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Abstract:

This paper is concerned with empirical approaches within the field of evolutionary economics. Evolutionary economics devotes special emphasis on the heterogeneity of actors with respect to their technological performance as well as to their inventive and innovative success. This causes major methodological problems which require appropriate measures and methods for their solution. This article attempts to introduce some tools which are able to measure and represent technological heterogeneity and its change and to investigate the determinants consistent with evolutionary theorizing. The tools suggested constitute basic building blocks of what may be called "evolumetrics".

Keywords: evolumetrics, non-parametric frontier functions, kernel density, quantile regression

JEL: C1, O3

1. Introduction

Neo-Schumpeterian and related evolutionary approaches highlight technological change and progress as major driving forces of economic development and growth. For understanding and analyzing these phenomena a specific methodological point of view is assumed which considers technological performance and technological progress as not uniformly distributed and homogeneous across actors, which may be individuals, firms, sectors, regions or even countries. In contrast, technological performance and change are considered as heterogeneous, in that actors employ different technologies (technological variety) or they run the same technology with different performance (technological asymmetry). This observable variety and asymmetry is due to different inventive and innovative success of actors which in turn is related to differences of technological knowledge used and accumulated, differences in technological opportunities, appropriability conditions, etc.

Any empirical analysis which explicitly aims at allowing and accounting for this heterogeneity is confronted with the problem of applying appropriate measures and methods for dealing explicitly with heterogeneous technological performance and change. This article attempts to introduce empirical tools which are able to measure, represent and investigate the determinants of technological heterogeneity and its change within an evolutionary framework. In the following we first show how heterogeneous technological structures and their change over time can be measured by applying the non-parametric frontier approach. This procedure relies on a specific index of total factor productivity which takes into account asymmetry in performance and variety in production functions and therefore is able to calculate local (or heterogeneous) technological advances. Second, by kernel density estimates the results obtained for technological heterogeneity and change can be visualized in the form of density plots. Third, searching for determinants of technological heterogeneity and its dynamics quantile regression analysis is introduced which allows to uncover beyond-the-mean relationships and dynamics.

2. Nonparametric Productivity Measurement

A first central problem is concerned with the measure one should apply in order to account for technology related and innovation determined heterogeneity. In the following we suppose total factor productivity and its change over time to be valid measures. By this we postulate a number of features that this measure has to satisfy in order to fit within the framework of a Neo-Schumpeterian or evolutionary approach.[1]

First of all, the measure of total factor productivity (TFP) and its change over time is a measure which is applicable to a broad range of innovative phenomena on the level of individuals, firms, sectors, regions or countries. Second, in order to account for better or worse technological performance – and thus to distinguish innovators from imitators – and to give a quantitative account of these differences or asymmetries the measure of total factor productivity should be determined by a frontier analysis where the frontier function or technology frontier is determined by the best-performing observations. All worse performing observations are in some distance to this technology frontier and this distance can be used as a measure for different technological performance. Third, in order to account also for variety in production functions or output mixes the TFP measure is determined by a nonparametric procedure. Fourth, tracking this measure over time by the Malmquist productivity index allows to take account of local technological change and to separate this from sole improvements in productive efficiency.

This brief discussion results in the suggestion of an empirical procedure which differs considerably from rather traditional approaches to determine total factor-productivity and its change. Explicitly it neither assumes a parametrically given technology (production function) which holds on the average nor determines technological change as affecting all actors equally.

2.1 Technology–Productivity Structures

The non-parametric frontier function approach basically relies on index numbers to measure total factor productivity similar to the one used in more standard productivity analysis.

[1] For an extensive discussion of these features see Cantner and Hanusch (2001).

In a sample of *n* observations for each observation $i \in \{1,...,n\}$ a productivity index h_i is defined by:

$$(1) \qquad h_i = \frac{\mathbf{u}'\mathbf{y}_i}{\mathbf{v}'\mathbf{x}_i}$$

Here $\mathbf{y}_i$ is a *s*-vector of outputs $r \in \{1,...,s\}$ and $\mathbf{x}_i$ a *m*-vector of inputs $j \in \{1,...,m\}$ of observation *i*. The *s*-vector ***u*** and the *m*-vector **v** contain the aggregation weights u_r and v_j, respectively and the prime denotes transposition.

The aggregation functions of the TFP index (1) for the inputs and outputs, respectively, are of a linear arithmetic type and can be determined by the non-parametric approach relying only on a minimal set of assumption – in particular, it is not assumed that all observations of the sample have a common identical production function.

