bureau of Statistics (NBS) collects this data through its annual Chinese Industrial Enterprise Census (CIEC). Our data cover 27 two-digit manufacturing industries for 31 provinces for the 1998-2005 time period. The CIEC is the most detailed and reliable database on Chinese industrial firms. It contains 165,119 firm-level samples in 1998 to 271,835 firm-level samples in 2005. This dataset covers more than 40 major industries and includes 70 indexes with basic enterprise and financial information, such as output, fixed assets, number of employees and wages. The census includes all the state-owned firms and non-state-owned enterprises with annual sales of more than 5 million *Yuan* RMB (called above-scale firms in Chinese industrial statistics terms).

Since these data are reported at the firm level, we aggregate them at the provincial level for regional aggregation. We further aggregate the data at the 2-digit industry level (China Industry Classification Code: 13-40, missing 38). Consistent with other studies (such as, Cai & Liu, 2009), and to obtain a clean sample from the original data set, we delete observations with negative or missing values in total assets, the number of employees, gross value of industrial output, net value of fixed assets, and sales.

The variables are defined as follows: the wage rate P_l is computed as the ratio of total wages to total number of employees. The price of intermediate inputs P_m is the purchasing price index of raw

material, fuel and power obtained from the NBS. Following Morrison (1993) and Paul *et al.* (2004), the price of private capital is measured as $p_k = p_{kindex}(d+r)(1+t)$, where p_{kindex} is the price index of investment in fixed assets from the NBS, while d is the depreciation rate, computed as the depreciation this year divided by the net fixed asset; r is the 5-year interest rate; and t is the effective rate of taxation. All price indices are normalized to equal one in 1998 to estimate the cost equation. C is the total production cost for each industry in every province. It includes total wages, net fixed assets, and intermediate inputs.

Data on infrastructure investment is from the *Comprehensive Statistics Data and Documents of 50 years of New China*, a publication by NBS. China Info Bank Database is the source for the standardized industrial prices index. Data on the stock of infrastructure capital is unavailable, so we separate the infrastructure into two components: one is the production and supply of electricity, water and fuel wherein total assets can be obtained from the database of a firm-level survey; the other is transportation infrastructure. Neither this survey nor the NBS has data on the stock of the infrastructure. We derive it by using the perpetual inventory method and setting the depreciation rate at 5%. The 1986 benchmark is estimated by dividing the infrastructure investment by the sum of the depreciation rate and the average growth rate of the capital stock for the period 1986—2007. The total infrastructure stock is computed by taking the sum of the two types of capital stock. Description of variables is presented in Table 1.

Table 1: Variable description

| Variable | Variable name (units) | Calculation method | Data source |
|----------|---|--|----------------------------|
| Y | Output (0.1 billion Yuan) | Aggregate value added of industrial enterprise at provincial level | CIEC |
| K | Capital (0.1 billion Yuan) | Aggregate net fixed assets of industrial enterprise at provincial level | CIEC |
| L | Number of employees (10 thousand) | Aggregate number of employees of industrial enterprise at provincial level | CIEC |
| P | Standardized industrial prices | Na | China Info Bank Database |
| t | Time | Na | CIEC |
| GU | Infrastructure investment (0.1 billion Yuan) | Aggregate investment of infrastructure at provincial level | Chinese Statistic Yearbook |
| G | Infrastructure capital stock (0.1 billion Yuan) | Calculated by perpetual inventory method with a 5% depreciation rate | CIEC |

4.2. Empirical approach

This study uses an econometric approach that allows decomposing annual productivity gains attributable to unexplained technological change, production scale, and infrastructure investment. While early studies examining productivity gain rely primarily on estimation of production functions, more recent analysis has benefitted from the findings from duality theory that shows productivity technology can be identified by estimating a cost function. Our study estimates a flexible long-run cost function to investigate productivity trends in Chinese manufacturing in line with many past research (Wilson & Zhou, 1997; and Gollop & Roberts, 1981, 1983, Bitzan & Peoples, 2014). The generalized cost function is specified as follows:

$$C = C(P_i, Y, GU, t) \text{ and } i = K, L, \text{ or } M \dots\dots\dots (1)$$

where the variable C denotes total cost and P_i is a vector of input prices such that P_L, P_K, and P_M respectively denote the price of labor, capital and materials; Y denotes output; GU is a variable depicting infrastructure investment; and t is a time trend variable that is included to capture the unexplained technological change.

