Alternative hypotheses of cross-country convergence. A non-parametric analysis of manufacturing sectors

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Abstract

I adopt the distribution dynamics framework to study labor productivity convergence, in the period 1980-1995, among 28 developed and developing countries, in different manufacturing sub-sectors, identified, as according their technological content into Resource Based, Low Technology, Medium Technology and High Technology. I find that, exception made for High Technology and Manufacturing as a whole, all sub-compartments are predicted to converge within small groups, validating the so-called club-convergence hypothesis. Thus, as high tech sectors are the ones opening the best growth-equity prospects, developing countries should target these kind of productions.

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1 Introduction

In the past forty-five years, world gross domestic product has steadily increased at an annual average rate of 3.5%.[1] Contemporaneously, GDP per capita and GDP per worker distributions have been characterized by two interesting features: first, the emergence of two distinct peaks, corresponding to poor and rich countries; and, second, the reduction of intra-distribution inequalities, that is a reduction in the spread between relatively poor and relatively rich economies, Durlauf and Quah (1999).

This stylized evidence, summarized in Figure 1, prompted a resurgence of interest in cross-country convergence. The point to be settled being whether or not developing countries are catching-up with their richer counterparts, in terms of income per capita or per worker. In this work I study labor productivity convergence tendencies, in the period 1980-1995, among 28 developed and developing countries, in different manufacturing sub-sectors, identified, as according to Lall (2000b) technological taxonomy, into Resource Based, Low Technology, Medium Technology and High Technology.[2] Table 1 reports sample's details.[3] More in detail, I employ an unified distribution dynamics framework, as originally developed by Quah (1996a), to examine the three textbook (and competing) convergence hypotheses, namely: absolute, conditional and club convergence.[4]

It is well known that according to the *absolute convergence* prediction, poor economies tend to grow faster than rich ones; then, contemporaneous per capita income differences are only transitory and will be null in the long run, Sala-i-Martin (1996). *Conditional convergence* asserts, instead, that the long run equalization of per capita income will arise only among countries that have identical structural characteristics (i.e. saving rates, inter-

[1] Own calculation from World Bank, World Development Indicators, for the period 1961-2007.

[2] The classification of Lall (2000b) distinguishes manufacturing compartments according to their research intensity, measured as Research and Development (R&D) expenditure share over sales' value. In particular, Resource Based industries are the ones in which the value of production is essentially given by the possession of primary resources (e.g. processed food, manufactured tobacco, refined petroleum products); Low Technology includes productions whose R&D expenditure is below 1% of sales' value (e.g. garments, footwear, pottery and cutlery); in Medium Technology, R&D expenditure is between 1% and 4% (e.g. automotive industry, agricultural machinery, perfumery and pesticides) and in High Technology R&D expenditure is greater than 4% of sales' value (e.g. electronics and scientific instruments).

[3] It must be noted that the choice of the countries and of the time span was dictated by data availability. Only very recently (i.e. April 2010) new disaggregated data for manufacturing have become available. The most promising data-set, with the aim of enriching the analysis with respect to both cross-sectional and time-series dimensions, seems to be the United Nations Industrial Development Organization (i.e. UNIDO), Industrial Statistics Database 2010 at the 2 digit level of the International Standard Industrial Classification (i.e. ISIC) Code (Revision 3). This is left for (near) future research.

[4] For an exhaustive review on the different convergence hypotheses and the so-called "controversy on convergence", in both its theoretical foundations and empirical assessments, see the articles of Durlauf (1996), Bernard and Jones (1996b), Galor (1996), Quah (1996b) and Sala-i-Martin (1996), all collected in *The Economic Journal* Vol.106, No.437.

temporal preferences, development stage,...), Barro(1991). Finally, when *club convergence* hypothesis is not rejected, it means that in the long run countries will converge only within small groups and not altogether. In other words, overall convergence comes up only if *both* countries' structural characteristics *and* initial conditions are evened out, Galor (1996).

With respect to club convergence, it is important to clarify that in this paper I will consider physical capital stock and technological level as the key drivers of clustering dynamics. That is, paraphrasing Galor and Zeira (1993), the initial distribution of capital stock (technology) affects aggregate output and investment both in the short and in the long run.Moreover, the choice of physical capital is inspired by the literature on critical thresholds while the one of technological level follows the tradition of technological catch-up and absorptive capabilities.[5]

My work represents a significative contribution to the convergence literature because this is the first study that assesses competing hypotheses concerning labor productivity convergence between advanced and laggard economies, in manufacturing sectors, employing distribution dynamics. In fact, previous analysis on alternative convergence predictions have been focused on the behavior of GDP per capita or aggregate labor productivity, either using parametric or non-parametric techniques.[6] Moreover, when convergence tendencies have been investigated in different economic sectors (i.e. agriculture, mining, services,...) or sub-sectors (i.e. manufacturing industries), only OECD countries have been considered. The sectoral analysis I am referring to are the ones of Broadberry (1993) and Bernard and Jones (1996a) and the sub-sectoral ones of Dollar and Wolff (1988)(1993), Boheim *et al.*(2000) and Caree *et al.*(2000). Interestingly, the sectoral studies fail to find convergence in manufacturing sector as a whole, while the sub-sectoral ones confirm such an hypothesis in all industrial compartments.

At this point, I want to mention that in Dal Bianco (2010) I investigated, through standard parametric tools, whether cross-countries convergence in Lall's technological sectors is manly due to capital accumulation (i.e. neoclassical convergence) or to technological catch-up (i.e. technological convergence), employing a panel of 50 developed and developing countries, observed at five-years intervals, for the period 1980-2000.[7] In particular,

[5]See Azariadiz and Drazen (1990) and Durlauf and Johnson (1995) for formal illustrations of critical threshold's frameworks; Baumol (1986) and Durlauf (1993) for, respectively, seminal contribution and formal treatment of technological catch-up and absorptive capacities.

[6]See Islam (2003) and Durlauf *et al.*(2005) for exhaustive and authoritative reviews.

[7]The careful reader might note that, in my parametric study, both the time series and the cross-sectional dimensions are larger than the present ones. This is mainly due to the choice of collecting the relevant variables at 5-years intervals. See footnote 3 for further details on data-limitations problems.

I found that both hypotheses hold in all sectors and countries and, more precisely, that capital accumulation is the fundamental convergence determinant for (and in) industrialized economies, while technological catch-up is more important for (and in) emerging ones. Although, given the econometric techniques employed, such results are exclusively indicative of the behavior of the average economy. Thus, as the issue of convergence is innerly related to the *relative* economic performance of distinct countries, in the present work I employ distribution dynamics precisely because it allows to track such a relative performance along time. Moreover, it has the great advantage of not requiring any sample split for the assessment of the club convergence prediction, as for example in Desgoits (1999), Bloom *et al.*(2003) and Graham and Temple (2006).

Finally, a by-product of the present exercise is represented by new series on Total Factor Productivity (i.e. TFP), estimated employing the superlative index approach of Caves(1982a) and Caves *et al.*(1982b), and on net physical capital stock, obtained applying the Perpetual Inventory Method, with delayed efficiency and random service life.[8]

Having explained the novelties of my contribution, I wish to further motivate the present research.

The choice of investigating manufacturing sectors is due to a twofold motivation. Very synthetically, the first is that if any cross-country convergence should be shown, it should be shown exactly here. Before explaining this statement, I pass to the second motivation that concerns, more specifically, the policy implications that could be retrieved from the analysis of manufacturing compartments. That is, as different countries might have strongest convergence tendencies in different industries due, for example, to comparative advantages that can cause employment shifts from less to more productive sectors, as shown by Dollar and Wolff (1988)(1993), such sector-specific growth potential might call for selective industrial policies or for the support of particular activities, as according the infant industry argument.[9]

Turning now to the first argument, this is grounded on both theoretical considerations and stylized evidence.

[8]Although of some potential interest, describing in detail the techniques employed will make the present work (even) longer. So that, I refer to Griffith *et al.*(2004) for further details on TFP estimation and to Maffezzoli (2006) for what concerns capital stock. With the latter respect, it might be worth to briefly mention that I set the curvature parameter of the efficiency function (i.e. β) equal to 0.5; that I used a truncated normal as mortality function; that I have used OECD's countries average sector-specific service lives and, finally, to initialize capital stock series I have followed Caselli (2005), setting the depreciation rate δ equal to 0.06. Needless to say, all the series are available upon request.

[9]See Lall (2000a) for an effective review.

In the first instance, since the seminal contribution of Lewis (1954), manufacturing has been identified as the locus of economic growth. In fact, once subsistence level of food is ensured by agriculture, the development of the industrial sector promotes intensive economic growth, that is an increasing per capita income over time.[10] In Figure (2.a), it could be appreciated the decline of agricultural value added together with the increasing share of industrial and service's production. Second, manufacturing is technologically the most dynamic sector in the world economy, in the sense that the greatest research efforts are made to launch new manufactures or to improve existing ones, Cornwall (1977). It is interesting to note that this evidence holds for both high and low income economies. In fact, according to the World Intellectual Property Organization, between 1985 and 2005, the number of patent applications, by both resident and non-resident inventors, has doubled in developed countries and it has increased by four times in developing ones. Third, as effectively described by the United Nations Conference on Trade and Development (i.e. UNCTAD) in its World Investment Reports, industrial production is nowadays world integrated. This feature is crucial in convergence analysis because developed and developing countries interact with each others and their growth paths are interlinked. The last two panels of Figure (2) give a flavor of the degree of world-integration, mapping Foreign Direct Investment and exports.[11] Noticeably, laggard economies' outward foreign investments are increasing and their high technology exports have reached the level of advanced economies'.

To reassess this evidence, it is worth starting from the argument of Bernard and Jones (1996a). That is, tradable goods are highly differentiated, as well as their production technologies, and that productive inputs' endowments vary a lot across countries. Although, the fact that capital is flowing towards (and from) low income economies and that frontier-technologies are getting diffused, lead to think that manufacturing is the perfect stage for cross-country convergence.

Passing now to the choice towards Lall's taxonomy, this is motivated by two considerations. First: as any sub-sectoral aggregation, Lall's one makes inter-sectoral comparisons possible and, as already mentioned, this fact drives to potentially nice policy implications. Second: it offers the possibility to establish a 1 to 1 correspondence between the employed classification and the International Standard Industrial Classification (i.e. ISIC) (Revision

[10] See, for example, Matsuyama (1992).

[11] For a very up-dated systematic review of the effects of Foreign Direct Investment on economic growth in low income countries, see Bruno and Campos (2010).

2), which is the one followed by the United Nations Industrial Development Organization (i.e.UNIDO) for the collection of sub-sectoral manufacturing data.[12] Table 2 reports the correspondence between ISIC and Lall's classifications. Not casually, UNIDO data constitute the basis for my empirical analysis. This represents a major advantage with respect to other classifications, like Pavitt (1984), that, although effective in distinguishing industrial compartments, present huge overlaps between their categories and ISIC's ones.

To conclude, I want to sketch the main results of my analysis. In particular, I found supportive evidence for absolute convergence in High Tech sectors and Manufacturing as a whole, while technological initial conditions determine the club convergence behavior of Resource Based and Medium Tech, while the ones on capital stock shape the clustering dynamics of Low Tech industries. The main policy lesson that can be retrieved is in line with the one of Lall (1997), that is: as high tech sectors open the better growth-equity prospects, with the minimum effort, developing countries should concentrate more on this kind of productions. This is because, in high tech sectors, even labor intensive activities, such as assembly, are more stable, skill-creating and positive externality generating than in traditional ones.

The paper is organized as follows. The second part presents the econometric methodology employed. Details on empirical implementation and data sources are thorough the text. The third illustrates and discusses the results obtained. Final comments and possible lines for future research conclude.