The basic principle of the non-parametric approach is to determine the indices h_i in such a way that they can be interpreted as efficiency ratings which implies a comparison of each observation with the relatively best observation(s). The most efficient observations of a sample are evaluated by $h_i = 1$, less efficient observations by $h_i < 1$. Comparing all observations with each other we achieve at an account of different technological performance where the differences are quantified by the measure h_i.

The following constrained maximization problem is used to compute such a h-value for a particular observation $i \in \{1,...,n\}$:

$$\begin{aligned} &\max h_i = \frac{\mathbf{u}'\mathbf{y}_i}{\mathbf{v}'\mathbf{x}_i} \\ (2) \qquad &\text{s.t.} \quad \frac{\mathbf{u}'\mathbf{y}_l}{\mathbf{v}'\mathbf{x}_l} \le 1 \;\; (l = 1,...,n) \\ &\qquad\quad \mathbf{u}, \mathbf{v} > 0. \end{aligned}$$

Problem (2) determines h_i subject to the constraints that the h_l of all observations (including *i* itself) of the sample are not larger than unity and therefore bound h_i in $(0,1]$. Moreover the elements of u and v are constrained to be strictly positive.

Since we employ linear arithmetic aggregation functions for inputs and outputs, (2) is a problem of linear fractional programming. Charnes and Cooper (1962) suggest a transformation of (2) into a standard linear program which can be solved with the well-known simplex algorithm. Performing this step and transforming the resulting primal to its corresponding dual problem, one arrives at the well-known Charnes/Cooper/Rhodes (1978) envelopment form of the non-parametric approach:

$$
\begin{array}{lrcl}
\min \theta_i & & & \\
\text{s.t.} & \mathbf{Y}\boldsymbol{\lambda}_i & \geq & \mathbf{y}_i \\
\theta_i \mathbf{x}_i - & \mathbf{X}\boldsymbol{\lambda}_i & \geq & 0 \\
& \boldsymbol{\lambda}_i & \geq & 0
\end{array} \tag{3}
$$

where **Y** and **X** are the $s \times n$-matrix of outputs and $m \times n$-matrix of inputs of all observations of the sample, respectively. The parameter θ_i expresses the percentage level to which the inputs of observation i can be proportionally reduced, in order to have this observation producing on the production frontier representing the best practice technologies – it is identical to h_i and is a relative measure of technological performance. Proceeding in this way and solving (3) for all observations in the sample, the non-parametric approach determines an efficiency or technology frontier constructed by the best-practice observations. The efficiency rating of each observation is measured relative to this frontier.

The n-vector $\boldsymbol{\lambda}_i$ states the weights of all (efficient) observations which serve as reference for observation *i*. Efficient observations (with $\theta_l = 1$) are characterized by $\lambda_{ii} = 1$ and zero for all other elements. Grouping all observations according to their respective reference observations allows to detect technological clusters which are distinguished by different input intensities, output intensities or input coefficients.

2.2 Technology–Productivity Dynamics

In order to track the productivity structure – determined by the above introduced measures – it is by no means sufficient to compare the results of consecutive periods because they are relative to different frontier functions. Consequently, to relate consecutive periods we have to compute relative measures which compare period *t* with *t*+1 and vice versa. The

measure chosen for this purpose is the Malmquist index of productivity change. A striking interesting feature of this index is that it can be decomposed into a measure of technological change and one of efficiency change, i.e. catching-up or falling behind.

The theoretical basis of the Malmquist-productivity index is found in the work of Malmquist (1953) and Caves/Christensen/Diewert (1982). Färe et al. (1994) have shown how the efficiency measure θ_i above can be used to compute the Malmquist index. Following this line of reasoning the Malmquist-productivity index M_i^{t+1} states the productivity change of observation *i* between *t* and *t*+1 and is defined as follows:

$$(6) \qquad M_i^{t+1} = \left(\frac{\theta_i^{t,t}}{\theta_i^{t+1,t}} \frac{\theta_i^{t,t+1}}{\theta_i^{t+1,t+1}} \right)^{0.5} .$$