A Taylor series expansion with a remainder is used to approximate this cost function (Friedlander & Spady, 1980). For the generalized cost function depicted by equation (1), a second order Taylor series expansion around the mean values of output, factor input prices, infrastructure investment and time is specified as follows:

$$\begin{aligned}
 C(P_i, Y, GU, t) = & \frac{C(\bar{P}_i, \bar{Y}, \bar{GU}, t)}{0!} + \sum_i \frac{\partial C}{\partial P_i} (P_i - \bar{P}_i) + \\
 & \frac{\partial C}{\partial Y} (Y - \bar{Y}) + \frac{\partial C}{\partial GU} (GU - \bar{GU}) \\
 & + \frac{\partial C}{\partial t} (t - \bar{t}) + \sum_i \sum_j \frac{\left(\frac{\partial^2 C}{\partial P_i \partial P_j}\right)}{2!} (P_i - \bar{P}_i) (P_j - \bar{P}_j) + \sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial Y}\right)}{2!} (P_i - \bar{P}_i) (Y - \bar{Y}) \\
 & + \sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial GU}\right)}{2!} (P_i - \bar{P}_i) (GU - \bar{GU}) + \sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial t}\right)}{2!} (P_i - \bar{P}_i) (t - \bar{t}) \\
 & + \frac{\left(\frac{\partial^2 C}{\partial Y \partial Y}\right)}{2!} (Y - \bar{Y})^2 + \sum_i \frac{\left(\frac{\partial^2 C}{\partial Y \partial P_i}\right)}{2!} (P_i - \bar{P}_i) (Y - \bar{Y}) + \frac{\left(\frac{\partial^2 C}{\partial Y \partial GU}\right)}{2!} (Y - \bar{Y}) (GU - \bar{GU}) \\
 & + \frac{\left(\frac{\partial^2 C}{\partial Y \partial t}\right)}{2!} (Y - \bar{Y}) (t - \bar{t}) + \frac{\partial^2 C}{\partial GU^2} (GU - \bar{GU})^2 + \frac{\left(\frac{\partial^2 C}{\partial GU \partial P_i}\right)}{2!} (GU - \bar{GU}) (P_i - \bar{P}_i) \\
 & + \frac{\left(\frac{\partial^2 C}{\partial GU Y \partial Y}\right)}{2!} (Y - \bar{Y}) (GU - \bar{GU}) + \frac{\left(\frac{\partial^2 C}{\partial GU \partial t}\right)}{2!} (GU - \bar{GU}) (t - \bar{t}) + \frac{\partial^2 C}{\partial t^2} (t - \bar{t})^2 + \frac{\left(\frac{\partial^2 C}{\partial t \partial P_i}\right)}{2!} (t - \bar{t}) (P_i - \bar{P}_i) \\
 & + \frac{\left(\frac{\partial^2 C}{\partial t \partial Y}\right)}{2!} (t - \bar{t}) (Y - \bar{Y}) + \frac{\left(\frac{\partial^2 C}{\partial t \partial GU}\right)}{2!} (t - \bar{t}) (GU - \bar{GU}) + R \dots\dots\dots (2)
 \end{aligned}$$

This Taylor series approximation is then transformed by taking the logarithms of the variables and substituting the partial derivatives with parameters. After applying the symmetry of second derivatives (for example, $\frac{\partial^2 C}{\partial P_i \partial Y} = \frac{\partial^2 C}{\partial Y \partial P_i}$), simplifying and rearranging the terms, the resulting equation gives the translog cost function specified as follows:⁴