2 Methodology

2.1 An Overview on Distribution Dynamics and Data

The kernel density estimator and the stochastic kernel are the two building blocks of distribution dynamics estimation. The former is employed to estimate the density of a random variable and it can be thought as a refinement of the histogram. In particular, while in the histogram the frequency distribution is calculated for disjoint states, with the kernel estimator the frequency distribution is estimated for a large number of overlapping

[12] In particular, Lall (2000b) technological taxonomy was originally developed employing the Standard International Trade Classification (i.e. SITC) (Revision 2). Thanks to Eurostat tables, which put in in correspondence ISIC Revision 2 with ISIC Revision 3, SITC Revision 2 with SITC Revision 3 and, finally, SITC Revision 3 with ISIC Revision 3, is then possible to obtain a 1 to 1 relation between UNIDO data and Lall's manufacturing sectors.

class intervals, which gives a much smoother appearance, resembling a probability density function. The stochastic kernel maps, instead, the density of a random variable at one point in time into the density in a subsequent period, where the density functions have been calculated through kernel density estimators. In other words, the stochastic kernel, which can be thought as a set of conditional densities, describes the law of motion of a sequence of distributions and it serves to retrieve the evolution of the probability distribution of a random variable along time, Quah (1993). As already mentioned, this tool is very convenient for convergence analysis. In fact, it allows to distinguish whether economies are converging overall or they are clustering within clubs.

My empirical analysis focuses on the evolution along time of labor productivity distribution and it employs two types of stochastic kernel:

1. unconditioned stochastic kernels
2. conditioned stochastic kernels

The unconditioned stochastic kernels give information on the likelihood that an economy, starting from a given relative position in the initial period t, will end up improving or worsening its relative position in the final period $t + s$. More technically, unconditioned stochastic kernels measure the transition probabilities from a labor productivity status to another in a given time span.

Unconditioned stochastic kernels are used here to detect polarization tendencies and to assess, as it will be clarified soon, the absolute convergence hypothesis.

Conditioned stochastic kernels are an extension of unconditioned ones and they allow to identify the factors that eventually lead to intra-distributional changes. In fact, the effects of conditioning are identified by changes in shape and location of the stochastic kernel with respect to the unconditioned case.

I will use conditioned stochastic kernels for assessing both the conditional and club convergence hypotheses.

More in detail, when distribution dynamics is employed, any convergence prediction is discharged if the corresponding long-run labor productivity distribution (i.e. ergodic distribution) is multi-peaked and relatively highly dispersed. So that, in my empirical exercise, I start with analyzing the behavior of labor productivity distribution, as estimated via unconditioned stochastic kernels, in order to assess the absolute convergence prediction; then, if the unconditioned ergodic is multi-peaked, I pass to evaluate conditional conver-

gence, looking to the time evolution of the labor productivity distribution conditioned to steady-state proxies; and, finally, if also this ergodic turns out to be multi-modal, providing supportive evidence for the club convergence hypothesis, I assess whether such a clustering dynamics can be ascribed to insufficient capital accumulation (technical upgrading) adding capital stock per worker (technological proxy) to the set of steady state conditioning factors. Thus, as this latter ergodic distribution is likely to be single-peaked, it can be concluded that its (previous) multimodal shape was due to capital stock (technology) initial conditions. So that, smoothing cross-country differences in terms of capital stock (technology) ensures labor productivity equalization in the long run.

For what concerns the data employed and their sources, the variable of interest is the log of manufacturing value added per worker in each country and sector. In particular, I tracked the time-evolution of the *relative* labor productivity distribution, that is I normalized individual countries' data with the ones of the leading economy. In this case, United States are the leader because they exhibit the highest labor productivity in all sectors, along the whole period considered. In the spirit of Quah (1996a) and Desmet and Fafchamps (2006), this normalization is useful for removing some of the trend from the cross-section and, thus, for avoiding degenerate long-run distributions.[13] Finally, it is important to clarify that sectoral labor productivity is expressed in 1996 international dollars to allow international and inter-temporal comparisons.

Concerning the steady state proxies, following Quah (1996a),[14] I took the investment rates in both physical and human capital and a development dummy, where the reference group is made by high-income economies. In the empirical implementation, such variables, dummy apart, are taken in natural logarithms and they are normalized with respect to US values.

In assessing club convergence determinants, I employed originally estimated sectoral capital stock and TFP series.[15] In particular, capital stock per worker is normalized to United States and it is expressed in natural logarithms. The technological variable, instead, is

[13]It is worth noting that a cross-country average, instead of the leader, could have been used. My choice is motivated on the basis of the technological transfer literature, according to which the dynamics of innovation in the leader country and imitation in the laggard economies is at the hearth of both growth and convergence processes. See with this respect, the seminal contributions of Gerschnkron (1954), Nelson and Phelps (1966), Pack and Westphal (1986) and Hansson and Henrekson (1994). Moreover, it is interesting to note that Caselli and Wilson (2004) tackle this issue looking to embodied technological change, that is capital stock.

[14]See Durlauf *et al.*(2005) and Sala-i-Martin *et al.*(2004) for up-to-date discussions on the problem of (significant) growth determinants.

[15]See Introduction and footnote 8, for further details on capital stock and TFP estimates.

modeled as an interacted TFP gap (i.e. TFPgap).[16] More clearly, following Griffith *et al.*(2004), TFPgap, calculated as the difference between leader's TFP and the one of any follower, is taken to proxy the potential for technological imitation while secondary schooling attainment rates, in logs and normalized with respect to United States, are used as absorption capability proxy.[17]

Turning to data sources, labor productivity were obtained combining UNIDO Industrial Statistics Database 2004, at 3-digits of ISIC Code (Revision 2), World Bank Development Indicators and the Penn World Tables (PWT 6.1).[18]

Sectoral investment rates in physical capital refer to Gross Fixed Capital Formation share to manufacturing value added, taken again from UNIDO. To proxy human capital accumulation rates in each country, I use the average years of schooling in the population over age 15. This series, together with secondary schooling attainment data, comes from Barro and Lee (2000) data-set. With respect to human capital variables, three aspects must be clarified. First, the Barro and Lee (2000) data are registered at five-years intervals. To overcome this difficulty, I interpolate the available data implicitly assuming that the between-observed values lie on a straight line. Second, my preference towards population over age 15, instead of 25, which is also available, is due to the fact that working age in developing countries can be quite low, as documented by Bennell (1996). Finally, the choice of secondary schooling as absorptive capability proxy is motivated on the basis of Gemmell (1996), which shows that for middle income countries, which are well represented in my sample, secondary education matters more than primary and tertiary ones.

2.2 Unconditioned stochastic kernels

In this section I provide a technical illustration of the methodology employed to estimate unconditioned transition probabilities, which are used to investigate the absolute convergence hypothesis.

[16] For further clarifications see Rogers(2003).

[17] For seminal contributions on absorptive capacities, see Baumol (1986) and Cohen and Levinthal (1989).

[18] From UNIDO I collected disaggregated data on workers and on manufacturing value added in Local Currency Unit (LCU); from World Bank Development Indicators (WDI), GDP data in LCU; finally, from Penn World Tables (PWT 6.1), GDP data expressed in Purchasing Power Parity. After having calculated sectoral value added in manufacturing as percentages of GDP, using World Bank and UNIDO data in LCU, I combined such percentages figures with WDI and PWT6.1. My preferred measure of real value added in manufacturing is based on Penn World Tables Real GDP Chain Index (RGDPCH). This is because RGDPCH does not suffer from the so-called 'Laspeyres fixed-based problem' and, then, it is the most appropriate measure when inter-temporal comparisons are at issue, Summers and Heston (1991).

Sectoral convergence tendencies are inferred analysing the dynamic behaviour of cross-country distribution of log relative labour productivity.[19]

Individual country i labour productivity, in sector j, at time t is called y_{it}, where I omitted the sector index for notational convenience (i.e. $y_{it} = log(Y_{ijt}/Y_{USjt})$). Cross country, sector specific, labour productivity distribution, at time t, is denoted as $f_{Y_t}(y_t)$, where Y_t indicates the corresponding random variable.

I assume that year-to-year changes in the distribution of labour productivity can be represented by an homogeneous Markow process, in such a way that, $\forall t$:

1. $f_{Y_{t+1}|Y_t}(y_{t+1}|y_t) = f_{Y_{t+1}|Y_t}(y_{t+1}|y_t, y_{t-1}, y_{t-2}, ...)$
2. $f_{Y_{t+1}|Y_t}(y_{t+1}|y_t) = f_{Y_t|Y_{t-1}}(y_t|y_{t-1})$

The first property guarantees that only previous period income distribution impacts on next period one (i.e. history does not matter). The homogeneity assumption in 2 ensures that the transition probabilities do not vary with the time. Although quite restrictive, both hypotheses are necessary for estimating long run transition probabilities given the available data.

Conditional density functions, $f_{Y_{t+1}|Y_t}(y_{t+1}|y_t)$, represent the cornerstone of distribution dynamics convergence analysis. This kind of distribution, in fact, encodes information about individual economies' passages over time. Thus, it sheds light on both intra-distribution dynamics and external shapes, making inference about convergence tendencies possible. For example, observing conditional density mappings, is it possible to know whether poor countries are catching-up with their richer counterparts, whether rich countries are still enriching, whether countries are converging overall or are clustering within clubs.

The empirical estimation of conditional densities is handled by non-parametric techniques. As for its definition, in the empirical implementation, the conditional distribution is obtained simply dividing the joint distribution by the marginal distribution. Formally:

$$f_{Y_{t+1}|Y_t}(y_{t+1}|y_t) = \frac{f_{Y_{t+1},Y_t}(y_{t+1}, y_t)}{f_{Y_t}(y_t)} \tag{1}$$

The joint distribution of (Y_{t+1}, Y_t) can be estimated non parametrically using a bivariate stochastic kernel, while the marginal distribution of Y_t is obtained by numerical integration

[19] Please note that in what follows 'relative labour productivity' and 'labour productivity' are used interchangeably.

of the joint distribution. Finally, the conditional distribution is simply obtained by dividing one to the other, after appropriate discretization of the joint support.[20]

Long run tendencies towards convergence are encoded by the ergodic distribution. This is the stationary distribution of labor productivity, which will be approached in the long run should certain technical conditions hold.[21] In particular, if the ergodic distribution is unimodal and has a low variance, then long run cross-country convergence can be claimed. Formally, the ergodic is the distribution f which solves the following functional equation:

$$f(y_{t+1}) = \int_{-\infty}^{+\infty} f_{Y_{t+1}|Y_t}(y_{t+1}|y_t) f(y_t) dy_t \tag{2}$$

In order to compute the ergodic distribution, it is necessary to make the support of Y discrete. It is important to note that, following Desmet and Fafchamps (2006), I employ such a discretization only for calculating the ergodic. The standard approach would have been, instead, to make the Y support discrete also for computing the joint and marginal distributions in Equation (1), as in Quah (1996a). But, as shown by Desmet and Fafchamps (2006), this leads to transition matrices which are usually quite coarse, due to the fact that the smoothing properties of the kernel estimators are not exploited.

Getting now into ergodic calculation's details, the support of Y is discretized in a set of N equally large intervals, where interval h is denoted as Ω_h.[22] Then, the probabilities of transition from one interval to another are calculated. Formally, the probability of transition from the interval Ω_h to another Ω_k, in one time period, is denoted as:

$$\alpha_{kh} = Pr(y_{t+1} \in \Omega_k | y_t \in \Omega_h)$$

At this point, it is useful to adopt a compact matrix notation. Hence, the ergodic distribution is the vector p that solves the following system of equations:

$$p = Ap$$

$$(I - A)p = 0$$

[20] Bivariate stochastic kernel estimation is performed using the command *kdens2* in STATA 8.2. Marginal, conditional and ergodic distributions are calculated in Matlab. All programs are available from the author upon request.