$\theta_i^{t,s}$ is the efficiency of observation *i* in period *t* when the frontier function of period *s* serves as reference measure. Simple manipulation of (6) leads to the following decomposition of the Malmquist index:

$$(7) \qquad M_i^{t+1} = \left(\frac{\theta_i^{t,t}}{\theta_i^{t+1,t+1}} \right) \left(\frac{\theta_i^{t+1,t+1}}{\theta_i^{t+1,t}} \frac{\theta_i^{t,t+1}}{\theta_i^{t,t}} \right)^{0.5} = ME_i^{t+1} \cdot MT_i^{t+1}$$

The second line in (7) states the decomposition of the productivity change into in technological change MT_i^{t+1} and change in productive efficiency ME_i^{t+1}. Whenever $ME_i^{t+1} < 1$ ($ME_i^{t+1} > 1$) we find catch-up (falling-behind). In contrast MT_i^{t+1} indicates movements of the frontier. With $MT_i^{t+1} < 1$ ($MT_i^{t+1} > 1$) we observe technological progress (technological regress) at the frontier.

The productivity change according to (6) is local in the sense that it is specific to the observation under consideration. In this respect the degree of this local change depends (a) on the observation's ability to shift towards the frontier (ME_i^{t+1}) and (b) on the behavior of the frontier (MT_i^{t+1}). As to (b) the respective change is also local in the sense that for observation *i* it is only relevant how the part of the frontier assigned to *i* (by way of the elements of the λ-vector) shifts. The decomposition of the index allows to distinguish these two movements.

3. Kernel Density Estimation

Once calculated one may want to have a first spot on the heterogeneity in technology or productivity levels or changes. For that, descriptive statistics have a certain appeal but even the quantification of the amount of heterogeneity in the sample by the standard deviation or the span may hide important characteristics such as multimodality. What is required is a statistical method that gives an impression of the shape of the density function of a variable while imposing only minimal a priori assumptions. The most appealing method for this task is kernel density estimation which is a kind of smoothing of a histogram to eliminate the dependence on the bin edges (see e.g. Scott (1992) and Wand and Jones (1995)).

Kernel density methods estimate the ordinate of a density function $f(y)$ at a certain point y by a weighted average of all n data points y_i $(i = 1,...,n)$, where the weights are assumed to decrease with an increasing distance of the data points from y (and therefore decreasing relevance for the estimation of the density at y). Formally, the density at the point y is calculated by

$$(8) \qquad \hat{f}(y) = \frac{1}{nb} \sum_{i=1}^{n} K\left[\frac{y - y_i}{b} \right].$$

Two elements in equation (8) influence the resulting density estimate. The first element is the kernel function $K(w)$ which controls the weights and is assumed to satisfy the general properties of a symmetric probability density function

$$(9) \qquad K(w) \geq 0 \ \forall w, \ \int K(w)dw = 1, \ \int wK(w)dw = 0 \text{ and } 0 < \int w^2 K(w)dw < \infty.$$

By construction of the kernel density estimator all continuity and differentiability properties of the kernel function carry over to the estimated density function. Common choices are the standard normal density and the functions listed in Scott (1992, p. 140). The kernel density estimate is in general rarely affected by the choice of the kernel function.

In contrast, second element in equation (8), the bandwidth parameter b, has substantial influence on the density estimate. A too large value of b leads to an oversmoothed density with a possible loss of detail, whereas a too low value of b results in undersmooth-

ing of the density which appears to be quite jagged and shows spurious structure in this case. The computation of *b* relies on different variants of cross-validation and is discussed e.g. in Wand and Jones (1995, ch. 3). Especially in cases where the data may be multimodally distributed simpler rules-of-thump are preferred, which tend to lead to an oversmoothed kernel density estimate.

The estimation of a whole density function rests on choosing a grid of values for y on which $\hat{f}(y)$ is computed. It has to be noted that the result of kernel density estimation is not an explicit functional form of the density but only a vector containing the ordinates of the density function at the chosen grid points is obtained. The whole procedure is purely nonparametric in that no assumptions about the shape of the density have to be made a priori. The outcome of such an analysis depends exclusively on the information contained in the data.

4. Quantile Regression

Measurement and representation/visualization of technological heterogeneity using nonparametric methods are important parts of empirical analyses in evolutionary economics. If we want to proceed to find possible sources of heterogeneous technological structures and development it would be unfortunate if we had to rely on correlation techniques like least squares regression analysis. Even nonparametric regression methods, although at first glance well suited to evolutionary principles because of their flexibility, are not appropriate because they only estimate the mean of a dependent variable conditional on one or more explanatory variables. What is required for evolutionary empirical analyses is a regression method that provides a characterization of the entire distribution of a dependent variable given a set of explanatory variables and not just its mean.