$$\begin{aligned}
 \ln C = & \alpha_0 \\
 & + \sum_i \alpha_i \ln \left(\frac{P_i}{\bar{P}_i}\right) + \beta_1 \ln \left(\frac{Y}{\bar{Y}}\right) + \sigma_1 \ln \left(\frac{GU}{\bar{GU}}\right) + \theta t \\
 & + \frac{1}{2} \sum_i \sum_j \alpha_{ij} \ln \left(\frac{P_i}{\bar{P}_i}\right) \ln \left(\frac{P_j}{\bar{P}_j}\right) + \sum_i \tau_i \ln \left(\frac{P_i}{\bar{P}_i}\right) \ln \left(\frac{Y}{\bar{Y}}\right) + \sum_i \vartheta_i \ln \left(\frac{P_i}{\bar{P}_i}\right) \ln \left(\frac{GU}{\bar{GU}}\right) \\
 & + \sum_i \delta_i \ln \left(\frac{P_i}{\bar{P}_i}\right) t + \frac{1}{2} \beta_2 \ln \left(\frac{Y}{\bar{Y}}\right) \ln \left(\frac{Y}{\bar{Y}}\right) + \phi \ln \left(\frac{Y}{\bar{Y}}\right) \ln \left(\frac{GU}{\bar{GU}}\right)
 \end{aligned}$$

⁴ Traditionally research using the translog cost function avoid taking the log of the normalized mean if the time trend is used to depict unexplained technological change. This study follows that convention.

$$\begin{aligned}
 & +\pi \ln \left(\frac{Y}{\bar{Y}} \right) t + \frac{1}{2} \sigma \ln \left(\frac{GU}{\bar{GU}} \right) \ln \left(\frac{GU}{\bar{GU}} \right) + \mu \ln \left(\frac{GU}{\bar{GU}} \right) t \\
 & + \frac{1}{2} \gamma t^2 + \epsilon \dots\dots\dots (3)
 \end{aligned}$$

Shephard’s Lemma is applied to obtain each input share equation. This is achieved by differentiating the translog cost function with respect to the log of factor price as shown below.

$$\frac{\partial \ln C}{\partial \ln P_i} = \alpha_i + \sum_j \alpha_{ij} \ln w_j + \sum_k \tau_{ik} \ln Y + \sum_m \vartheta_{im} \ln a_m + \gamma_i t + \epsilon \dots\dots\dots (4)$$

Since at the industry mean $P_i = \bar{P}_i, Y = \bar{Y}_k, GU = \bar{GU}, t = 0$, then $\frac{\partial \ln C}{\partial \ln P_i} = \alpha_i$. Thus α_L, α_k , and α_M represent labor capital and material’s share of total cost respectively. In addition β_k represents economies of scale and ∂_i represent the technology effect on the factor inputs. The input shares equations together with the cost function are estimated using a seemingly unrelated regression method. The whole system of equations estimated is shown as follows:

$$\begin{aligned}
 \ln C = & \alpha_0 + \\
 & + \sum_i \alpha_i \ln \left(\frac{P_i}{\bar{P}_i} \right) + \beta_1 \ln \left(\frac{Y}{\bar{Y}} \right) + \sigma_1 \ln \left(\frac{GU}{\bar{GU}} \right) + \theta t \\
 & + \frac{1}{2} \sum_i \sum_j \alpha_{ij} \ln \left(\frac{P_i}{\bar{P}_i} \right) \ln \left(\frac{P_j}{\bar{P}_j} \right) + \sum_i \tau_i \ln \left(\frac{P_i}{\bar{P}_i} \right) \ln \left(\frac{Y}{\bar{Y}} \right) + \sum_i \vartheta_i \ln \left(\frac{P_i}{\bar{P}_i} \right) \ln \left(\frac{GU}{\bar{GU}} \right) \\
 & + \sum_i \partial_i \ln \left(\frac{P_i}{\bar{P}_i} \right) t + \frac{1}{2} \beta_2 \ln \left(\frac{Y}{\bar{Y}} \right) \ln \left(\frac{Y}{\bar{Y}} \right) \varphi + \varphi \ln \left(\frac{Y}{\bar{Y}} \right) \ln \left(\frac{GU}{\bar{GU}} \right) \pi + \pi \ln \left(\frac{Y}{\bar{Y}} \right) t \\
 & + \frac{1}{2} \sigma_2 \ln \left(\frac{GU}{\bar{GU}} \right) \ln \left(\frac{GU}{\bar{GU}} \right) + \mu \ln \left(\frac{GU}{\bar{GU}} \right) t + \frac{1}{2} \gamma t^2 + \epsilon \dots\dots\dots (5)
 \end{aligned}$$

$$\frac{\partial \ln C}{\partial \ln P_i} = \alpha_i + \sum_j \alpha_{ij} \ln P_j + \tau_i \ln Y + \vartheta_i \ln GU + \gamma_i t + \mu \dots\dots\dots (6)$$