[21] See Stockey, Lucas and Prescott (1989); Luenberger (1979).

[22] To avoid crude ergodic calculations, it is necessary to work with a sufficiently high N. My calculations have been done for N=50. Using N=200 and N=500 do not alter any conclusions but it has the disadvantage of slowing down computer's routines. Also the program for ergodic calculation is available upon request.

where each component of the vector p represents the probability of Y assuming a value comprised in a given Ω and A is the matrix of transition probabilities α_{kh}.
Since each column of matrix A is a conditional density and, then, its elements sum to 1; A does not have full rank and, by consequence, the system does not have a unique solution. To find a unique solution it is standard to simply drop one row of A (to make its columns linearly independent) and then add the restriction that the entries of vector p sum to 1.[23]
Then, matrix A is rewritten as B:

$$\text{B}=\begin{pmatrix} 1-\alpha_{11} & \dots & -\alpha_{1N} \\ \dots & 1-\alpha_{ii} & \dots \\ -\alpha_{N-1,1} & ... & -\alpha_{N-1,N} \\ 1 & ... & 1 \end{pmatrix}$$

The modified system is then:

$$Bp = b$$

where the vector b, for the constraint added, has all entries equal to 0 except the last one, which is equal to 1.
At this point, the unique ergodic distribution, p, can be easily found inverting B:

$$p = B^{-1}b$$

2.3 Conditioned stochastic kernels and conditioning techniques

This part outlines the conditioning technique I used to assess conditional convergence and club convergence determinants.
Under the conditional convergence hypothesis, cross-country productivity equalization can not be found in the original relative labor productivity distribution, f_Y, but in the conditioned one, $f_{Y|X}$, where X denotes steady state proxies. Then, the object of interest are the transition probabilities of the part of labor productivity not explained by the steady state proxies (i.e. the residuals, $\widehat{\epsilon}$). Employing the former notation, such transition

[23]This constraint must hold for the definition of probability.

probabilities are formally written as:

$$f_{Y_{t+1}|Y_t,X_t}(y_{t+1}|y_t, x_t) \tag{3}$$

Exploiting Chamberlain(1984) results, the part of labor productivity orthogonal to auxiliary variables is computed as Ordinary Least Squares (OLS) residuals of the projection of labor productivity growth on each of the steady state proxies.[24] Such calculation involves three steps:

1. estimating the part of countries' relative productivity *growth rate explained* by conditioning steady state variables;
2. finding the *initial level* of relative labor productivity *explained* by conditioning steady state variables ;
3. combining the previous results to find the *level* of relative labor productivity *unexplained* by the auxiliary variables (i.e. orthogonal to steady state proxies).

Call g_{it} the growth rate of y_{it} (i.e. log relative productivity in country i, sector j at time t), where again the sector index is omitted for notational convenience. Name $\widehat{g_{it}}$ the part of g_{it} explained steady state proxies, which are: investment rate in both physical and human capital, indicated as r_{it} and h_{it}, and the dummy development, $ddev$. Finally, the part of labor productivity orthogonal to steady state proxies, which is the object of interest, is called $\widehat{\epsilon}_{it}$.

Step 1. is implemented regressing g_{it} on a two sided distributed lag of conditioning variables and saving the fitted values. For each steady state proxies one of such regressions is run. Then, cumulating the fitted values, by country and sector, the part of countries' relative productivity growth rate explained by conditioning steady state variables, $\widehat{g_{it}}$, is obtained.

Note that in empirical work, multi-sided regressions are employed to handle endogeneity issues, which are represented in this specific case by the likely bidirectional causality between labor productivity growth rate and steady state proxies. This technique, introduced by Sims (1972), has been extensively used by Quah, who noted that just 2 leads and 2

[24] Quoting Quah(1996a), Chamberlain(1984) finds that:

> the projection of growth on investment, not allowing for individual effects, is precisely the best linear predictor and, thus, correctly gives residuals that are the components unexplained by (or, more correctly, orthogonal to) investment.

lags are sufficient to clear the estimated growth rate from feedback effects, Quah (1996a). Step 2. is taken running a pooled OLS regression of y_{it} on time averages of steady state proxies (i.e. $\overline{r_{it}}$ and $\overline{h_{it}}$) and the estimated growth rate (i.e.$\widehat{g_{it}}$). For each sector, the coefficients that solves the following minimization problem are used to pin down the initial level of labor productivity explained by steady state variables, $\widehat{y_{i0}}$:[25]

$$min_{\beta_1,\beta_2,\beta_3} \sum_i \sum_t [y_{it} - (\beta_1 \overline{r_{it}} + \beta_2 \overline{h_{it}} + \beta_3 ddev + \widehat{g_{it}})]^2$$

In fact, thanks to the estimated coefficients, $\widehat{\beta}s$, the initial level of log relative labor productivity explained by conditioning variables can be expressed as:

$$\widehat{y_{i0}} = \widehat{\beta}_1 \overline{r_{it}} + \widehat{\beta}_2 \overline{h_{it}} + \widehat{\beta}_3 ddev$$

Then, adding the growth rates of step 1, the level of relative labor productivity explained by steady state variable is calculated as:

$$\widehat{y_{it}} = \widehat{y_{i0}} + \widehat{g_{it}}$$

Finally, $\widehat{\epsilon_{it}}$, which represents the productivity level not accounted for (or conditional to) steady state proxies is simply found subtracting from actual the estimated relative labor productivity:

$$\widehat{\epsilon}_{it} = y_{it} - \widehat{y_{it}}$$

Once country and sector specific $\widehat{\epsilon_{it}}$ series have been calculated, the empirical implementation for assessing conditional convergence is the same as absolute (or unconditional) convergence.

In particular, bivariate stochastic kernel densities fit cross-country, sector specific, distribution of relative productivity orthogonal to steady state variables, which I denote as $f_{\widehat{E_{t+1}},\widehat{E_t}}(\widehat{\epsilon_{t+1}}, \widehat{\epsilon}_t)$. By numerical integration of the joint distribution, the marginal density $f_{\widehat{E_t}}(\widehat{\epsilon}_t)$ is obtained. Finally, the transition probabilities of Equation(3) are found dividing the joint distribution, $f_{\widehat{E_{t+1}},\widehat{E_t}}(\widehat{\epsilon_{t+1}}, \widehat{\epsilon}_t)$, by the marginal distribution, $f_{\widehat{E_t}}(\widehat{\epsilon}_t)$.

Long-run distribution of relative labor productivity conditioned to steady state variables is retrieved from the ergodic distribution of random variable $\widehat{\epsilon}_t$. Such a distribution is

[25] As Quah(1996a) explains, this technique exploits the cross section variation of conditioning variables to compute the initial value of productivity explained steady state proxies.

calculated as for the unconditional case (previous section).

Turning now to club convergence analysis, it should be intuitive that the conditioning scheme described so far can be easily extended to determine the relative strength of club convergence inner drivers.

In particular, when club convergence hypothesis holds, the object of interest becomes the dynamics of labor productivity distribution conditioned to both steady state proxies and club convergence driving forces, namely capital and technological initial conditions. Formally, the following transition probabilities have to be computed:

$$f_{Y_{t+1}|Y_t,X_t,Z_t}(y_{t+1}|y_t, x_t, z_t) \tag{4}$$

where the variable Z represents either initial capital stock or initial technological level, which has been proxied by TFPgap and school attainment rate.

To retrieve the relative strength of capital stock (or technology) as club convergence determinant, relative labor productivity orthogonal to both steady state proxies and capital stock (or technology) initial level must be calculated. This is done implementing the three steps previously described, taking into consideration capital stock (or technology) as extra conditioning variable.

By the same tokens as before, the density in Equation (4) and the ergodic distributions are computed.

3 Results

3.1 Interpreting results

I now provide the fundamental tools for inferring convergence tendencies from Figures 3 to 16, which constitute the first set of results of my analysis. Such diagrams, mapping unconditioned and conditioned stochastic kernels allow to investigate all the convergence hypotheses under scrutiny.

Panels (a) and (b) of the aforementioned figures describe eight-years horizon evolution of labor productivity distributions and they are used to establish medium run tendencies to convergence.[26] More precisely, the first type of graphs shows a tridimentional plot of

[26] I also calculated transitions over one year horizon. Although the results do not change significantly over such a shorter period, mobility is slightly lower and emerging patterns seem more difficult to trace.

transition probabilities; the second, mapping the level curves, represents the stochastic kernels in just two dimensions. In both diagrams, the floor axis, marked as Period t and Period $t + 8$, measure the log of relative productivity in different times. To make graph interpretation easier, Table 3 reports Period t and Period $t + 8$ relative labor productivity values in percentage terms with respect to the United States (i.e. the leader).

From such graphs, *convergence* tendencies in the medium run can be claimed if the kernel rotates clockwise and accumulates on a single ridge parallel to Period t axis. That is, relative productivity levels become equal across countries, regardless of economies' initial position. *Persistence* is found when the mass concentrates along the 45 degrees line. So, countries' initial and the final positions coincide. *Improvements*, with respect to the initial position, are detected if the mass piles above the 45 degrees line; by the same token, *worsening* occur when the mass lies below the diagonal. *Club convergence* is signalled by distinct peaks along the diagonal.

As explained in the methodological section, long run tendencies, should the current dynamics persist, are assessed through ergodic distributions, as in Panels (c).[27] It is worth recalling that, in general terms, supportive evidence for any alternative convergence hypothesis is found when the correspondent ergodic distribution is unimodal and has a low variance.

3.2 Discussing results

The general results of my analysis can be inferred from the evidence provided by Figures 3 to 16 and by Table 4, which report the supports and some basic descriptive statistics for the ergodic distributions, estimated under the relevant alternative convergence hypotheses. In particular, my findings are consistent with the hypothesis of club convergence in Resource Based (i.e. RB), Low Technology (i.e. LT) and Medium Technology (i.e. MT) sectors and with the one of absolute convergence in High Techonology (i.e. HT) and Manufacturing as a whole (i.e. TOT). More precisely, technological and capital initial conditions seem to be the inner drivers of clustering behavior in, respectively, RB and LT while the dynamics of MT industries is less clear-cut. Then, exception made for MT, observing the counter plots

[27] It might be of some interest to note that the shape of the ergodic distribution is likely to be anticipated by standard mobility analysis.

of the relevant graphs,[28] it could be appreciated that cross-country productivity differences tend to shrink over time. That is, poor countries are likely to improve their relative position (i.e. mass piled above the 45 degrees line), while rich are more likely to get worse (i.e. mass below the same diagonal). Moreover, looking to the ergodics of the same figures and to Table 4, it could be seen that the relevant long run distributions are single-peaked and exhibit the lowest dispersion (i.e. coefficient of variation).[29]

Getting into more details now, it is interesting to discuss first two facts that seem quite well established in the literature: that manufacturing as a whole converges in absolute terms, while its sub-sectors do not, and the absence of supportive evidence for the conditional convergence hypothesis.

With the first respect, this result is consistent with the findings of Dollar and Wolff (1988)(1993) and Dal Bianco (2010), for what concerns manufacturing sectors, and with the ones of Bernard and Jones (1996a), with respect to disaggregated GDP (i.e. agriculture, mining, industry and services). In particular, these works show that converging tendencies in the aggregate sector are different from the ones prevailing in its sub-sectors. More specifically, the aggregate converges faster than its parts, because the cross-section dispersion is lower for the aggregate than for the parts. Looking to Table 4, it could be seen that this kind of explanation holds also in the present case. Moreover, it is worth noting that the similar patterns of HT and TOT can not be automatically interpreted as if the technology intense compartments were leading the whole industrial performance. In fact, if on the one hand it is true that, in the period considered, HT has grown faster than all other sectors (i.e. 8% vs 4% on average); on the other, HT accounts for only the 12% of total manufacturing production.