A promising method in this respect is the approach of quantile regression which has the potential to uncover differences in the response of the dependent variable to changes of the explanatory variables at different points of the conditional distribution. By that a large amount of information about the heterogeneity of the reactions of the sample items to changes of their characteristics or their environment can be gained. In addition to

these conceptual advantages, the coefficient estimates obtained with quantile regression are robust with respect to outliers in the dependent variable and in the case of nonnormal errors quantile regression estimates may be more efficient than least squares estimates (Buchinsky (1998), Koenker and Hallock (2001)).

To understand the logic of quantile regression we first consider the case of a univariate real valued random variable y with a continuous cumulative distribution function $F(y)$. The τ-th, $\tau \in [0,1]$, (population) quantile of this random variable is defined as $Q_\tau(y) = \inf\{y : F(y) \geq \tau\} = F^{-1}(\tau)$. Thus, the quantile function represents the same information about the heterogeneity of the observations as does the cumulative distribution function, although in a different way. From the definition of the quantile it is clear that the calculation involves a sorting operation of the observations. The key point here is that we can replace this sorting operation by the operation of optimization. Doing so, the τ-th quantile can equivalently be defined as the solution to the minimization problem

$$\min_{\xi \in \Re} \mathrm{E}(\rho_\tau(y-\xi)) \tag{10}$$

where $\rho_\tau(u) = u \cdot (\tau - I(u<0))$ denotes the "check function" and $I(\cdot)$ represents the usual indicator function which is equal to unity if $u<0$ and zero otherwise. Since $\rho_\tau(\cdot)$ can be interpreted as an asymmetric loss function, equation (10) is equivalent to straightforward minimization of expected loss

$$\begin{aligned} \mathrm{E}(\rho_\tau(y-\xi)) &= \int_{-\infty}^{\infty} (y-\xi)\cdot(\tau - I(y-\xi<0))dF(y) \\ &= (\tau-1)\cdot\int_{-\infty}^{\xi}(y-\xi)dF(y) + \tau\cdot\int_{\xi}^{\infty}(y-\xi)dF(y) \end{aligned} \tag{11}$$

with respect to the parameter ξ. Employing the integration-by-parts formula, the first-order condition to this minimization problem is

$$\frac{d\mathrm{E}(\rho_\tau(y-\xi))}{d\xi} = -(\tau-1)\cdot F(\xi) - \tau + \tau\cdot F(\xi) = F(\xi) - \tau = 0$$

and its solution $\xi = F^{-1}(\tau)$ is exactly the definition of the τ-th quantile. If $F(\cdot)$ is strictly monotone this solution is unique. A special case of this solution is the median

$F^{-1}(\frac{1}{2})$ which is the solution to the minimization of absolute expected loss (the case $\tau = \frac{1}{2}$).

Replacing $F(y)$ by the empirical distribution function $F_n(y) = n^{-1}\Sigma_{i=1}^{n} I(y_i \le y)$ for a sample of size n, $\mathbf{y} = (y_1,...,y_n)'$, the expected loss is replaced by $n^{-1}\Sigma_{i=1}^{n}\rho_\tau(y_i - \xi))$ and the minimization of the latter yields the τ-th sample quantile. This problem can be expressed as a linear programming problem

$$(12) \qquad \min_{(\xi,\mathbf{u},\mathbf{v})\in\Re\times\Re_+^{2n}} \{\tau\mathbf{e}'\mathbf{u} + (1-\tau)\mathbf{e}'\mathbf{v} \mid \xi\mathbf{e} + \mathbf{u} - \mathbf{v} = \mathbf{y}\},$$

where **u** and **v** are *n*-vectors of slack variables that represent the positive and negative parts of the vector of residuals and **e** is a conformable vector of ones.

