



On-the-job training and productivity: Firm-level evidence from a large developing country



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ABSTRACT

We investigate the effects of on-the-job training on firm productivity and wages using a large panel data set constituted of all large and medium size manufacturing firms in China over 2003–2007. We estimate firm productivity carefully with a recent semiparametric method and combine the propensity score matching and the difference-in-differences techniques to estimate the treatment effect of training. We find consistent evidence that i) training helps boost firm productivity and wages; ii) the higher the training expenditure per capita, the higher the increase in productivity and wages; iii) firms benefit more from training than workers. These findings are not sensitive to industrial capital intensity or firm ownership structure.

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1. Introduction

Human capital is important for economic growth and firms' competitiveness. Economists have paid much attention to the study of human capital investment (including school education and on-the-job training). Relative to the large literature on the effect of school education, for the effect of firm-provided on-the-job training the research (especially firm-level research) is few and the results are not clearcut (see a review by [Blundell, Dearden, Meghir, & Sianesi, 1999](#)). The main difficulties on the study of on-the-job training lie in two aspects: the limited availability of detailed firm-level data, and the potential bias in econometric estimation due to the unobserved firm heterogeneity and the endogeneity problems.

This paper (among the first of few) advances the research on the effect of training in both of these two dimensions. We obtain a large panel dataset containing all large- and medium-scale Chinese manufacturing firms with detailed operation and training information, and we combine the propensity score matching (PSM) method and the difference-in-differences (DID) technique to calculate the causal treatment effect of training. We find that firm investment in training does pay, either measuring training in the extensive margin (i.e., whether firms invest in worker training or not) or in the intensive margin (i.e., the training

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expenditure per worker). The results from different estimation models are generally consistent in the sign and the magnitude, and are not sensitive to industrial capital intensity or firm ownership structure. In our preferred DID-PSM estimation with carefully estimated productivity measures and more control variables, training participation raises firm productivity by 9.61%, while raises wages by 3.42%. As for training intensity, a 1% increase in training expenditure per worker boosts firm productivity by 0.1174%, while raises wages by 0.0878%. These results imply substantial returns to on-the-job training and that firms benefit more from training than workers.

Because of the importance of on-the-job training in human capital accumulation, economists have made notable efforts to estimate the effect of training. However, due to data limitations, early literature generally relies on proxying firm productivity with wages in studying the effect of training on productivity (for example, Bartel, 1994, 1995; Blanchflower & Lynch, 1994; Blundell, Dearden, & Meghir, 1996) or estimates the effect based on cross-sectional data (for example, Barrett & O'Connell, 2001; Black & Lynch, 1996) which is hard to control for potential firm-specific time-invariant heterogeneity and other unobserved shocks which affect both training and productivity. Some recent studies have made efforts to construct industry-level panel data to deal with the econometric problem (for example, Conti, 2005; Dearden, Reed, & Van Reenen, 2006). However, as emphasized by Dearden et al. (2006), the aggregation may introduce biases and also capture the spillover of training across firms. A small number of papers employ firm-level panel data to test the effect of training on firm productivity. For example, Black and Lynch (2001) obtain data for 672 US plants in two years, Almeida and Carneiro (2009) for 1500 large firms for Portugal, Zwick (2006) for German and Ballot, Fakhfakh, and Taymaz (2006) for French and Swedish firms in limited industries, and Colombo and Stanca (2008) for Italian firms. However, the generalization of the results from these papers is constrained by the limited representativeness of the sample.

This paper complements and contributes to the current literature in several ways. Firstly, we obtain the training and operation information for all “representative” manufacturing firms of China. Secondly, all the above-mentioned papers study different countries (almost all are developed countries), but none for China. China is an interesting case for the research of training. China is now the second largest world economy, the largest developing country with almost the fastest growth rate. China's manufacturing capability has been expanded promptly in recent years and the government is fighting to upgrade its industrial structure by emphasizing the role of human capital.¹ This process has shaken and will continue to shake the whole world. Given the acknowledged fact that the Chinese education system is not that effective and qualified skilled workers are unabundant,² the firm investment in human capital (training) is expected to play important roles in the process of China's structural change. However, it is surprising that there is no research on the effect of training in China. We help fill in this gap.

Thirdly, for econometric techniques, we first follow the literature (for example, Dearden et al., 2006) to exploit the panel structure of our data with the within effect model. Furthermore, we combine the propensity score matching technique and the difference-in-differences method to check the treatment effect of training. This treatment effect approach is widely used in other research fields³ but has not been found in studying the relationship between on-the-job training and firm productivity till now.

Fourthly, we estimate the dependent variable, firm productivity, more carefully by employing the semiparametric method developed by Levinsohn and Petrin (2003), which requires high quality firm-level data. In the previous literature, firm productivity is generally measured with the simple labor productivity (output per worker or value added per worker) or traditional total factor productivity (TFP) from Solow residuals. However, the labor productivity measure does not take into account the role of other inputs such as capital investment, and the traditional TFP estimation may suffer from the simultaneity problem. Levinsohn and Petrin's (2003) method is proposed to deal with this simultaneity problem and is widely used in productivity studies.⁴ Our rich data affords the careful calculation of productivity with the Levinsohn and Petrin (2003) method.

The remainder of the paper is organized as follows. In Section 2 we introduce the econometrical methodologies used. Section 3 describes the dataset and the variables. In Section 4 we report all empirical results, and discuss the effects of training in the extensive margin and the intensive margin, respectively. Section 5 concludes the analysis.

2. Empirical methodologies

In this paper, we firstly employ the within estimator to estimate the effect of training. We then further calculate the treatment effect of training by combining the propensity score matching and the difference-in-differences techniques.

Our basic within estimator specification is as follows:

$$Y_{it} = \alpha + \beta TRAIN_{it} + X'_{it}\gamma + D_i + D_t + \varepsilon_{it} \quad (1)$$

¹ In recent years, the Chinese central government has made a series of programs to develop its human capital. For example, in 2002, the Chinese government published the National Program for Qualified Personnel Development (2002–2005), and in 2010, the government further published the National Program for Medium and Long-term Talent Development (2010–2020). In these programs the Chinese government explicitly and repeatedly announced its “Strategy of reinvigorating China through human resource development (*rencai qiangguo zhanlue*)”.

² This fact is also true for other developing countries and is a distinct feature from developed countries.

³ For example, on cross-border mergers and acquisitions (Liu, Lu, & Qiu, 2016; Liu, Lu, & Zhang, 2015), on FDI spillovers (Liu, Lu, & Zhang, 2014), etc.

⁴ There is still another method to estimate productivity, i.e., Olley and Pakes (1996), which uses investment as proxy. As we don't have exact investment and exit/entry information of the firms, and also as Levinsohn and Petrin (2003) point out that investment does not smoothly respond to productivity shocks, we do not employ this method.

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