Passing now to conditional convergence, from Figure 19 and Table 4, it could be seen that when steady states differences are taken into account, the location of the ergodic distributions of RB, LT and MT shift towards higher values, because some countries overtake the leader (i.e. log relative productivity greater than zero), but such distributions are not characterized by unimodality and low dispersion. This finding, consistently with the ones of Quah(1996a) and Bandyopadhyay (2006), shows that structural factors, although relevant for enhancing the level of labor productivity in each country and, thus, cross-country

[28] The relevant graphs are Panel(b) of Figures: 6, RB, Club convergence technology; 9, LT, Club convergence capital; 15 and 16, HT and TOT absolute convergence.

[29] I prefer the coefficient of variation (i.e. standard deviation divided by the mean) to the standard deviation because the former indicator overcomes the problems related to a changing mean.

average, as predicted by the standard neoclassical growth model, are unable to affect the dynamics of the entire distribution, as according to the theory of poverty traps, Azariadis and Stachurski (2004).

At this point I want to show that my results on labor productivity club convergence are consistent with the predicted dynamics of capital accumulation and technological upgrading. In the spirit of Johnson (2005), Figure 17 and Figure 18 show the ergodic distributions of relative physical capital stock per worker and the interacted TFPgap, while Table 5 synthetically reports the main lines for interpreting this evidence. In particular, looking to HT and overall manufacturing, it could be easily seen that both capital and technology are predicted to converge in the long run, so that the club convergence hypothesis can be discharged. On the contrary, considering LT, as the ergodic distribution of capital stock is bimodal and the one of TFPgap is not, one might expect that capital stock would be at the root of club convergence in this sector. Or, put in other terms, that cross-country convergence will be reached only if capital stock differences will be evened out. Similar reasoning applies to technological clubs in RB and MT, although it is worth anticipating that MT sectors deserve some further clarifications.

For a detailed discussion of my results, I mainly refer to Figures 19 and 20 and, again, to Table 4. These graphs report cross-country intra-sectoral and inter-sectoral long-run scenarios. From the economic policy point of view, this exercise appears particularly valuable. In fact, comparing the ergodics resulting from alternative convergence predictions, within the same sector, it is possible to retrieve some indications on the sector-specific long-run growth and inequality perspectives. The inter-sectoral comparisons, instead, allows to evaluate which sector is relatively most promising, again in terms of the levels and the dispersion of living standards.

I start with commenting the behavior of each technological sector, as in Figure 19.

Regarding RB, my finding is that dissimilar technological initial conditions are preventing from overall convergence. In particular, for how I constructed the technological proxy, backwardness might be due either to a limited-in-scope imitative potential or to insufficient absorptive capabilities. Concerning the first explanation, although it is very difficult to say which technology is potentially relevant for a specific sector, in the sense put forward by Baumol (1986), Lall (2001) suggests to consider the focal activities of Multinational Corporations (i.e. MNCs). As shown by UNCTAD (2002),(2003),(2005), in the past 30 years, top 50 world MNCs has been investing in High Technology sectors while top 50 de-

veloping countries's MNCs, 33 of whom from South East Asia, operate in LT and service sectors. Thus, the limited investment in traditional sectors, which account for an average 77% of laggards economies' manufacturing value added, might have lowered the potential for technological upgrading. However, it must also be noted that, according to UNCTAD (2005), the degree of mechanization in RB sectors has sensibly increased in the last 50 years. So that, technological backwardness might be due to insufficient capacities of understanding, employing and exploiting new technologies. Finally, looking to Table 4, it could be seen that the predicted mean income associated with smooth technological initial conditions lies between the one linked to conditional convergence and the one of "club capital convergence".[30] The first fact might be explained recalling the importance of a relatively wide technological gap, which is predicted to shrink once technology is diffused; the second one, instead, seems to suggest that the accumulation of (rough) capital will not ensure sensible economic growth nor cross-country equity.

Turning now to LT, it is evident that labor productivity gap will be closed in the long-run through capital accumulation and not through technological catch-up. This result, in line with the established literature, is hardly surprising. In fact, it must be recognized that such industries employ mature technologies, already spread around the world, and they are characterized by low knowledge barriers, in the sense that the absorptive capacities necessary for technological progress are limited and, then, imitative activities are easier, Lall (2000b), (2001), Caree *et al.*(2000) and Dal Bianco (2010). Further confirmative evidence on this point is found when looking to the very low predicted mean income associated to "club technological convergence". With some caution, it might be said the growth potential associated to innovative and imitative efforts in these industries is quite limited when compared to the opportunities opened by increasing the scale of production.

As already mentioned, the results concerning MT industries are quite tricky. On the one hand, the long run behavior of club convergence determinants reported in Figures 17 and 18 lead to the conclusion that the lack of cross-country convergence is due to technological initial conditions but, on the other, Figure 19, Panel (c), clearly shows that also capital stock plays a role. Moreover, one could be tempted to assert that my results are consistent with the conditional convergence prediction. I think this is not the case. In fact, looking to Table 4, it could be seen that the cross-section dispersion increases with respect

[30]Note, with some indulgence, that with the expression "club capital convergence" ("club technological convergence") I refer to the labor productivity distributions (i.e. conditioned stochastic kernels) conditioned by steady state variables and capital stock (technological) initial conditions.

to the absolute convergence case. So that, the bottom line of the analysis is that neither structural factors, nor capital or technological differences alone can account for club convergence dynamics. This might be due, and this is the explanation I propose, to MT industries' peculiar features. Narrative evidence suggests that they have complex technical requirements and they demand for large-scale production. Thus, to fill the productivity gap developing countries have to properly develop dynamic advantages (i.e. technology and skill) as well as strengthen credit markets, in order to reach the critical threshold level of capital stock per worker.

Concerning HT, as mentioned, my analysis supports the absolute convergence hypothesis. That is, in the long run countries will converge to the same productivity level, regardless their structural and initial conditions.[31] This result sounds quite surprising. In fact, due to the high technological content of such productions, technical and capital deficiencies in developing countries might have been expected. However, at least two interpretations can be proposed.

The first one starts from technological catch-up literature predictions and it is supported by the established literature. In words: foreign capital inflows, together with targeted educational and industrial policies, have provided good initial conditions in HT industries and have effectively rescued laggard economies, making labor productivity convergence possible. In fact, if, on the one hand convergence studies on manufacturing sectors in developed economies find that labor productivity and TFP convergence has been weaker in High Tech industries than in traditional sectors, Caree *et al.*(2000) and Scarpetta and Tressel(2004), on the other, when developing countries are included in the cross-section, standard parametric analysis shows that high-tech compartments exhibit the fastest converge speed, Dal Bianco (2010). However, this point should be investigated further. Narrative evidence, in fact, suggests that, in the period considered, the majority of HT production in low income countries was due to the delocalization strategies of Western firms, UNCTAD (2005). Thus, developing countries might have acted just as outdoor plants, assembling foreign intermediates, and, typically, re-exporting them, Singh (2006). As solving this problematic issue goes beyond the scope of the present work, this is left for future research.

The second one relates, instead, to sample selection problems. The present analysis is

[31] To confirm the robustness of unconditional convergence prediction, I have used as counterfactuals HT labor productivity distributions conditioned to steady state proxies alone and together with capital or technological initial conditions. As these ergodics are multi-peaked, the unconditional convergence prediction is validated. To save space I did not report these results, which are available upon request.

based on a cross-section of just 28 countries, among which old and new Asian Tigers are well represented. As clearly demonstrated by Lall (1997), these economies are very productive in HT industries, so that this result may lack of representativeness and it might be biased towards convergence. Although, it must be said that this evidence could be consistent with future scenarios. According to Sala-i-Martin (2006), in fact, world's income per capita differences have shrunk in the last 50 years because of the spectacular growth rates of initially poor countries.[32] What prevents from thinking that new tigers will roar? Turning now to inter-sectoral comparisons, observing Figure 20, Panel (a), it could be said for sure that HT is the compartment that pays more with the the minimum effort, in terms of both growth and equity. Panel (e), instead, shows that when cross-country equity is at issue or, put in other terms, under the relevant convergence hypothesis, RB sectors are the ones that open the better prospects: highest mean income and lowest dispersion. But the precondition to be met, in this case, is to smooth out steady state and technological differences. Finally, when comparing the scenarios which ensure the highest intra-sectoral mean, as in Panel (f), it could be seen that, again, HT industries ensure the better combination in terms of long-run labor productivity and cross-sectional dispersion. Although potential biased by sample selection, my analysis supports the hypothesis of Lall (1997), that is HT sectors ensure the relatively higher productivity gains. So that, from the policy perspective, it seems advisable that instead of relying on static comparative advantages associated to LT sectors, low income economies concentrate their industrial policy in the search of dynamic comparative advantages, as the ones of opened by HT production. This is because, in high tech sectors, even labor intensive activities, such as assembly, are more stable, skill-creating and positive externality generating than in traditional ones.

4 Conclusions

In this paper I have assessed through an unified distribution dynamics framework the hypotheses of absolute, conditional and club convergence, among 28 industrialized and emerging economies, in different manufacturing sub-sectors, during the period 1980-1995. My analysis has shown that, exception made for High Technology and Manufacturing as a

[32] Sala-i-Martin employs distribution analysis to show that China's and India's growth experiences caused the increase of world's living standards and the decrease of world income inequality.

whole, all sub-compartments are predicted to "go clubbing". From the policy perspective, the main recommendation is that laggard economies concentrate their industrial policies on high tech productions.

I am sure that this kind of analysis will be enriched a lot expanding both the cross-section and the time series dimensions of the data employed. So that, I will soon take advantage of the latest release of UNIDO Industrial dataset, in order to strengthen my results and to mitigate the sample selection problem.

Moreover, another interesting research path is given by the the comparison of tradable and non-tradable sectors. In particular, are tradable sectors converging faster than non-tradable ones? Has the development of non-tradable sector an indirect impact on the convergence dynamics of tradable one? If so, which manufacturing industries are affected? Can we explain inter-sectoral dynamics through the comparative advantage argument?