Turning now to the case of linear regression it is familiar that the solution to the least squares problem $\min_{\boldsymbol{\beta}\in\Re^k} \Sigma_{i=1}^{n}(y_i - \mathbf{x}_i'\boldsymbol{\beta})^2$, where $\mathbf{x}_i$ denotes the *k*-vector of the explanatory variables of observation $i \in \{1,...,n\}$, allows to estimate the conditional mean of *y* given **x**. Koenker and Bassett (1978) show that by minimizing the sum of asymmetrically weighted (again through the check function) absolute residuals

$$(13) \qquad \min_{\boldsymbol{\beta}\in\Re^k} \Sigma_{i=1}^{n}\rho_\tau(y_i - \mathbf{x}_i'\boldsymbol{\beta})$$

and denoting the solution by $\hat{\boldsymbol{\beta}}_\tau$, the so-called regression quantile, we can estimate the τ-th conditional quantile function by $\hat{Q}_\tau(y \mid \mathbf{x}) = \mathbf{x}'\hat{\boldsymbol{\beta}}_\tau$. This is analogous to the problem of estimating a single unconditional quantile in the case $\xi = \mathbf{x}'\boldsymbol{\beta}$. Varying τ between 0 to 1 one can trace the entire conditional distribution of *y* given **x**. The marginal change $\partial\hat{Q}_\tau(y \mid \mathbf{x})/\partial x_{ij} = \hat{\beta}_{j\tau}$ has the same interpretation as the coefficient estimate of a linear least squares regression.

The above minimization problem again has a computationally convenient linear programming representation (see the appendix of Koenker and Bassett (1978))

$$(14) \qquad \min_{(\boldsymbol{\beta},\mathbf{u},\mathbf{v})\in\Re^k\times\Re_+^{2n}} \{\tau\mathbf{e}'\mathbf{u} + (1-\tau)\mathbf{e}'\mathbf{v} \mid \mathbf{X}\boldsymbol{\beta} + \mathbf{u} - \mathbf{v} = \mathbf{y}\},$$

where **X** denotes the usual *n*×*k* regression design matrix with rows $\mathbf{x}_i'$. The solution to this kind of problems is numerically straightforward by the simplex or related algorithms.

Buchinsky (1998) demonstrates that the first-order condition of the quantile regression problem can be interpreted as a conditional moment function which fits into the GMM framework of Hansen (1982). From that insight consistency and asymptotic normality of the regression quantiles can be easily established under certain regularity conditions (for details see Buchinsky (1998, pp. 95ff.)). Different approaches to estimate the covariance matrix of the regression quantiles and test are discussed extensively there. Confidence intervals for the regression quantiles can be calculated by regression rank score inversion (Koenker (1994)) or computationally intensive bootstrap methods (see e.g. Buchinsky (1998, pp. 102ff.)). Both methods have good coverage properties in iid as well as heteroskedastic situations.

Also available for quantile regression is a goodness-of-fit statistic, proposed by Koenker and Machado (1999), which is a natural analog to R^2 in a least squares context and can be calculated by $R_\tau = 1 - \hat{V}_\tau / \tilde{V}_\tau$ for the τ-th regression quantile. Here, $\hat{V}_\tau = \min_{\boldsymbol{\beta} \in \Re^k} \Sigma_{i=1}^n \rho_\tau (y_i - \mathbf{x}_i' \boldsymbol{\beta})$ is the minimized value of the unconstrained objective function for the τ-th regression quantile and $\tilde{V}_\tau = \min_{\beta_1 \in \Re} \Sigma_{i=1}^n \rho_\tau (y_i - \beta_1)$ is the minimized value of the constrained objective function for the τ-th regression quantile with only the intercept included as a regressor. $R_\tau \in [0,1]$ thus quantifies the explanatory power of the regression specification in addition to a simple regression on a constant.

It is important to recognize that all computed quantities (the regression quantiles, the confidence intervals and the goodness-of-fit statistic) refer to a specific quantile τ. Calculating these quantities for a sequence of quantiles allows to realize the promized complete characterization of the conditional distribution of *y* beyond the more limited information content that a traditional least squares regression provides. The regression quantiles estimate the effects of change of the explanatory variables on the position of the respective quantiles.

Therefore, the quantile regression approach is able to uncover different effects of the explanatory variables in differents part of the support of the conditional distribution of the dependent variable. For each quantile it can be determined whether the effect of a specific explanatory variable is positive or negative and how strong this effect is compared to other quantiles. This provides a huge amount of information about the heterogeneity of the reactions of the sample items beyond the determination of the average reaction.

5. Conclusion

Although there exist other methods which are appealing from an evolutionary point of view such as Markov chain methods and cluster analysis we have presented here three tools that are well suited to measure, visualize and explain technological differences and their change over time. Especially kernel density estimator and quantile regression have a much broader applicability than just the analysis of productivity data. All three methods share the capability to obtain distribution related information from the data that go far beyond the sole consideration of mean and variance. This qualifies them as basic building blocks that may constitute an emerging branch of empirical research for which we suggest the expressive label “evolumetrics”.

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