Share equations are estimated for all the inputs excluding one in order to avoid singularity in estimated covariance matrix in the errors (Takada *et al.*, 1995). Furthermore, the parameter estimates in the share equations also need to satisfy the following conditions of homogeneity and symmetry:

$$\sum_i \alpha_i = 1, \sum_i \alpha_{ij} = \sum_j \alpha_{ij} = 0, \sum_i \tau_i = \sum_i \vartheta_i = \sum_i \gamma_i = 0, \alpha_{ij} = \alpha_{ji}.$$

Using this approach we are able to identify cost changes, and therefore productivity changes, that result from unexplained technological change, scale effects, and changes in infrastructure investment, when holding input prices constant. Gollop and Roberts (1981, 1983) show the reduction in average costs over time (when holding input prices constant) can be separated into a portion that is attributed to movements along the firm’s average cost curve (scale economies) and a portion that is attributed to shifts in the firm’s average cost curve (technological change and investment in infrastructure). To obtain expressions for the productivity gains realized due to technological change over time, scale economies, and changes in infrastructure investment, we start by defining the rate of change in total costs over time (holding input prices constant):

$$\frac{d \ln TC}{dt} = \frac{\partial \ln C}{\partial \ln Y} \frac{\partial \ln Y}{\partial t} + \frac{\partial \ln C}{\partial \ln GU} \frac{\partial \ln GU}{\partial t} + \frac{\partial \ln C}{\partial t} \dots\dots\dots (7)$$

Equation (7) is used to derive the rate of change in average cost by subtracting the rate of change in output over time from the rate of change in total costs, as depicted below:

$$\frac{d\ln AC}{dt} = \frac{\partial \ln C}{\partial \ln Y} \frac{\partial \ln Y}{\partial t} - \frac{\partial \ln Y}{\partial t} + \frac{\partial \ln C}{\partial \ln GU} \frac{\partial \ln GU}{\partial t} + \frac{\partial \ln C}{\partial t} \dots \dots \dots (8)$$

Duality theory indicates that productivity growth is depicted as the negative of this rate of change in average costs. Thus productivity growth is measured using the following equation:

$$Productivity\ growth = -\frac{d\ln AC}{dt} = \left(1 - \frac{\partial \ln C}{\partial \ln Y}\right) \frac{\partial \ln Y}{\partial t} - \frac{\partial \ln C}{\partial \ln GU} \frac{\partial \ln GU}{\partial t} - \frac{\partial \ln C}{\partial t} \dots \dots \dots (9)$$

In equation (9) the first component of the differential on right-hand-side represents productivity growth resulting from a change in output (scale); the second component represents productivity growth resulting from a change in infrastructure investment; and the last component represents productivity growth resulting from a change in unexplained technology. In this study we model productivity growth resulting from each of these effects for the industry average in each year of our data. Thus, decreases in average cost from the previous year are separated into these components by using cost function parameter estimates and industry averages of explanatory variables. For instance, a two-year average of explanatory variables is used to measure changes due to unexplained technological change, infrastructure investment, and scale for any given year as follows⁵:

$$Decreasing\ AC\ from\ unexplained\ technological\ change\ in\ year\ t = -\frac{\partial \ln C}{\partial t} \Big|_{YR_t} = \\ -\left[\theta + \sum_i \vartheta_i \left(\frac{\ln P_i(YR_t) + \ln P_i(YR_{t-1})}{2}\right) + \pi \left(\frac{\ln Y(YR_t) + \ln Y(YR_{t-1})}{2}\right) + \mu \left(\frac{\ln GU(YR_t) + \ln GU(YR_{t-1})}{2}\right) + \right. \\ \left. \gamma \left(\frac{t+(t-1)}{2}\right)\right]$$

where P_i denotes factor input prices. Including input prices in the equation allows for analysis of unexplained technological change while holding input prices constant.

