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Estimating the bias in technical change: A nonparametric approach

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HIGHLIGHTS

- A nonparametric methodology to determine the direction of technical change is proposed.
- The model applies input-specific distance functions to track shifts of the production frontier.
- Technical change of 81 countries during 1970–2014 is analyzed.
- We find that technical change has become increasingly capital-using in industrialized countries.
- Directions in technical change have converged among countries since the productive decade.

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ABSTRACT

In this note we propose a nonparametric methodology to estimate the bias in technical change. We apply the model to estimate the direction of technical progress for a sample of 81 countries covering the period 1970–2014. Our results confirm previous findings that during the 1980s technical change in industrialized countries has become increasingly capital-using. Moreover, we find that patterns in the bias of technical change have converged among different country groups after the productive decade 1995–2004.

1. Introduction

Following the seminal contribution by Binswanger (1974), numerous studies have estimated the bias in technical change accounting for multiple inputs. These approaches apply parametric methods, hence impose specific functional forms of the cost or production functions. Moreover, they depend on price data to disentangle changes in input ratios caused by changes in relative prices from those caused by biased technical change.[1] To overcome the dependency on a specific functional form of the frontier function and price data, Färe et al. (1997) have proposed a nonparametric approach to biased technical change based on applying distance functions and decompositions of productivity indices.

In this note we present a novel nonparametric methodology to estimate the direction of technical change endogenously by using input-specific distance functions. We demonstrate how an appropriate normalization of the resulting estimates allows to analyze biases in technical change without having to calculate and decompose productivity indices. Our model is applied to analyze patterns in biased technical change for a sample of 81 countries covering the period 1970–2014.

This note is structured as follows: Section 2 presents the methodology while Section 3 discusses the results of the empirical application. Finally, Section 4 concludes.

2. Methodology

In our model we consider a production process where $m = 1, \ldots, M$ inputs $\boldsymbol{x}_t \in \mathbb{R}_+^M$ are used to produce a scalar output $y_t \in \mathbb{R}_+$ in period $t = 1, \ldots, T$. The technology set of period t contains all technically feasible input–output combinations:

$$\mathcal{T}_t = \{(\boldsymbol{x}_t, y_t) : \boldsymbol{x}_t \text{ can produce } y_t\}. \quad (1)$$

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[1] See e.g. Antràs (2004) and Berndt (1976) for discussions on the influence of (price) data quality on the results of analyses of biases in technical change.

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On this set we impose the conventional neoclassical axioms (e.g. convexity, free disposability of inputs and outputs) proposed by Shephard (1970). Moreover, we assume that the technology exhibits constant returns to scale (CRS). We denote by $\partial\mathcal{T}_t$ the closure (frontier) of the technology set.

To estimate $\mathcal{T}_t$, we apply the nonparametric data envelopment (DEA) estimator by Charnes et al. (1978). Given a sample of $i = 1, \ldots, n$ observations with input–output combinations $(\boldsymbol{x}_{it}, y_{it})$, the nonparametric estimator satisfying the Shephard axioms reads as:

$$\widehat{\mathcal{T}}_t = \left\{(\boldsymbol{x}_t, y_t) : \boldsymbol{x}_t \geqq \boldsymbol{X}_t\boldsymbol{\lambda}_t,\ y_t \leqq \boldsymbol{y}_t^{\intercal}\boldsymbol{\lambda}_t,\ \boldsymbol{\lambda}_t \geqq \boldsymbol{0}\right\}. \tag{2}$$

Here, $\boldsymbol{X}_t$ denotes the $M \times n$ matrix of inputs, while $\boldsymbol{y}_t^{\intercal}$ denotes the transposed $n \times 1$ vector of outputs. In addition, $\boldsymbol{\lambda}_t$ denotes the $n \times 1$ vector of weight factors which are used for constructing convex combinations of observations. They are restricted to be non-negative implying that the estimated technology set satisfies CRS.

