# Quantitative Economics for the Evaluation of the European Policy

Dipartimento di Economia e Management



Irene Brunetti Davide Fiaschi Angela Parenti<sup>1</sup>

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¹ireneb@ec.unipi.it, davide.fiaschi@unipi.it, and aparenti@ec.unipi.it. 🗈 → 😩 → 💂 💉 🤊 🤜

# Distribution dynamics

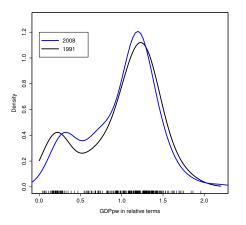


Figura: Estimated distributions of (relative) GDP per worker in 1991 and 2008 in 257 NUTS-2 European regions.

# Distribution Dynamics (Quah 1993, 1996, 1997)

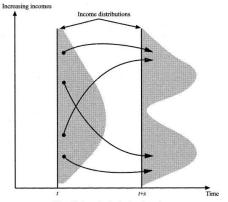


Fig. 1. Twin-peaks distribution dynamics.

Define a **set of states** for Y/L:  $s = \{s_1, s_2, ..., s_K\}$ .

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The **probability** of region i to transit from state k to state q with lag  $\tau$  is defined as:

$$p_{qk} = Pr(Y/L_{i,t+\tau} \in s_q | Y/L_{i,t} \in s_k). \tag{1}$$

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If the dynamics of distribution follows a **Markov process**, then the dynamics of the masses of probability related to different states can be represented by:

$$\pi_{t+\tau} = \pi_t P, \tag{2}$$

where  $\pi_t = (\pi_{1,t}, ..., \pi_{K,t})$  (row vector) and  $\pi_{k,t}$  is the mass of probability of distribution in state k at period t and P, which collect all  $p_{qk}$ , is called the **Markov transition matrix** (dimensions KxK).

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$$\pi_{\infty} = \pi_{\infty} P. \tag{3}$$

# Distribution dynamics (cont.d)

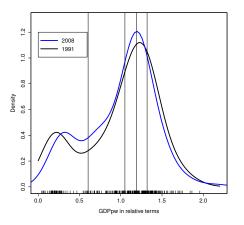


Figura: Estimated distributions of (relative) GDP per worker in 1991 and 2008 in 257 NUTS-2 European regions and state space by the quantiles of distribution

## Estimated Markov matrix with discrete state space

Stat	1	2	3	4	5
Rang	0.06-0.60	0.60-1.05	1.05-1.19	1.19-1.32	1.32-2.22

Tabella: Definition of the space states based on the quantile distribution of observations

$t \parallel t + 10$	1	2	3	4	5
1	388.00	31.00	0.00	0.00	0.00
2	16.00	331.00	16.00	6.00	0.00
3	0.00	79.00	214.00	83.00	22.00
4	0.00	12.00	140.00	184.00	106.00
5	0.00	0.00	54.00	107.00	266.00

Tabella: Markov matrix for our sample

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#### Estimated Markov transition matrix

$t \parallel t + 10$	1	2	3	4	5
1	0.93	0.07	0.00	0.00	0.00
2	0.04	0.90	0.04	0.02	0.00
3	0.00	0.20	0.54	0.21	0.06
4	0.00	0.03	0.32	0.42	0.24
5	0.00	0.00	0.13	0.25	0.62

Tabella: Markov transition matrix for our sample

where the **maximum likelihood estimator** of transition probability is given by:

$$\hat{p}_{qk} = \frac{\text{number of observations starting from state k and arrived to state q}}{\text{total number of observations starting from state k}}$$

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## Estimated ergodic distribution

From the estimate of  $\hat{P}$  we can estimate the ergodic distribution:

$$\hat{\pi}_{\infty} = \hat{\pi}_{\infty} \hat{P};$$

in particular:

State	1	2	3	4	5
Mass of probability	0.26	0.45	0.12	0.09	0.07

Tabella: Ergodic distribution

## Another definition of states spaces ...

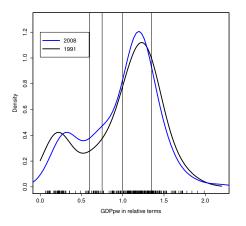


Figura: Estimated distributions of (relative) GDP per worker in 1991 and 2008 in 257 NUTS-2 European regions and alternative state space