$$Decreasing\ AC\ from\ change\ in\ infrastructure\ investment\ in\ year\ t \\ = \left(-\frac{\partial \ln C}{\partial \ln GU} \Big|_{YR_t}\right) \left(\frac{\partial \ln GU}{\partial t} \Big|_{YR_t}\right) = \\ \left[-\left\{\sigma_1 + \sum_i \vartheta_i \left(\frac{\ln P_i(YR_t) + \ln P_i(YR_{t-1})}{2}\right) + \varphi \left(\frac{\ln Y(YR_t) + \ln Y(YR_{t-1})}{2}\right) + \sigma_2 \left(\frac{\ln GU(YR_t) + \ln GU(YR_{t-1})}{2}\right) + \right. \right. \\ \left. \left. \gamma \left(\frac{t+(t-1)}{2}\right)\right]\right] \left[(\ln GU(YR_t) - \ln GU(YR_{t-1}))\right]$$

$$Decreasing\ AC\ from\ scale\ in\ year\ t = \left(1 - \frac{\partial \ln C}{\partial \ln Y} \Big|_{YR_t}\right) \left(\frac{\partial \ln Y}{\partial t} \Big|_{YR_t}\right) = \\ \left[1 - \left\{\beta_1 + \sum_i \tau_i \left(\frac{\ln P_{w_i}(YR_t) + \ln P_i(YR_{t-1})}{2}\right) + \beta_2 \left(\frac{\ln Y(YR_t) + \ln Y(YR_{t-1})}{2}\right) + \varphi \left(\frac{\ln GU(YR_t) + \ln GU(YR_{t-1})}{2}\right) + \right. \right. \\ \left. \left. \pi \left(\frac{t+(t-1)}{2}\right)\right]\right] \left[(\ln Y(YR_t) - \ln Y(YR_{t-1}))\right]$$

In terms of unexplained technological change, the model can also identify whether technology is factor using or factor saving for different factors of production. That is, we can look at time-factor price interaction terms to identify the impacts of input price changes on unexplained technological change and the changing input shares associated with technological change. Positive time-factor price interactions suggest an increase in the factor share over time (factor using) and a hindrance on technical change associated with price increases for that factor. On the other hand, negative time-factor price interactions suggest a decrease in factor share over time (factor saving) and a benefit to technological change associated with price increases of that factor, because increasing the price of that factor encourages substitution to other factors of production associated with technological progress (Rich, 2004).

⁵ Gollop and Roberts (1981) and Bitzan and Peoples (2014) also used a two year average of independent variables in measuring productivity effects due to scale and technical changes in the U.S. Electric Power Industry. Note that the notation YR_t denotes observation year at time ‘t’.

5. PRODUCTIVITY RESULTS DERIVED FROM ESTIMATING THE COST FUNCTIONS

Generally, the properties needed to satisfy the regularity conditions for a cost function are met. The estimated cost functions increase with increasing input prices and monotonicity is satisfied for industry output. Last, the estimated cost functions are also concave in input prices for nearly all observations.⁶

Before examining what the cost estimation results suggest about the influence of unexplained technological change, scale, and infrastructure investment on manufacturing productivity, an analysis of the estimated coefficients on the explanatory variables is presented. A summary of the findings on the first order terms of the 27 cost functions is presented in Table 2⁷.

Table 2: Summary of sign and statistical significance of parameter estimates on first order terms

| Parameter Estimate Sign | P _L | P _K | P _M | Y | GU | t |
|--|----------------|----------------|----------------|----|----|----|
| Positive and Statistically Significant | 27 | 27 | 27 | 27 | 11 | 3 |
| Negative and Statistically Significant | 0 | 0 | 0 | 0 | 4 | 15 |
| Not Statistically Significant | 0 | 0 | 0 | 0 | 12 | 9 |

Note: Separate Results for Each of the Cost Equations Estimated for 27 Industries

These findings indicate that the estimated coefficient on the first order terms for input prices and output are all positive and statistically significant. Although not presented in the table, the value of these parameters suggests that materials constitute the largest cost share of the three inputs, as the cost of materials comprise between 50 to 70 percent of cost attributable to the price of inputs.⁸ Labor constitutes the smallest share of input costs ranging from 4 to 5 percent of total input cost. The estimated coefficients on the output variable for each cost estimate vary from a range of 0.90 to 1.24 and are all statistically significant.

Findings on the two remaining first order terms reveal much greater variation in the sign and statistical significance of their estimated coefficients. The majority of the estimated coefficients on the infrastructure investment variable lack statistical significance. For infrastructure investment parameter estimates that are statistically significant, most are positive. The majority of the estimated coefficients on the unexplained technological change (time trend) are negative and statistically significant. A summary of the findings on the second order terms is presented in Table 3.

