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Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing☆

Loren Brandt [a], Johannes Van Biesebroeck [b,*], Yifan Zhang [c]

[a] University of Toronto, Canada
[b] K.U. Leuven and CEPR, Centre for Economic Studies, Naamsestraat 69, 3000 Leuven, Belgium
[c] Lingnan University, Hong Kong

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ABSTRACT

We present the first comprehensive set of firm-level total factor productivity (TFP) estimates for China's manufacturing sector that spans China's entry into the WTO. For our preferred estimate, which adjusts for a number of potential sources of measurement error and bias, the weighted average annual productivity growth for incumbents is 2.85% for a gross output production function and 7.96% for a value added production function over the period 1998–2007. This is among the highest compared to other countries. Productivity growth at the industry level is even higher, reflecting the dynamic force of creative destruction. Over the entire period, net entry accounts for over two thirds of total TFP growth. In contrast to earlier studies looking at total non-agriculture including services, we find that TFP growth dominates input accumulation as a source of output growth.

1. Introduction

China has enjoyed impressive labor productivity growth averaging nearly 8% for a period now spanning three decades. Considerable debate persists over the sources of this growth and the relative contributions of improvements in total factor productivity (TFP) versus the mobilization of additional resources, notably physical and human capital. Studies using aggregate data and combining agriculture and non-agriculture typically find TFP contributing approximately half of labor productivity growth (Bosworth and Collins, 2008; Perkins and Rawski, 2008).

In a widely cited study focusing solely on the non-agriculture sector covering the period up through 1998, Young (2003) paints a much less impressive picture of China's growth story. Correcting for potential biases in official deflators and the measurement of human capita, but otherwise using official data, Young reduces the estimate of productivity growth for the sector between 1978 and 1998 from a very respectable 3% to a more pedestrian 1.4%. Over this period, non-agriculture was the source of nearly 80% of GDP.[1]

The aggregate results hide important heterogeneity. TFP growth in industry, which represents forty percent of GDP and is the source of 90% of exports, is likely to be much higher than in the service sector, to which reform and market liberalization have only come with a long lag (Bosworth and Collins, 2008). Earlier empirical studies also identify a significant gap in productivity in industry between the rapidly expanding non-state sector and state-owned firms (Groves, et al., 1994; Jefferson and Rawski, 1994). Qualitatively, rising firm capabilities and productivity in industry have been linked to the expanding role of market forces, massive entry of new firms, and intense competition (Brandt et al., 2008).

An analysis of Chinese manufacturing on par with that carried out for other countries has been handicapped by a lack of firm-level data sets. This constraint is gradually being relaxed, allowing more in-depth analysis at the micro level of key aspects of behavior in manufacturing that are missed at the macro level—see, for example, Bai et al. (2006), Dougherty et al. (2007), Hsieh and Klenow (2009), and Park et al. (2010). This paper builds on that work.

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* Corresponding author.
E-mail address: jo.vanbiesebroeck@econ.kuleuven.be (J. Van Biesebroeck).

[1] Brandt and Zhu (2010) revise Young's original estimates upwards, reflecting revisions to official GDP figures, and biases in Young's deflator for services.

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Drawing on an unbalanced panel of firms between 1998 and 2007 that represents approximately 90% of gross output in manufacturing, we present the first comprehensive set of firm-level productivity estimates for Chinese manufacturing that spans China's entry into the World Trade Organization (WTO). The absolute size of China's manufacturing sector and its exports make this important in its own right. Over the period we examine, we find firm-level TFP growth of manufacturing firms averaging 2.85% for a gross output production function and 7.96% for a value added production function.

Total TFP growth for the manufacturing sector was even higher due to massive entry of new firms with above average productivity levels and growth rates and the exodus of inefficient incumbents. When new firms replace exiting firms, the reallocation of input factors tends to enhance efficiency. Over the full sample period, our results identify net entry as the source of more than two thirds of total productivity growth, exceeding its contribution in U.S. manufacturing (Haltiwanger, 1997).[2]

In all, we find that TFP growth coming from improvements in continuing firms (the intensive margin of TFP growth) and through net entry (the extensive margin of TFP growth) was the source of over half of value added growth in manufacturing over the 1998–2007 period. TFP's contribution to labor productivity growth is even higher at two-thirds. The rest of the growth in value-added was the result of increases in total capital and labor use in manufacturing, much of which was associated with the entry of new firms. Our findings for the manufacturing sector are sharply at odds with the view of Young (2003) and others (Zheng et al., 2006) that productivity growth outside of agriculture has been mundane or ordinary. However, our results reveal that aggregate TFP growth in Chinese manufacturing remains constrained by limited efficiency-enhancing input reallocations between active firms, confirming results in Hsieh and Klenow (2009).