Building upon this nonparametric method, the direction of technical change can be estimated by solving the nonlinear programming problem:

$$\max_{\substack{\beta,\boldsymbol{\gamma}_x,\boldsymbol{\lambda}_t,\\ \boldsymbol{\lambda}_{t+1},d}} \frac{\boldsymbol{1}_M^{\intercal}\boldsymbol{\gamma}_x}{\boldsymbol{1}_M^{\intercal}\beta\boldsymbol{\gamma}_x} = \frac{1}{\beta}$$

$$\begin{array}{lrcll}
\text{s.t.} & \boldsymbol{x}_{it} - \beta\boldsymbol{\gamma}_x \odot \boldsymbol{x}_{it} & = & \boldsymbol{X}_t\boldsymbol{\lambda}_t & \multirow{2}{*}{\Big\}\ \text{Distance to } \partial\mathcal{T}_t} \\
& y_{it} & = & \boldsymbol{y}_t^{\intercal}\boldsymbol{\lambda}_t & \\
& \boldsymbol{x}_{it} - \boldsymbol{\gamma}_x \odot \boldsymbol{x}_{it} & = & \boldsymbol{X}_{t+1}\boldsymbol{\lambda}_{t+1} & \Big\}\ \text{Distance to } \partial\mathcal{T}_{t+1} \\
& y_{it} & = & \boldsymbol{y}_{t+1}^{\intercal}\boldsymbol{\lambda}_{t+1} & \\
& \boldsymbol{\lambda}_t & \geqq & \boldsymbol{0} & \Big\}\ \text{CRS} \\
& \boldsymbol{\lambda}_{t+1} & \geqq & \boldsymbol{0} & \\
& \boldsymbol{\gamma}_x - d\boldsymbol{z}_M & \leqq & \boldsymbol{0} & \\
& \boldsymbol{\gamma}_x + (1-d)\boldsymbol{z}_M & \geqq & \boldsymbol{0} & \Bigg\}\ \beta,\boldsymbol{\gamma}_x \geqq \boldsymbol{0} \text{ if } d=1 \text{ or } \beta,\boldsymbol{\gamma}_x \leqq \boldsymbol{0} \text{ if } d=0 \\
& \beta - dz & \leqq & 0 & \\
& \beta + (1-d)z & \geqq & 0 & \\
& d & \in & \{0, 1\}. &
\end{array} \tag{3}$$

Here, $\boldsymbol{\gamma}_x$ denotes the $M \times 1$ vector of extended Färe–Lovell inefficiency measures by Briec (2000) which are endogenously determined to measure the input-specific distance of observation i in period t to the frontier of period $t + 1$.[2] The measure β scales the inputs in the direction imposed by $\boldsymbol{\gamma}_x$ until the frontier of period t is reached. Therefore, the distances to the frontiers of periods t and $t + 1$ are measured along the same direction. This direction maximizes the objective function, hence the distance to $\partial\mathcal{T}^{t+1}$ divided by the distance to $\partial\mathcal{T}_t$, which is a measure of the shift in the frontier. The inequality restrictions on the input–output combinations are replaced by equality restrictions to ensure that only fully efficient points on the frontiers are considered as benchmarks.

Note that in case of technical regress, $\boldsymbol{\gamma}_x$ may become negative if the frontier shifts behind observation i. Since $(\boldsymbol{x}_{it}, y_{it}) \in \widehat{\mathcal{T}}_t$, $\beta\boldsymbol{\gamma}_x$ has to be non-negative implying that β is negative in this case as well. This restriction is imposed by introducing the binary variable d as well as the arbitrary (large) integer z. The inequality restrictions ensure that all distance measures are either positive or negative.

If observation i is located on the frontier of period t, the programming problem has no feasible solution since $\beta = 0$ and $1/\beta$ is not defined. In this case, we estimate the direction of technical change by maximizing the numerator of the objective function $\boldsymbol{1}_M^{\intercal}\boldsymbol{\gamma}_x$ and setting $\beta = 0$ in the restrictions.

[2] $\odot$ denotes the direct product, $\boldsymbol{1}_M$ ($\boldsymbol{z}_M$) denotes the $M \times 1$ all-one (all-z) vector.