Table 3: Findings on selected second order terms input prices interacted with unexplained technology, infrastructure investment and scale

| Column number | Unexplained Technology | | | Infrastructure Investment | | | Scale | | |
|-------------------------|------------------------|----|----|---------------------------|----|----|-------|----|----|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Effect on Factor Inputs | K | L | M | K | L | M | K | L | M |
| Input Saving | 21 | 17 | 2 | 10 | 5 | 10 | 17 | 22 | 4 |
| Input using | 0 | 3 | 21 | 11 | 12 | 10 | 5 | 2 | 19 |
| Neutral | 6 | 7 | 4 | 6 | 10 | 7 | 5 | 3 | 4 |

⁶ Concavity is satisfied for a least 80 percent of the observations for 22 of the 27 industry samples. Only textile, chemical products, communications equipment, processing of ferrous metals and tobacco satisfy this condition for less than 80 percent of the observations. Excluding tobacco production, over 70 percent of the observations for these four industries satisfy this condition. Concavity in input prices is satisfied for two-thirds of the observations for tobacco production.

⁷ Due to space limits estimates of coefficients for first order, second order, interaction terms of cost function for each industry sample are not reported. Rather a summary of results derived from estimating the translog cost function for 27 industries is presented in Table 2.

⁸ Results including the value of all the estimated coefficients for cost determinants for all 27 cost functions are available from the authors on request.

In columns 1 to 3 time-factor input price interaction terms suggests that unexplained technological change is mainly capital and labor saving as the sign in these parameter estimates are negative and statistically significant for 21 and 17 of the industries for capital and labor, respectively. Findings also suggest six and seven of the remaining industries in this sample suggest capital and labor technical changing neutrality. In contrast to the unexplained technological change, results for capital and labor findings on the time-factor input price interaction term findings for materials suggest only two of the industries in our sample indicate technical change is associated with the use of less of this factor input. On the other hand, technical change is material using for 21 of the industries in our sample.

In columns 4-6 of Table 3, infrastructure investment-factor input price interaction terms reveal investment in infrastructure is as likely to be input saving as it is to be input using for capital and material. Such investment is slightly less likely to have a neutral effect on capital and material. In contrast investment in infrastructure is labor using in more than twice as many manufacturing industries that experience a decline in labor demand with investment in infrastructure. In addition, infrastructure investment is labor neutral for exactly twice as many industries experiencing labor savings due to such investment. Findings in columns 7-9 of Table 3 suggest that industry size (scale) is capital and labor saving for a large share of the industries in our sample. The estimated coefficient on the scale-input factor price variables suggests increased capital and labor usage for only five and two industries, respectively. Industry size, however is primarily factor input using for materials, as the use of this input increases with scale for 19 of the 27 industries.

Finding using the translog cost results to compute and decompose annual productivity growth is reported in Table 4.

Table 4: Results for productivity decomposition derived from separately estimating the cost equation for each of 27 industries

| Industries | Unexplained Technology (%) | Infrastructure Investment (%) | Scale (%) | Annual Productivity Growth (%) |
|---|----------------------------|-------------------------------|-----------|--------------------------------|
| Processing of food from agricultural products | 1 | 3 | 0 | 4 |
| Foods | 3 | 2 | 2 | 7 |
| Beverage | 2 | 1 | -3 | 0 |
| Tobacco | 5 | 1 | -3 | 3 |
| Textile | 7 | 1 | -8 | -1 |
| Textile footwear apparel | 1 | 1 | -1 | 1 |
| Leather, fur, leather, footwear and caps | 6 | -2 | -1 | 3 |
| Processing of timber, wood, and bamboo | 7 | -2 | -2 | 3 |
| Furniture | 0 | 0 | -4 | -4 |
| Paper and paper products | 3 | 1 | -3 | 0 |
| Printing, reproduction of recording media | 2 | -1 | 0 | 1 |
| Articles for culture, education and sports | 1 | 4 | -1 | 4 |
| Processing of petroleum, coking, and nucleus fuel | 3 | 0 | -1 | 2 |
| Chemical raw material and chemical products | 4 | 0 | -4 | 0 |
| Pharmaceuticals | 3 | -3 | 0 | 0 |
| Chemical Fibers | 3 | 3 | 2 | 8 |
| Rubber | 4 | -3 | 0 | 2 |
| Plastic | 4 | 0 | -10 | -5 |
| Non-metallic mineral products | 5 | -4 | -2 | -1 |
| Manufactured and processing of ferrous metals | 8 | 5 | 0 | 13 |