Tables and Graphs

Table 1: Country Sample

Developed OECD	**Developed NON OECD**	**Developing Middle Income**	**Developing Low Income**
Australia	Cyprus	Bolivia	Bangladesh
Austria	Hong-Kong	Chile	India
Finland	Israel	Egypt	
Greece	Singapore	Indonesia	
Italy		Iran	
Japan		Jordan	
Korea		Malaysia	
Norway		Philippines	
Spain		Sri Lanka	
United Kingdom		Turkey	
United States		Venezuela	

Table 2: Correspondence between ISIC 3-digits and Lall's Technological Taxonomy

Sector ISIC 3-digits	**Lall(2000) Tech.Sector**	**Tech.Sector Acronym**	**Tech.Sector Number**
Food (311) Beverages (313) Tobacco (314)	Resource Based	RB	1
Textiles (321) Clothing (322) Leather Products (323) Footwear (324)	Low Technology	LT	2
Wood Products (331)	Resource Based	RB	1
Furniture (332)	Low Technology	LT	2
Paper and Paper Products (341)	Resource Based	RB	1
Printing and Publishing (342)	Low Technology	LT	2
Chemicals (351, 352)	Medium Technology	MT	3
Petroleum (353, 354)	Resource Based	RB	1
Rubber (355)	Resource Based	RB	1
Plastic products (356)	Medium Technology	MT	3
Pottery (361)	Low Technology	LT	2
Glass (362)	Low Technology	LT	2
Other non metallic mineral products (369)	Resource Based	RB	1
Basic metals (371, 372)	Low Technology	LT	2
Metal products (381)	Low Technology	LT	2
Non electrical machinery (382)	Medium Technology	MT	3
Electrical machinery (383)	High Technology	HT	4
Transport equipment (384)	Medium Technology	MT	3
Instruments (385)	High Technology	HT	4
Other manufacturing (390)	Low Technology	LT	2

Table 3: Graphs Scale

Logarithmic scale $y_{ijt} = log\left(\frac{Y_{ijt}}{Y_{USjt}}\right)$	**Labour productivity in % with respect to US**
-4	2%
-3.5	3%
-3	5%
-2.5	8%
-2	13%
-1.5	22%
-1	37%
-0.5	60%
0	**100%**
0.5	164%
1	271%
1.5	448%

Table 4: Ergodic distributions: support in real US Dollars and descriptive statistics

Ergodic distributions, different convergence hypotheses				
Support of log relative labour productivity, y_{ijt}	Support in real PPP US$	Support in real PPP US$	Support in real PPP US$	Support in real PPP US$
Resource Based	**Absolute**	**Conditional**	**Club, Capital**	**Club, Tech.**
-4,5	841			
-4	1.386			
-3,5	2.286		2.286	
-3	3.768		3.768	
-2,5	6.213		6.213	6.213
-2	10.243		10.243	10.243
-1,5	16.889	16.889	16.889	16.889
-1	27.845	27.845	27.845	27.845
-0,5	45.908	45.908	45.908	45.908
0	75.689	75.689	75.689	75.689
0,5		124.790		124.790
1		205.745		
Descriptive statistics, real PPP US$				
Mean	17.212	78.502	27.469	42.521
Median	13.231	64.899	25.784	39.906
Std.Deviation	11.000	53.844	17.110	17.521
Coef. of variation	0,64	0,69	0,62	0,41

Ergodic distributions, different convergence hypotheses				
Support of log relative labour productivity, y_{ijt}	Support in real PPP US$	Support in real PPP US$	Support in real PPP US$	Support in real PPP US$
Low Technology	**Absolute**	**Conditional**	**Club, Capital**	**Club, Tech.**
-4,5	519			
-4	855			
-3,5	1.410			1.410
-3	2.324		2.324	2.324
-2,5	3.832		3.832	3.832
-2	6.317		6.317	6.317
-1,5	10.415	10.415	10.415	10.415
-1	17.172	17.172	17.172	17.172
-0,5	28.312	28.312	28.312	28.312
0	46.678	46.678	46.678	46.678
0,5	76.959	76.959	76.959	
1		126.885		
1,5		209.198		
Descriptive statistics, real PPP US$				
Mean	13.673	44.635	22.276	11.678
Median	10.249	38.636	20.301	11.068
Std.Deviation	9.439	26.516	11.309	7.638
Coef. of variation	0,69	0,59	0,51	0,65

Medium Technology	**Absolute**	**Conditional**	**Club, Capital**	**Club, Tech.**
-3,5	2.170		2.170	2.170
-3	3.578		3.578	3.578
-2,5	5.899		5.899	5.899
-2	9.725	9.725	9.725	9.725
-1,5	16.034	16.034	16.034	16.034
-1	26.436	26.436	26.436	26.436
-0,5	43.585	43.585	43.585	43.585
0	71.860	71.860	71.860	71.860
0,5	118.477	118.477	118.477	
1		195.336		
Descriptive statistics, real PPP US$				
Mean	15.428	16.847	16.655	7.956
Median	21.339	18.335	23.236	8.681
Std.Deviation	9.653	12.649	11.063	6.784
Coef. of variation	0,63	0,75	0,66	0,85

High Technology	**Absolute**	**Manufacturing**	**Absolute**
-4	1.112	-3	3.065
-3,5	1.834	-2,5	5.054
-3	3.023	-2	8.333
-2,5	4.984	-1,5	13.738
-2	8.218	-1	22.651
-1,5	13.549	-0,5	37.345
-1	22.338	0	61.571
-0,5	36.830		
0	60.722		
0,5	100.114		
Descriptive statistics, real PPP US$			
Mean	31.122	**Mean**	20.357
Median	36.723	**Median**	24.799
Std.Deviation	13.627	**Std.Deviation**	8.335
Coef. of variation	0,44	**Coef. of variation**	0,41

Table 5: On club convergence determinants

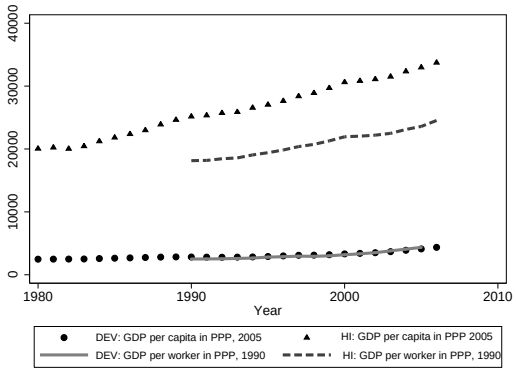
	K stock per worker, descriptive statistics				Relative K stock: accumulation dynamics, Rif. Fig.17		
	Period Average HI	**Std.dev**	**Period Average LI**	**Std.dev**	**Time evolution**	**Shape of the erdogic**	**Implication**
RB	985.436	2.968.748	154.264	164.286	Less dispersed, gap closing	Unimodal	No Capital Clubs
LT	899.704	3.055.337	146.787	204.808	Towards bimodality	Bimodal	Capital Clubs
MT	3.594.214	1,31E+07	160.921	167.413	Gap closed	Unimodal	No Capital Clubs
HT	3.952.371	1,54E+07	151.298	176.156	Gap closed	Unimodal	No Capital Clubs
TOT	1.345.205	4.636.589	150.203	176.645	Gap closed	Unimodal	No Capital Clubs
	Interacted TFPgap, descriptive statistics				**TFPgap: technological catch-up dynamics, Rif.Fig.18**		
	Period Average HI	**Std.dev**	**Period Average LI**	**Std.dev**	**Time evolution**	**Shape of the erdogic**	**Implication**
RB	0,7377354	0,2941024	0,4045931	0,1885647	Towards bimodality	Bimodal	Technological Clubs
LT	1,074025	0,4002664	0,7330089	0,3013904	Gap shrinking	Unimodal	No Technological Clubs
MT	0,915929	0,3512655	0,5759011	0,2637018	Gap shrinking but bimodality	Bimodal	Technological Clubs
HT	1,328706	0,4978432	0,9014077	0,3786814	Gap shrinking	Unimodal	No Technological Clubs
TOT	1,006063	0,3788675	0,6224753	0,2436899	Gap shrinking	Unimodal	No Technological Clubs

Expected labor productivity long-run behavior

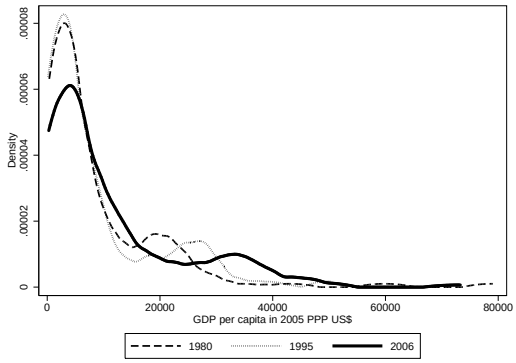
RB: Clubs due to technological initial conditions	LT: Clubs due to capital initial conditions	MT: Clubs due to technological initial conditions	HT: No Clubs	TOT: No Clubs

Figure 1: Stylized evidence on GDP per capita.

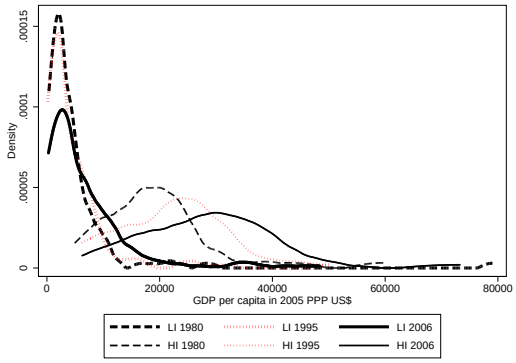
Source: World Bank, World Development Indicators, 2010.



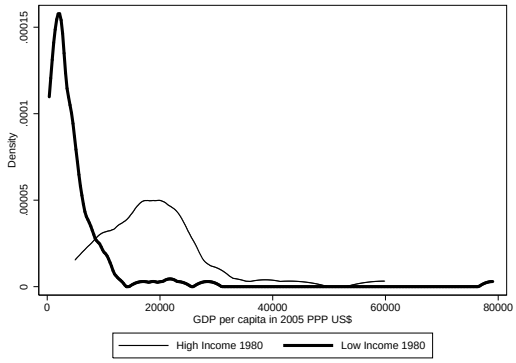
(a) GDP growth



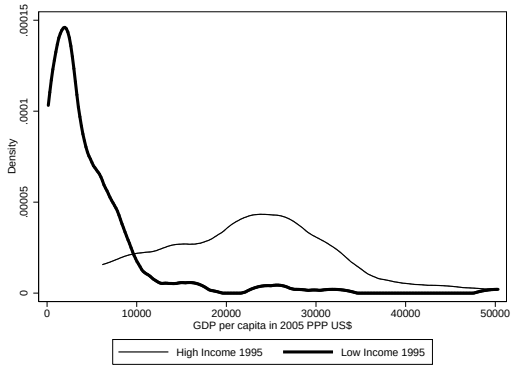
(b) World distribution, selected years



(c) High Income and Developing countries' distributions, selected years



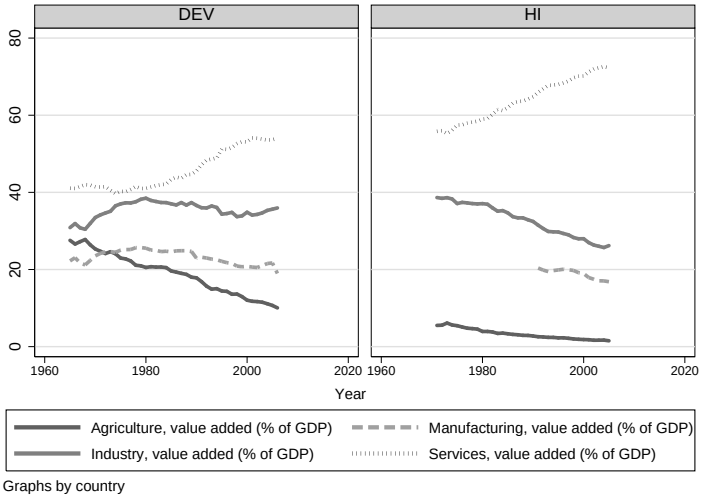
(d) High Income and Developing countries' distributions in 1980



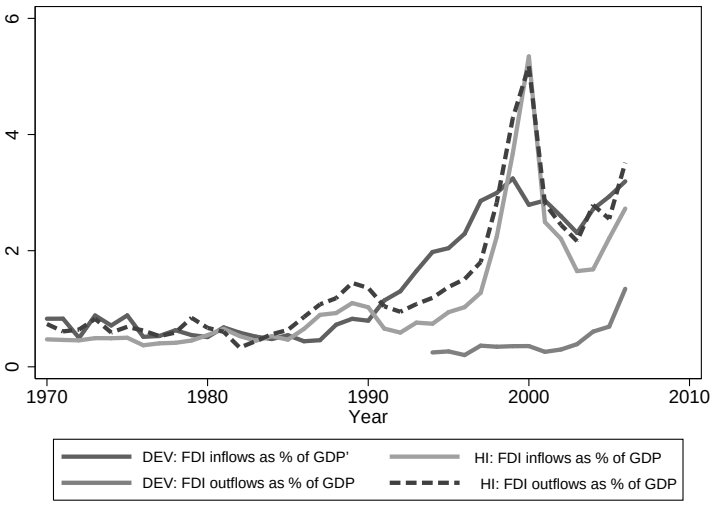
(e) High Income and Developing countries' distributions in 1995

Figure 2: Other stylized facts

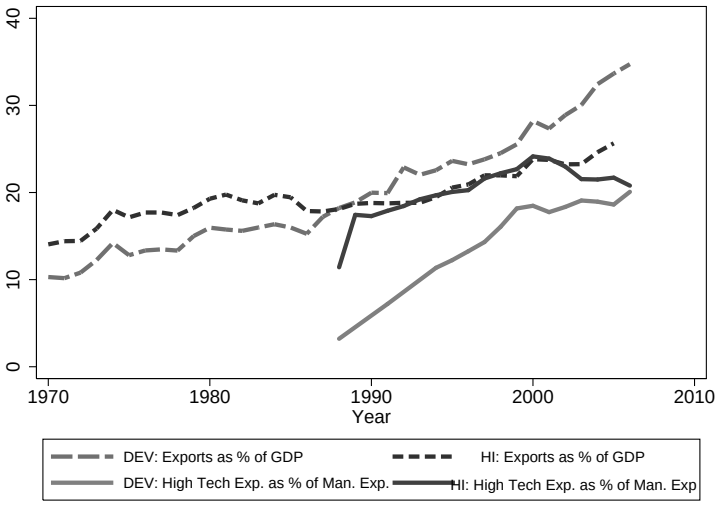
Source: World Bank, World Development Indicators, 2010.