# Another definition of states spaces ... (cont.d)

State	1	2	3	4	5
Range	0.06-0.60	0.60-0.75	0.75-1.00	1.00-1.35	1.35-2.22

Tabella: Another definition of the space states

$t \parallel t + 10$	1	2	3	4	5
1	0.93	0.07	0.00	0.00	0.00
2	0.12	0.67	0.20	0.01	0.00
3	0.00	0.14	0.76	0.10	0.00
4	0.00	0.00	0.09	0.79	0.13
5	0.00	0.00	0.00	0.41	0.59

Tabella: Markov transition matrix for our sample

# Another definition of states spaces ... (cont.d)

State	1	2	3	4	5
Range	0.06-0.60	0.60-0.75	0.75-1.00	1.00-1.35	1.35-2.22

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Tabella: Markov transition matrix for our sample

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Mass of probability	0.25	0.16	0.23	0.28	0.09

Tabella: Ergodic distribution

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Markov matrix with continuous state space becomes a **conditioned distribution**. also denoted **stochastic kernel**:

$$g_{\tau}\left(Y/L_{i,t+\tau}|Y/L_{i,t}\right) \equiv \frac{f\left(Y/L_{i,t+\tau},Y/L_{i,t}\right)}{r\left(Y/L_{i,t}\right)}$$

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Accordingly the **ergodic distribution** solves:

$$f_{\infty}(x) = \int_{0}^{\infty} g_{\tau}(x|z) f_{\infty}(z) dz, \qquad (4)$$

where x and z are two levels of Y/L,  $g_{\tau}(x|z)$  is the density of x, given z,  $\tau$  periods ahead, under the constraint

$$\int_0^\infty f_\infty(x) \, dx = 1. \tag{5}$$

#### Ergodic distribution with normalized variable

Since in our estimates all variables are normalized with respect to their average, the ergodic distribution must respect the additional constraint:

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Then the true ergodic distribution is:

$$f_{\infty}(x) = \tilde{\mu}_{x}\tilde{f}_{\infty}(x), \qquad (7)$$

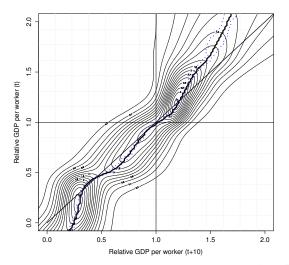
where:

$$\tilde{\mu}_{x} = \int_{0}^{\infty} \tilde{f}_{\infty}(x) x dx \tag{8}$$

and  $\tilde{f}_{\infty}$  satisfies Eqq. (4) and (5).



#### Stochastic kernel





The bold line represents the **median** of the estimated conditioned distribution  $g_{\tau}(Y/L_{i,t+\tau}|Y/L_{i,t})$ , denoted by med  $(Y/L_{i,t})$ .



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• if med  $(Y/L_{i,t}) > Y/L_{i,t}$  then we expect that **locally** the mass is shifting ahead around  $Y/L_{i,t}$ 

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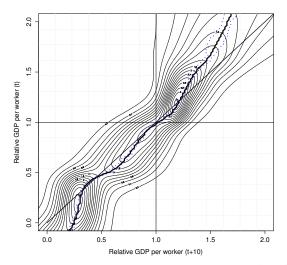
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Another perspective to see the estimated stochastic kernel is to think about it how a stochastic difference equation:

$$Y/L_{i,t+\tau} = \phi(Y/L_{i,t}) + \varepsilon_{i,t+\tau}$$
(9)

 $\Rightarrow$  if around an equilibrium med  $(Y/L_{i,t})$  crosses from below, this equilibrium is **stable**, if it crosses from above, this equilibrium is **unstable**.

#### Stochastic kernel



## Estimated ergodic distribution

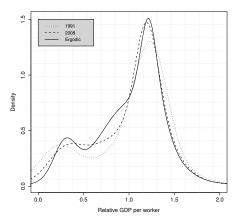


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