| | | | | |
|---|----|----|-----|----|
| Manufactured and processing of Non-ferrous metals | 3 | 3 | -7 | -2 |
| Metal products | 1 | 2 | 2 | 5 |
| General purpose machinery | 9 | -1 | -4 | 4 |
| Special purpose machinery | 5 | -1 | 3 | 7 |
| Transport equipment | 8 | -3 | -3 | 1 |
| Electrical machinery and equipment | 21 | -2 | -11 | 8 |
| Communications equipment, computer and other electronic equipment | 4 | 1 | 0 | 5 |

The results show that 23 of the 27 industries experienced productivity gains for the 1998 to 2005 observation sample. The largest gains are reported for companies that manufacture ferrous metal, as their growth averaged 13 percent annually. Firms manufacturing plastic goods are found to experience the largest productivity declines, equaling 5 percent annually.

Using Gollop and Roberts' decomposition approach, it reveals that unexplained technological change is a key contributor to productivity growth. For instance, the findings indicate increasing annual productivity due to unexplained technology progress for all industries in the sample except for furniture manufacturing. Unexplained technology progress' largest impact occurs for companies manufacturing general-purpose machinery, as this determinant contributes to annual productivity gains of 9 percent.

The finding also indicates that infrastructure investment contributes to productivity gains for most industries. Companies manufacturing ferrous metal experience the largest productivity gains due to such investment, while companies producing textile for footwear apparel experience the largest productivity loss attributable to infrastructure investment.

For scale, findings reveal a different story: it shows company size is the only determinant of those examined in this study that primarily contributes to annual productivity declines. For instance, declines due to large operating output occur for 21 of the 27 manufacturing industries. Electrical machinery equipment experiences the largest decline in productivity attributable to increasing output, while companies manufacturing special purpose machinery experience the largest increase in annual productivity attributable to increasing output.

6. CONCLUDING REMARKS

Sustaining high productivity growth is essential for China to maintain its economic growth and international competitiveness in manufacturing. Existing research presents inconclusive evidence on the rate of productivity growth and their sources. Our study furnishes further evidence on the analysis of China's productivity growth and identifies sources for the growth. Adopting a flexible form cost function, our study estimates the annual productivity growth rates for 27 manufacturing industries over the 1998-2005 time period. Three sources contributing to the growth are examined: unexplained technological change, scale, and infrastructure investment. The factor input demand effect of these productivity determinants is also examined, with special emphasis on the demand for labor.

Our findings reveal that for all industries, except furniture manufacturing, unexplained technological change contributes to productivity growth. Infrastructure investment contributes to productivity growth for the 16 out of the 27 industries investigated in this study. Scale contributes to productivity growth in only 6 manufacturing industries. These results on technology's influence on productivity support the Chinese government's policy encouraging investment in R&D and FDI. In addition, findings on the interaction of wage and unexplained technological change indicate labor-input saving, which is consistent with the notion that unexplained technological change enhances worker productivity.

Findings on the productivity effects of infrastructure investment generally support the government's emphasis on financially supporting better roads, transmission of electricity and supply of water and fuel. However, findings, that indicate approximately one-third of the industries did not experience productivity gains due to infrastructure investment, are consistent with the observation of past research for other countries. This latter finding on infrastructure investment in China highlights the importance of investigating the merits of up-grading existing infrastructure projects rather than excess investing in new projects.

Last, findings on industry scale suggest the existence of inefficiencies associated with large operations. This provides evidence that over capacity is an issue that warrants policy attention while China grows its economy to an enormous size. Nonetheless, productivity findings from this study indicate a highly productive manufacturing sector in the Chinese economy.

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| Funding: This study received no specific financial support. |
| Competing Interests: The author declares that s/he has no conflict of interests. |
| Acknowledgments: In memory of Bin Wang. The authors are also grateful for suggestions and comments offered by participants of the firm and industry productivity session at the 2015 Chinese Economists Society's conference in Chongqing, China, June 13-14, 2015. |
| Views and opinions expressed in this study are the views and opinions of the authors, Asian Journal of Empirical Research shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content. |

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