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# Nonparametric analysis of regional income dynamics: The case of Greece

### Georgios Fotopoulos\*

University of Patras, Department of Economics, University Campus-Rio, Patras 26504, Greece

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#### **Abstract**

The analysis relies on estimating a stochastic kernel and the associated with it ergodic density. It also derives nonparametric quantiles to better assess relative regional-income mobility. The long-run density implied by the estimates suggests neither strong polarization nor convergence.

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#### 1. Introduction

The aim of this paper is to analyze regional income dynamics in Greece over the 1980–2000 period. It uses a continuous state-space stochastic process approach first introduced by Quah (1997). This research augments the analysis usually made within the adopted approach and the subject matter by (a) introducing a more detailed account of intra-distribution mobility directly relating to the stochastic process and using nonparametrically estimated quantiles of the cumulative distribution of relative

<sup>\*</sup> Tel.: +30 2610 996132; fax: +30 2610 996265. *E-mail address:* gfotop@upatras.gr.

incomes conditional on their past realizations, and (b) by deriving the ergodic (long-run) density as proposed in recent literature (Johnson, 2000, 2005).

#### 2. Methodology and data

Let  $\mathbf{X} = X\{X_t\}_{t \in \mathbb{N}}$  ( $\mathbb{N}$  is for natural numbers) be a continuous state Markov chain such that  $X_t$  has a distribution function  $\phi_t$ . Then the process  $\mathbf{X}$  satisfies (e.g. Meyn and Tweedie, 1996):  $Pr(X_{t+\tau} \in \mathbf{A}|X_j, j \leq t; X_t = x) = P^{\tau}(x, A)$ , where  $A \subseteq E \subseteq \mathbb{R}$  and E is the state space of  $\mathbf{X}$  and a subset of real numbers ( $\mathbb{R}$ ). The conditional distribution function,  $P^{\tau}$ , may also be called a "stochastic kernel" (Meyn and Tweedie, 1996, pp. 65–67; Stokey et al., 1989 p. 226). The independence of  $P^{\tau}$  on the values of  $X_j$ ,  $j \leq t$  is the Markovian property whereas the independence of  $P^{\tau}$  on t is the time homogeneity property. Now  $P^{\tau}$  and  $\phi_t$  satisfy, under certain conditions (Quah, 1997), the following equation:  $\phi_{t+\tau} = \int_E P^{\tau}(x,A)\phi_t(\mathrm{d}x)$  which implies that  $f_{t+\tau}(y) = \int_E f_{\tau}(y|x)f_t(x)\mathrm{d}x$ , where  $f_{\tau}(x)$  and  $f_{\tau}(y|x)$  are the density functions of  $\phi_t$  and  $P^{\tau}$ , respectively, when they exist.

A nonparametric estimate of the stochastic kernel is based on estimating  $\hat{f}_{\tau}(y|x) = \frac{\hat{f}(y,x)}{\hat{f}(x)}$  where f(y,x) is the joint density of y and x. To estimate the joint distribution, a product Gaussian kernel was used:  $\hat{f}(x,y) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h_x \sqrt{2\pi}} e^{-0.5 \left(\frac{x-x_i}{h_x}\right)^2} \frac{1}{h_y \sqrt{2\pi}} e^{-0.5 \left(\frac{y-y_i}{h_y}\right)^2}$  where  $(h_x,h_y)$  represent bandwidths calculated with the direct plug in method (Sheather and Jones, 1991) applied separately in each dimension.<sup>2</sup> The empirical estimate of the marginal pdf of x is given by:

$$\hat{f}(x) = \int_{-\infty}^{\infty} \hat{f}(x, y) dy = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h_x \sqrt{2\pi}} e^{-0.5 \left(\frac{x - x_i}{h_x}\right)^2} \int_{-\infty}^{\infty} \frac{1}{h_y \sqrt{2\pi}} e^{-0.5 \left(\frac{y - y_i}{h_y}\right)^2} dy$$
$$= \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h_x \sqrt{2\pi}} e^{-0.5 \left(\frac{x_i - x}{h_x}\right)^2}$$

Other kernel options are available when dealing with bivariate density estimation. Silverman (1986, p. 76) considers several alternatives. Wand and Jones (1995, p. 103) indicate that the product kernel and the spherically symmetric kernel are two popular ways to construct multivariate kernel functions in a way that the kernel itself is a multivariate density. The authors demonstrate that, in the bivariate case, there is little difference in efficiency between the two alternatives which are generally different apart from the normal density case. In addition, the multivariate standard normal density is a product kernel that minimizes integrated mean squared error (MISE) over the class of product kernels (Pagan and Ullah, 1999, p. 59). Thus, the product Gaussian kernel has been a popular choice that is relatively easy to estimate.

Since the stochastic kernel may be seen as a transition matrix with a continuum of rows and columns, the relationship between two distributions over a time interval of length  $\tau$  can be written as:

<sup>&</sup>lt;sup>1</sup> The method used was originally suggested for analyzing household income dynamics by Trede (1998) using realizations of the relevant distribution in two points in time.

<sup>&</sup>lt;sup>2</sup> Some experimentation has been done using other bandwidth selection criteria (also applied separately in each dimension) without altering much the picture of the process obtained.

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