(a) Structural Change

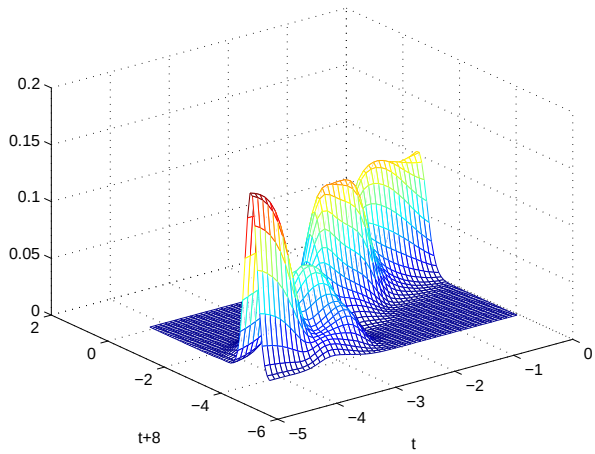


(b) Foreign Direct Investment

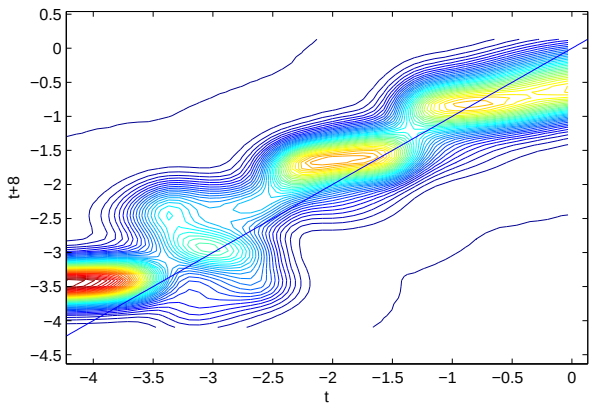


(c) Exports

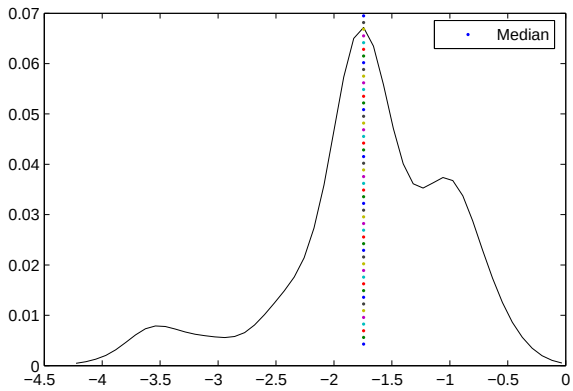
Figure 3: Resource Based: Absolute Convergence



(a) Kernel density

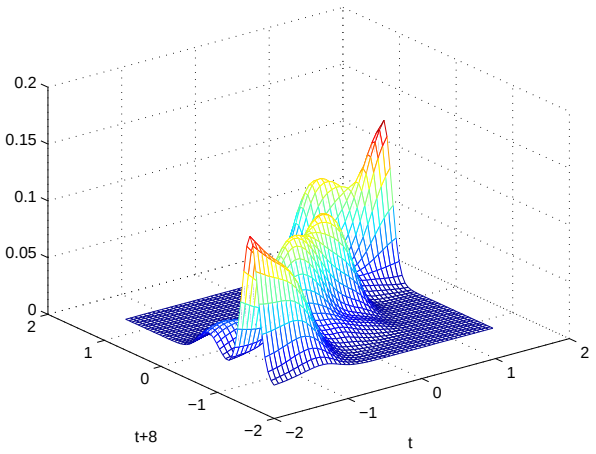


(b) Contour plot

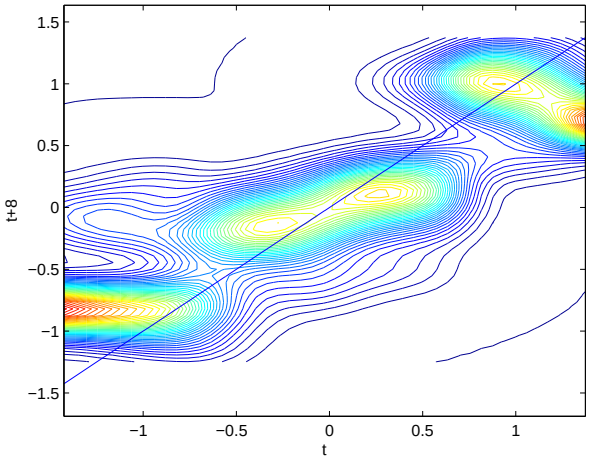


(c) Ergodic distribution

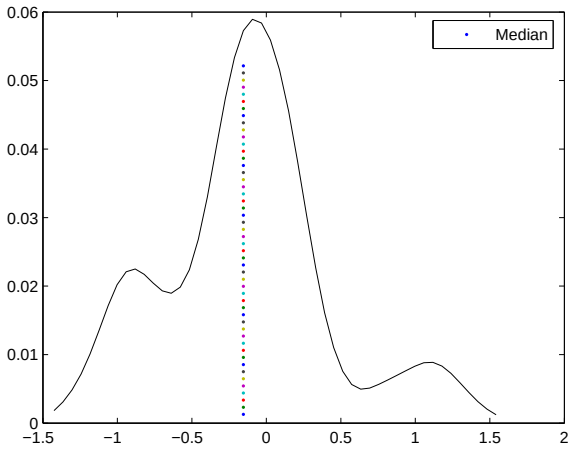
Figure 4: Resource Based: Conditional Convergence



(a) Kernel density

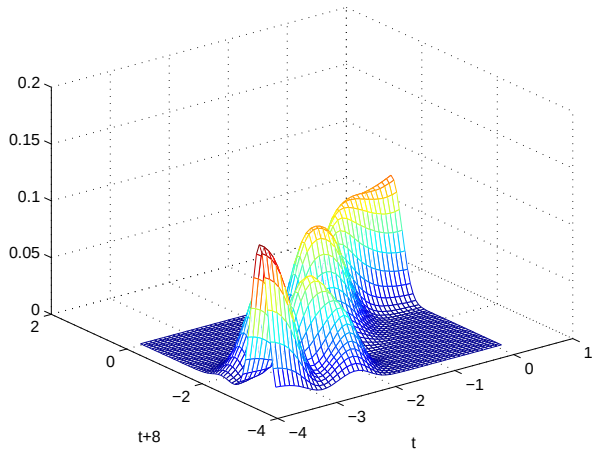


(b) Contour plot



(c) Ergodic distribution

Figure 5: Resource Based: Club Convergence, Capital Stock



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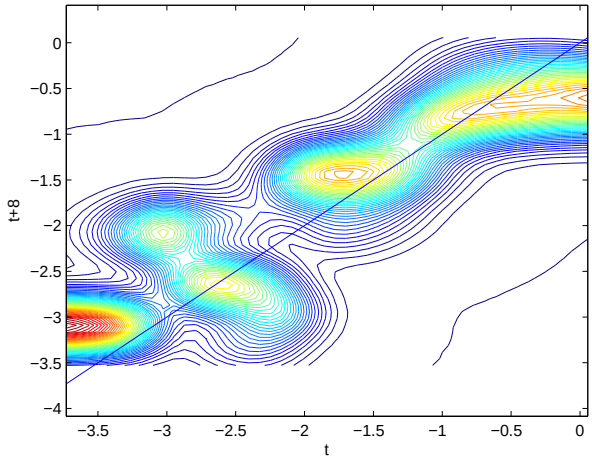

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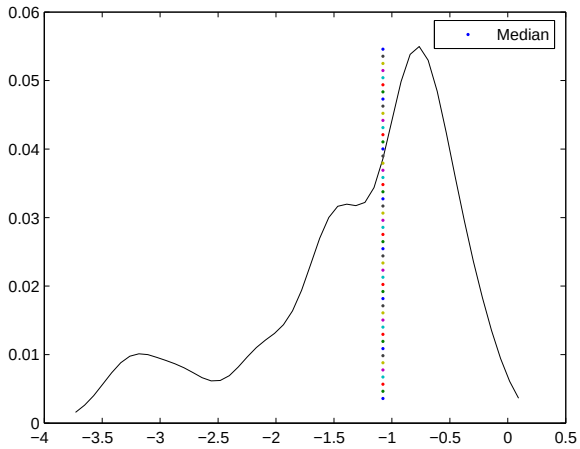
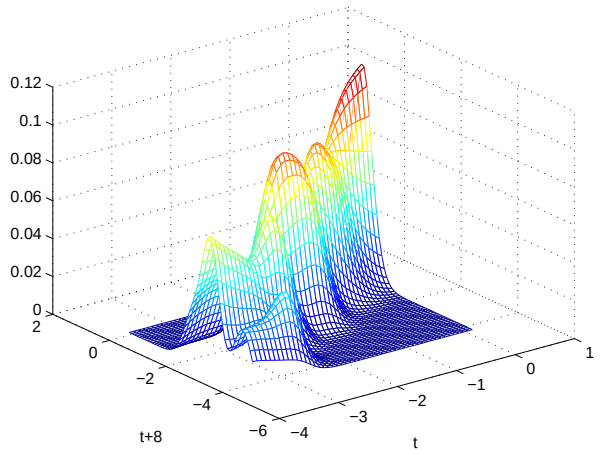


(c) Ergodic distribution

Figure 6: Resource Based: Club Convergence, Technology



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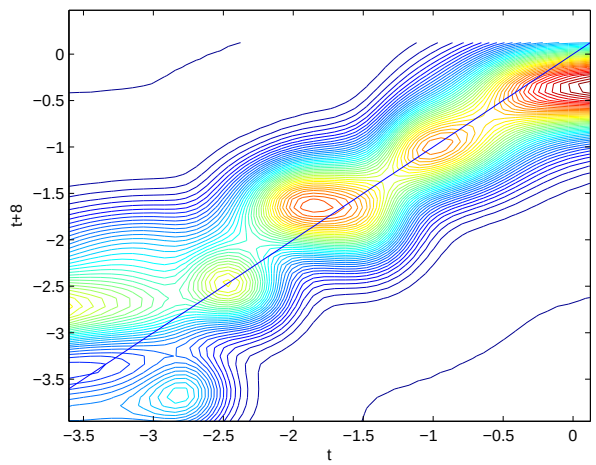

