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On modeling the determinants of TFP growth☆

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ABSTRACT

We investigate the determinants of TFP growth of Italian manufacturing firms. Using stochastic frontier techniques, we consider three approaches for taking into account the influence of external factors, i.e., the determinants or drivers of growth. First, in our novel approach external factors may influence the technological progress, that is the shift of the frontier. To model this possible unexplored effect, we extend the standard time trend model to make it a function of the external factors. Then, following more standard approaches, we model external factors as either influencing the distance from the frontier, i.e., inefficiency, or the shape of the technology. Using a sample of manufacturing firms in 1998–2003, we find that technological investments and spillovers, human capital and regional banking inefficiency all have a significant effect on TFP growth.

1. Introduction

The influence of external (or exogenous, environmental) factors in stochastic frontier models has been modeled with two alternative approaches. One assumes that the external factors influence the shape or structure of the technology, i.e., how conventional inputs are converted to outputs, while the other assumes that they directly influence the degree of technical efficiency, i.e., the efficiency with which inputs are converted into outputs (see, e.g., Coelli et al., 1999 or Kumbhakar and Lovell, 2000). In the literature on productivity measurement, however, no contribution explicitly considers the impact of environmental factors on the technological change, i.e., on the shift of the technological possibilities over time.

In this paper we propose a model where external factors can affect the technological change. To this end, we adapt the time trend model of technical change (Baltagi and Griffin, 1988), recently used by Kumbhakar (2004) to accommodate TFP into econometric models. Following Battese and Coelli (1992, 1995), and extending the methodology presented in Aiello et al. (2011), we employ a time varying inefficiency model. Using a stochastic frontier approach, we propose a model for output growth decomposition to investigate the main determinants of growth. This

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allows to distinguish whether environmental factors, i.e., the determinants or drivers of growth, have an impact on the structure of the technology, on the technical efficiency (technological catch-up), or on the technical change.

Researchers interested in estimating productivity can choose from different methodologies, such as non-parametric, parametric, and semiparametric ones, each one with its strengths and weaknesses. Van Beveren (2012), for instance, compares fixed effects, instrumental variable, and semiparametric estimators to investigate how they can deal with the methodological issues arising when estimating TFP at the firm level. She considers the well-known simultaneity bias, i.e., when there is correlation between the level of inputs chosen and unobserved productivity shocks; selection bias, which arises when the exit decisions of firms are not taken into account, a bias which is further increased by the use of a balanced panel; omitted price bias, due to the use of industry-level price indices applied to deflate firm-level sales and input expenditure, given that input choices are correlated with unobserved firm-level price differences; and last, the bias introduced by considering data at the firm level in the case of multi-product firms, which would require information on the product-mix, product-level output, inputs and prices. Ackerberg et al. (2007) provide an excellent technical review of these issues. Van Beveren (2012) finds that the semi-parametric estimators are to be preferred to both the GMM and fixed effects estimators. However, the choice of which estimator to use will essentially also depend on the data at hand and the underlying assumptions researchers are willing to assume or impose after testing the data.

Van Biesebroeck (2007) compares the robustness of five widely used techniques, such as index numbers, data envelopment analysis (DEA), stochastic frontier (SF), instrumental variables (GMM) and semiparametric estimation. Using simulated samples of firms, he introduces randomness via factor price heterogeneity, measurement error, and differences in production technology. He shows that the index number approach produces among the most robust estimates when firms are likely to employ different technologies, unless there is a lot of measurement error. DEA is robust in the productivity level estimation if technology varies across firms and there are variable returns to scale. Given that OLS is generally not advisable due to the simultaneity problem, he shows that SF produces accurate productivity level estimates when productivity differences are constant over time, output is measured accurately, and firms share the same technology. On the other hand, with a lot of measurement error or technological heterogeneity, the GMM estimator provides the most robust productivity level and growth estimates among the parametric methods. Last, semiparametric estimators appear valuable when firms are subject to idiosyncratic productivity shocks that are not entirely transitory. Overall, the SF results tend to be worse than for either GMM or the semiparametric (i.e., Olley and Pakes, 1996) estimators, even though the differences are small. The results of SF, moreover, are weakest when there are no fixed effects in productivity and measurement error in output. Otherwise, the SF method provides good productivity level estimates.

Being aware of the strengths and weaknesses of different TFP estimation methods and given our data, in this paper we develop and apply a new approach for dealing with external variables within a stochastic frontier model which better deals with measurement errors. We believe that this contribution has interest in itself, given the flexibility of SF that is not matched by other techniques. The index number approach, indeed, does not allow to consider external variables, while DEA can deal with external variables using bootstrap techniques but only up to a point, i.e., when they affect either the shape of the frontier or the distance from the frontier. In other words, there are not contributions yet in the non-parametric literature that consider the impact of external variables on technological progress, as we do in this paper. We recognize that problems of productivity estimates robustness are important, and we are aware that the SF method may not be the most robust in all instances. However, we believe that the comparison with other methods goes beyond the scope of this paper, and is left as a topic for future work. In this paper therefore we investigate the effects of the external drivers of growth. Being able to ascertain through which channels the growth drivers affect TFP growth can be interesting for different reasons. Recent contributions of endogenous growth theories, for instance, emphasize the different roles that “appropriate” institutions and policies may play in either backward or advanced economies, and the distinction between innovation activities and adoption of existing technologies from the (world) technology frontier (Acemoglu et al., 2006). In this context, low skilled human capital appears better suited to technology adoption, while skilled human capital has a growth enhancing impact which increases with the level of development, i.e., with the proximity to the frontier (Vandenbussche et al., 2006). Our approach can be applied to test whether and how education affects productivity. In our study with Italian manufacturing data over the period 1998–2003, for instance, we find that our measure of human capital (i.e., average years of schooling in the labor force) has a negative impact on total factor productivity.[2]

Similar considerations, and those related to the appropriateness of institutional and policy choices, can be extended to consider the role of financial institutions, technological spillovers, and the like. From a policy point of view, finding that investments in economic infrastructures – or in R&D, in information and communication technologies, in foreign direct investments, and so on – have an impact either on technical progress, technological catch-up or factor accumulation has interesting policy implications since it allows to target, for instance, innovating firms. On the other hand, if a policy maker would like to give incentives to adopting firms, those usually located below the frontier, she could investigate on which drivers to base the policy intervention.

[2] Notice that our specific measure of human capital is defined at the firm level and therefore potentially endogenous. Still, we use it because it is an important control variable and a further example of how to take into account these variables in our modeling approach.