These findings have important implications for government policy. First, the high firm-level TFP growth estimates imply that Chinese manufacturing output growth will not disappear any time soon as input accumulation diminishes. The labor force will peak in a few years (Perkins and Rawski, 2008), and rates of investment are expected to come down as China rebalances. TFP growth will also help firms in China weather rising labor and other input costs. Second, increasing competitive pressure and the adoption of new technology are often mentioned as drivers of TFP growth. Learning is not only important to the upgrading efforts and productivity growth among continuing firms, but is also equally important to the contribution of new entrants. For entrants, there are two dimensions to learning: first, identifying new opportunities making successful entry possible and second, improving productivity subsequent to entry. Policies that facilitate both kinds of learning are the key to sustained growth in the medium term. Third, as input growth slows and the technology gap with advanced countries narrows, further reforms to enhance efficient allocation of resources still provide important growth potential. A policy of liberalizing entry and facilitating exit has already played an important role in this regard. Removal of constraints that underpin productivity differences among existing firms, including those between the state and non-state sectors will have to be tackled next.

Working with firm-level data for China has its difficulties. One of the additional contributions of this paper is to carefully describe and document these data. We make publically available online the complementary data we have constructed, including deflators, industry concordances, adjustment to capital stock series, etc. that are required to make full use of the data. Furthermore, in light of important concerns of Young and others, we examine the robustness of our results to a host of measurement issues. We show how alternative treatment of key variables often reduces productivity growth, but does not alter the basic picture.[3]

A particularly important aspect of the data work was the construction of linkages over time in firm-level observations when firm ID codes changed. This often occurs when active firms are restructured and it is important not to classify such instances as exit and subsequent entry. We find that one-sixth of the Chinese firms in our sample have at least one ID change. The ability to track firms as they are being restructured is an important precondition to being able to conclude that net entry has been the dominant force in productivity growth in Chinese manufacturing.

The remainder of the paper is organized as follows. In the next section we describe our methodology for measuring productivity. Section 3 describes the data set and the construction of the key variables. An online Appendix provides more detailed documentation. In Section 4 we describe the Chinese results at the firm level, the performance of entrants and exiting firms, and the aggregate productivity growth experience. The latter allows us to "line up" our findings for industry with estimates from the literature for the entire economy. We also decompose the productivity residual to identify the types of heterogeneity most important to the aggregate evolution of productivity. Section 5 concludes.

2. Productivity measurement

The most widely used measure of productivity is labor productivity, the ratio of value added to the number of hours worked or the number of workers. In China's national accounts the share of labor earnings in GDP is only around one half for the full economy and it is even lower in manufacturing. Not accounting for capital intensity is likely to paint a misleading picture.

Multi-factor productivity is only defined relative to a particular production technology – input aggregator – which we can characterize by a production function:

$$Q_{it} = A_{it} F_{it}(X_{it}). \tag{1}$$

It is inherently a relative concept, and we can write it in general as

$$\ln\left(A_{it} / A_{j\tau}\right)_k = \ln\left(Q_{it} / Q_{j\tau}\right) - \ln\left(F_k(X_{it}) / F_k\left(X_{j\tau}\right)\right). \tag{2}$$

For productivity growth comparisons, the same firm enters the numerator and denominator $(i = j)$ and for productivity level comparisons we fix time instead $(t = \tau)$. Even though the production function in Eq. (1) is allowed to differ between firms and over time–as denoted by the subscript on the input aggregator–we have to use a uniform technology (k) for both units to perform the productivity comparison in Eq. (2).

To accurately measure productivity, one needs to accurately measure inputs and outputs and to estimate the input substitution possibilities that the technology allows. The first task is described at length in the next section; we now turn to the second task. Van Biesebroeck (2007, 2008) compares alternative methodologies to estimate productivity and finds different estimates to exhibit very high correlations. The assumption of a uniform production technology for all firms in an industry stands out as one modeling choice that the results are sometimes sensitive to.[4] Therefore, we implement two estimation procedures.

[2] Recent qualitative work of Brandt et al. (2008) and work with cross-sectional data for 1998 and 2005 by Jefferson et al. (2008), already point to entry and exit as important drivers of the dynamism in the manufacturing sector. Here, we provide decomposition results for China's manufacturing sector that are directly comparable to other studies in the literature.

[3] In particular, using different price deflators does influence absolute growth estimates, but the relative contribution of TFP growth and input accumulation in output or labor productivity growth are only affected to the extent that price deflators are biased differently for wages, capital, and output.

[4] This mattered in particular for the evaluation of learning-by-exporting effects.