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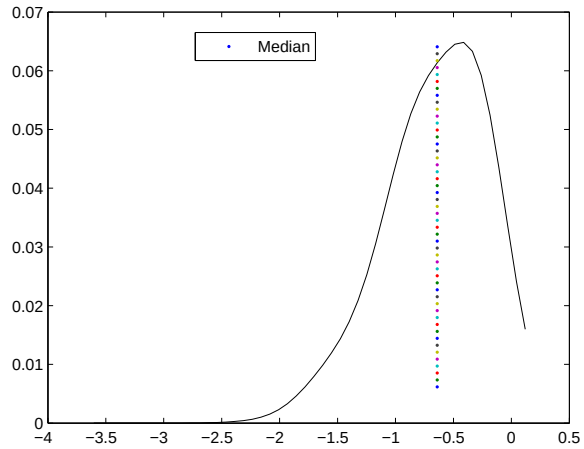
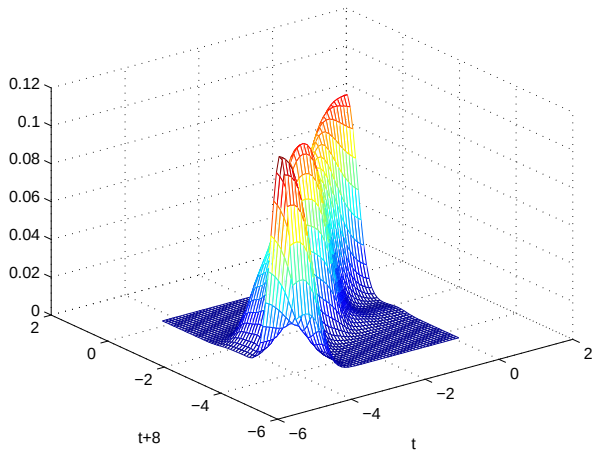


(c) Ergodic distribution

Figure 7: Low Technology: Absolute Convergence



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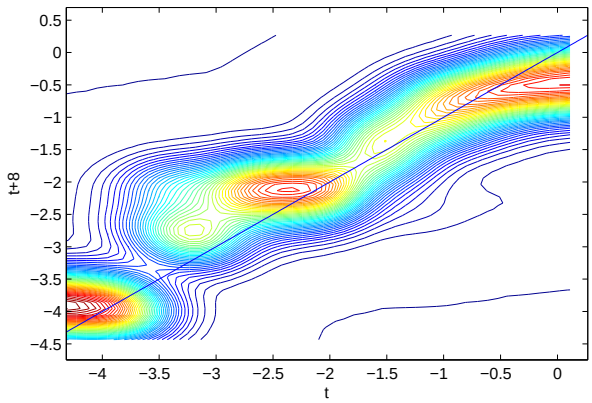

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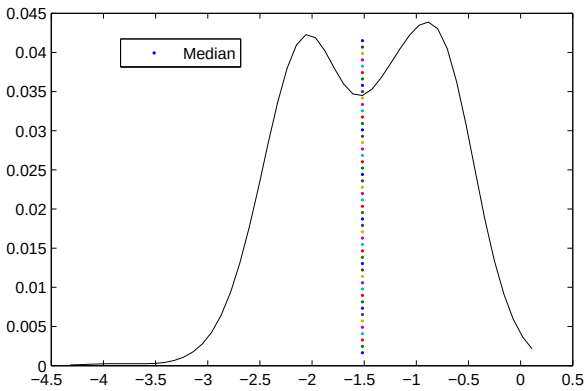
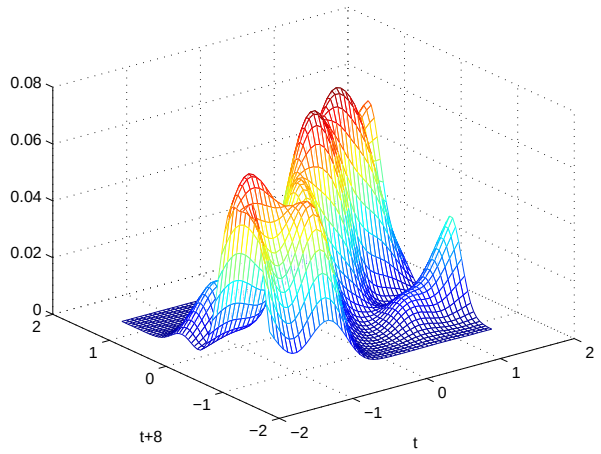


(c) Ergodic distribution

Figure 8: Low Technology: Conditional Convergence



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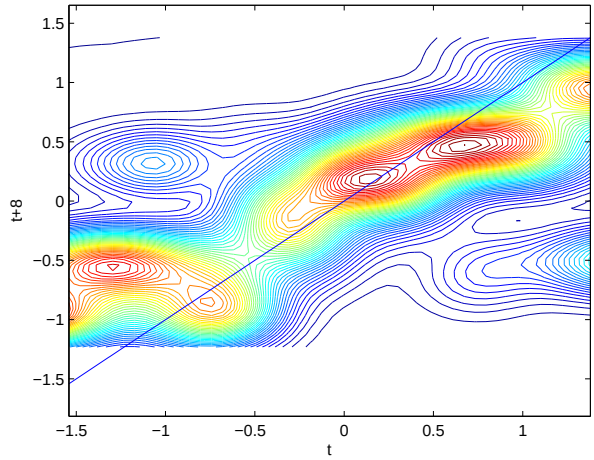

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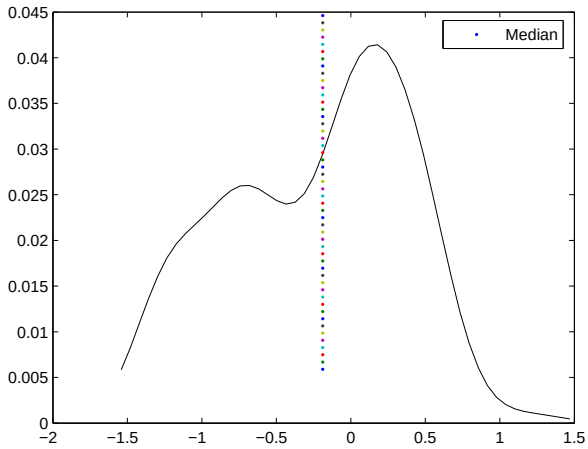
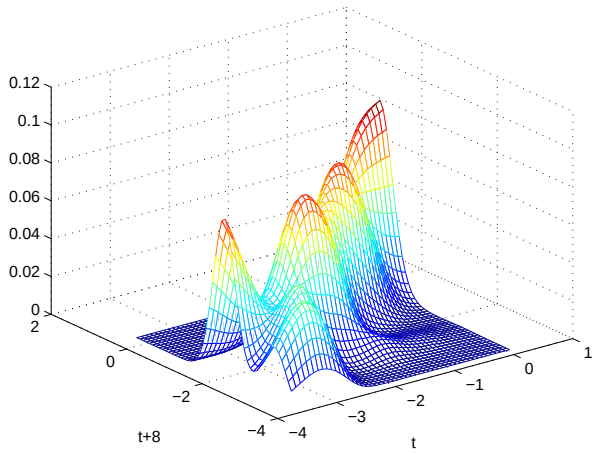


(c) Ergodic distribution

Figure 9: Low Technology: Club Convergence, Capital Stock



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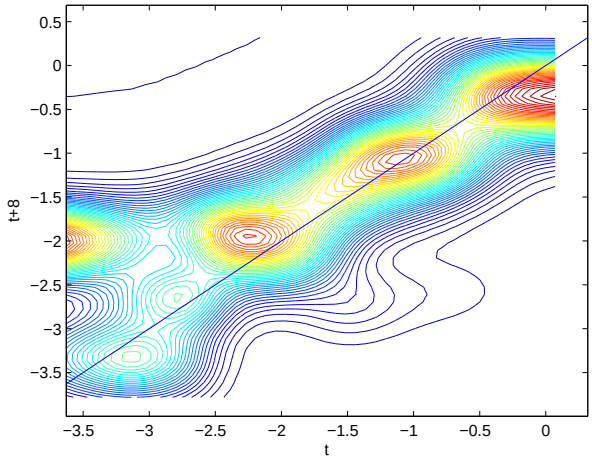

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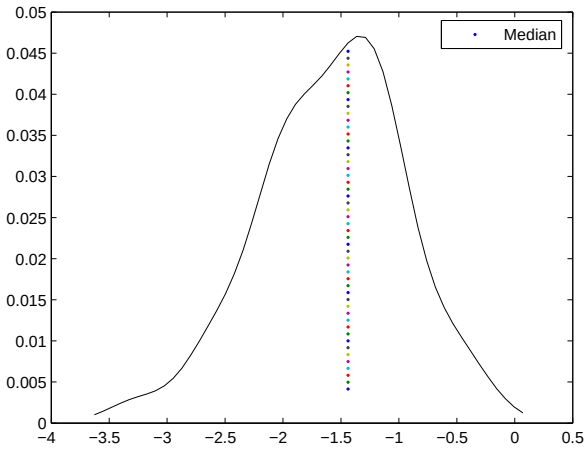
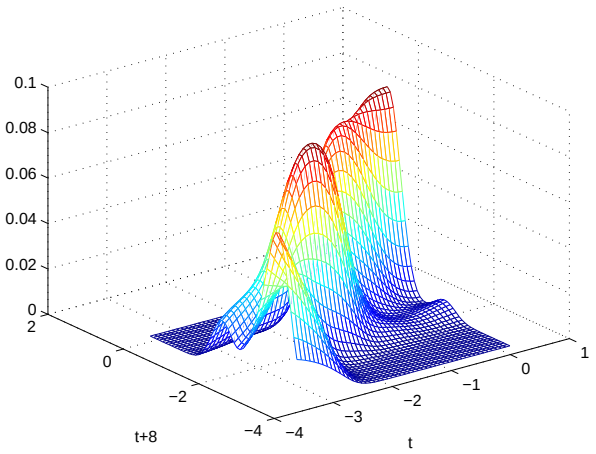


(c) Ergodic distribution

Figure 10: Low Technology: Club Convergence, Technology



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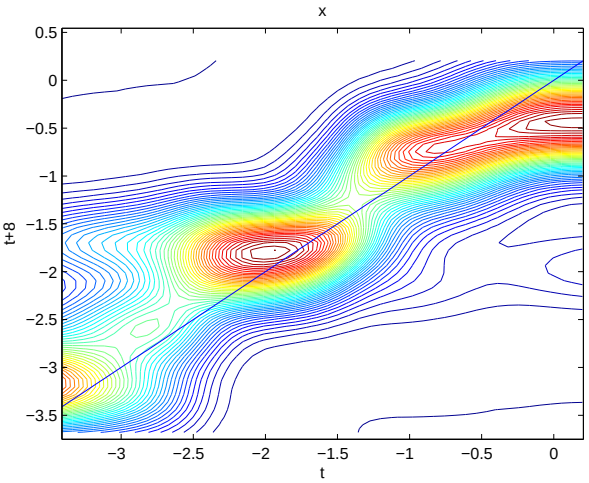