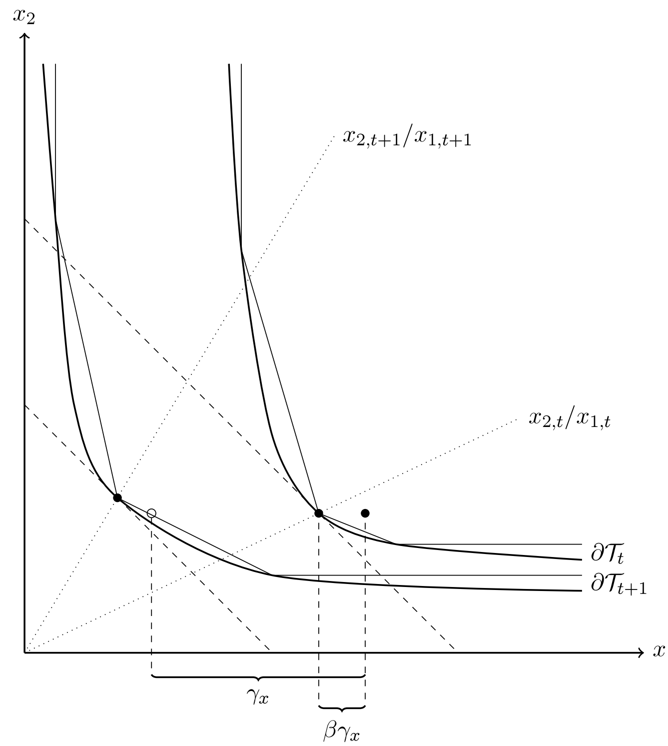

Fig. 1. Measurement of bias in technical change.

Dividing each constraint for period t by β and defining $\theta = 1/\beta$ and $\widetilde{\boldsymbol{\lambda}}_t = \boldsymbol{\lambda}_t/\beta$, (3) can be transformed into the mixed binary linear programming problem:

$$\max_{\substack{\theta,\boldsymbol{\gamma}_x,\widetilde{\boldsymbol{\lambda}}_t,\\ \boldsymbol{\lambda}_{t+1},d}} \theta$$

$$\begin{array}{lrcl}
\text{s.t.} & \theta\boldsymbol{x}_{it} - \boldsymbol{\gamma}_x \odot \boldsymbol{x}_{it} & = & \boldsymbol{X}_t\widetilde{\boldsymbol{\lambda}}_t \\
& \theta y_{it} & = & \boldsymbol{y}_t^{\intercal}\widetilde{\boldsymbol{\lambda}}_t \\
& \boldsymbol{x}_{it} - \boldsymbol{\gamma}_x \odot \boldsymbol{x}_{it} & = & \boldsymbol{X}_{t+1}\boldsymbol{\lambda}_{t+1} \\
& y_{it} & = & \boldsymbol{y}_{t+1}^{\intercal}\boldsymbol{\lambda}_{t+1} \\
& \boldsymbol{\lambda}_{t+1} & \geqq & \boldsymbol{0} \\
& \boldsymbol{\gamma}_x - d\boldsymbol{z}_M & \leqq & \boldsymbol{0} \\
& \boldsymbol{\gamma}_x + (1-d)\boldsymbol{z}_M & \geqq & \boldsymbol{0} \\
& \theta - dz & \leqq & 0 \\
& \theta + (1-d)z & \geqq & 0 \\
& \widetilde{\boldsymbol{\lambda}}_t - d\boldsymbol{z}_n & \leqq & \boldsymbol{0} \\
& \widetilde{\boldsymbol{\lambda}}_t + (1-d)\boldsymbol{z}_n & \geqq & \boldsymbol{0} \\
& d & \in & \{0, 1\}.
\end{array} \tag{4}$$

The transformed variables $\widetilde{\boldsymbol{\lambda}}_t = \boldsymbol{\lambda}_t/\beta$ have the same sign as β. Therefore, the binary restrictions are imposed on these variables as well. Note that the optimal convex combination of observations which maximizes the shift in the frontier may not be spanning the frontier itself.[3] Therefore, we identify the optimal frontier parts by following Jiang et al. (2012) and applying (4) to each combination of efficient observations.

To evaluate whether technical change is biased, the resulting distance measures $\boldsymbol{\gamma}_x$ can be normalized to

$$\widetilde{\gamma}_{x_m} = \frac{\gamma_{x_m}}{\sum_{j=1}^{M}\gamma_{x_j}} \in [0, 1]. \tag{5}$$

[3] Since $(\boldsymbol{x}_A, y_A) \in \partial\mathcal{T}$ and $(\boldsymbol{x}_B, y_B) \in \partial\mathcal{T} \not\Rightarrow \lambda(\boldsymbol{x}_A, y_A) + (1-\lambda)(\boldsymbol{x}_B, y_B) \in \partial\mathcal{T}$, $\lambda \in [0, 1]$.