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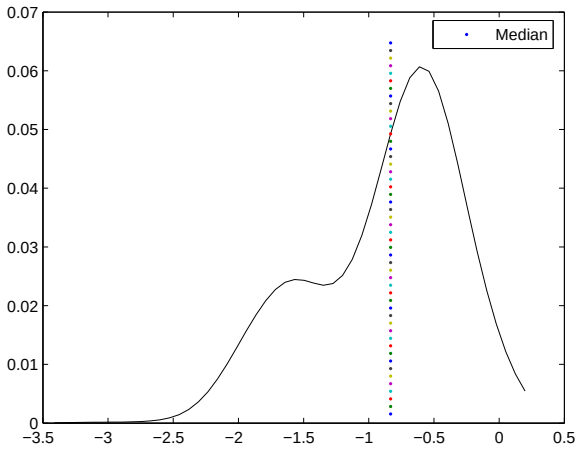
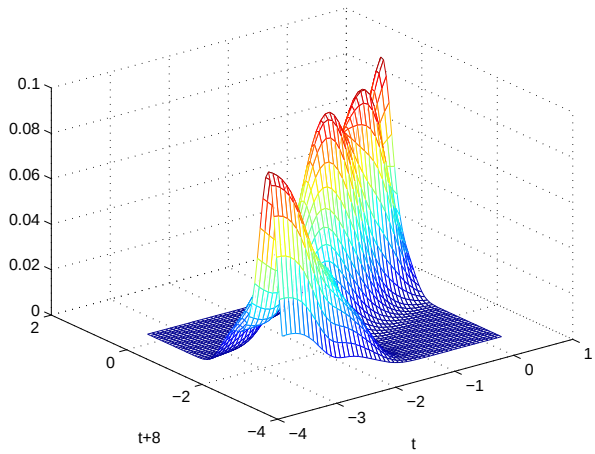


(c) Ergodic distribution

Figure 11: Medium Technology: Absolute Convergence



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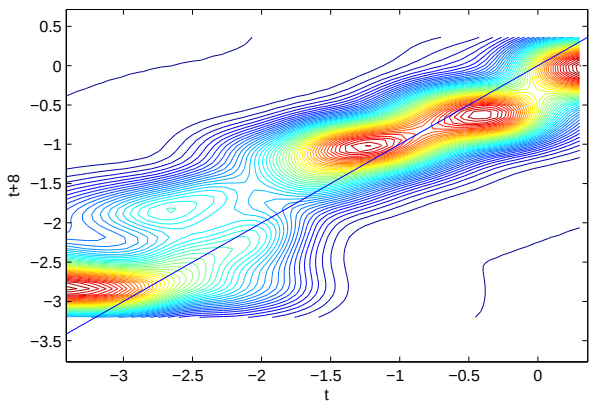

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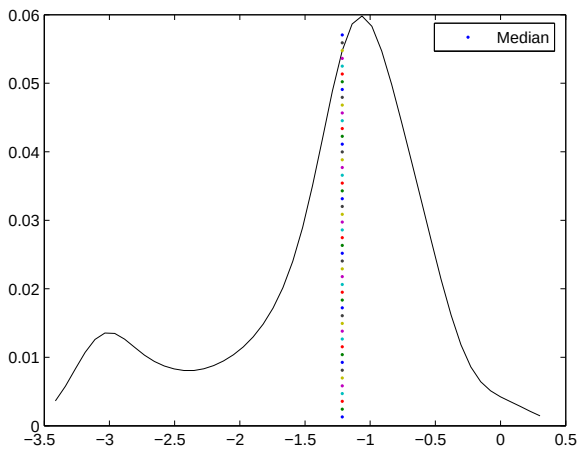
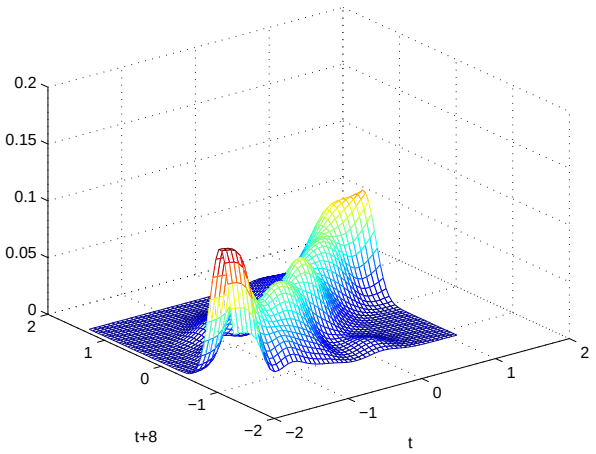


(c) Ergodic distribution

Figure 12: Medium Technology: Conditional Convergence



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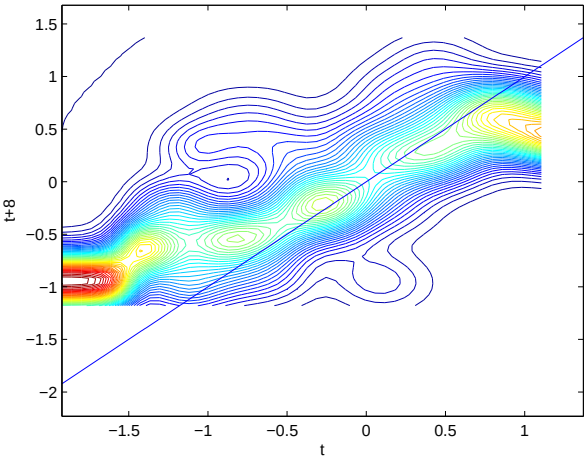

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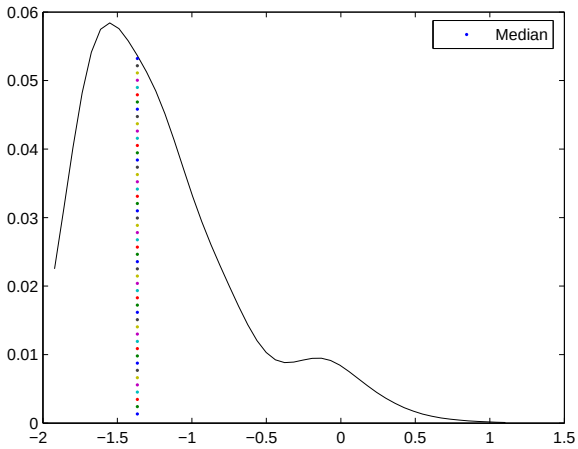
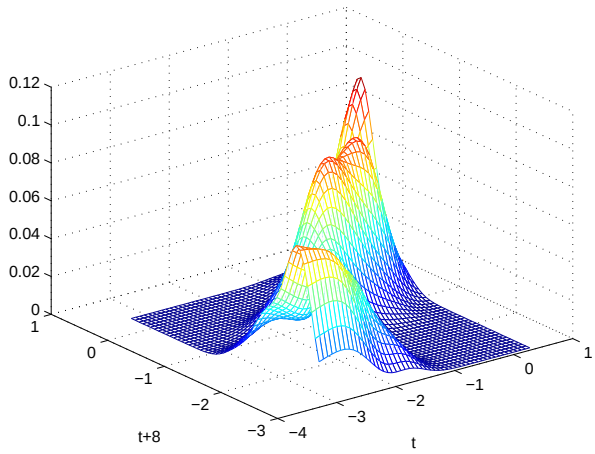


(c) Ergodic distribution

Figure 13: Medium Technology: Club Convergence, Capital Stock



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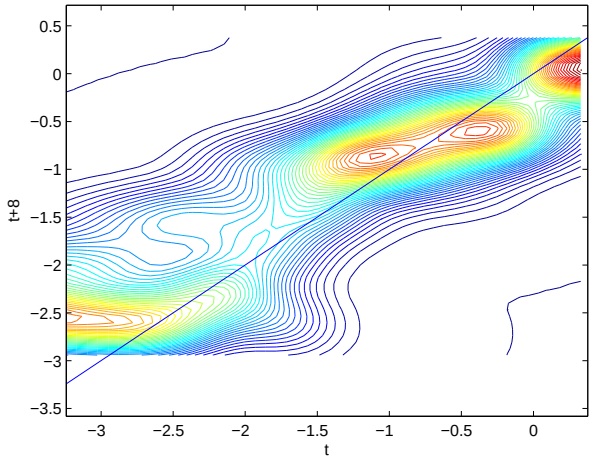

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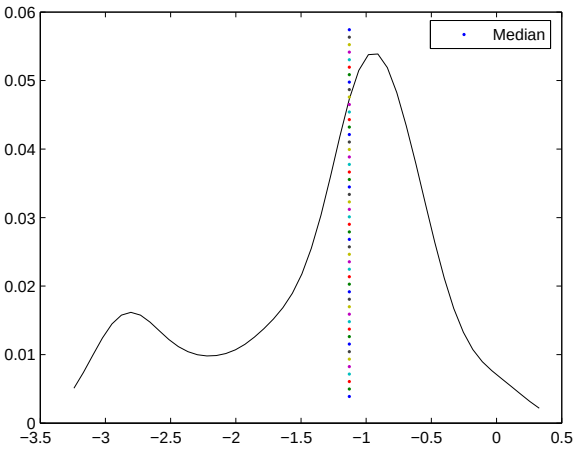
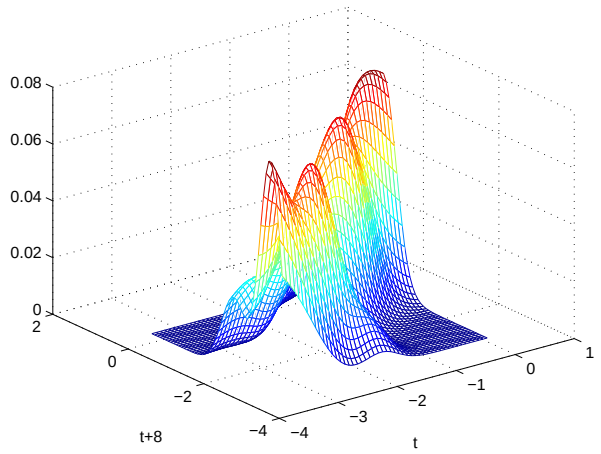


(c) Ergodic distribution

Figure 14: Medium Technology: Club Convergence, Technology



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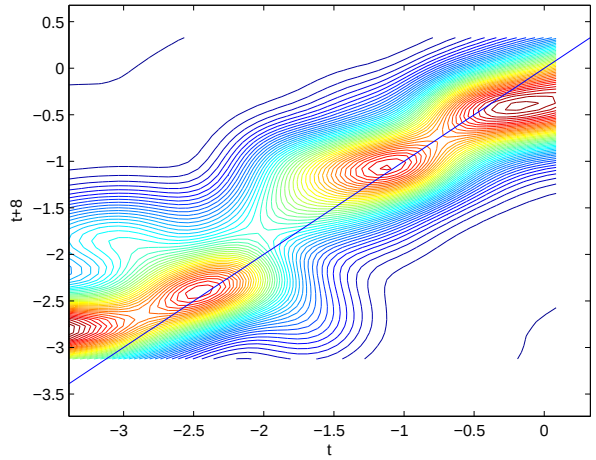

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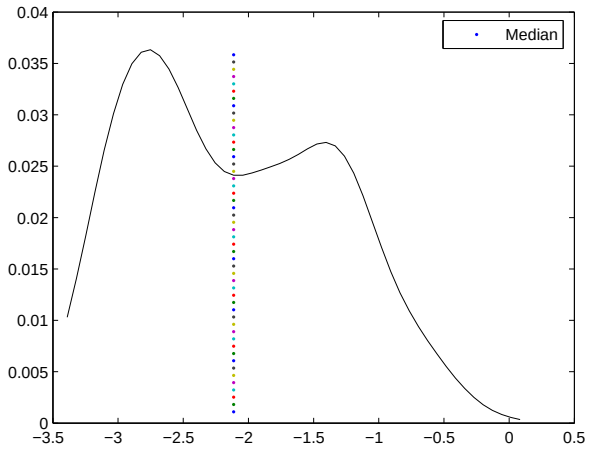
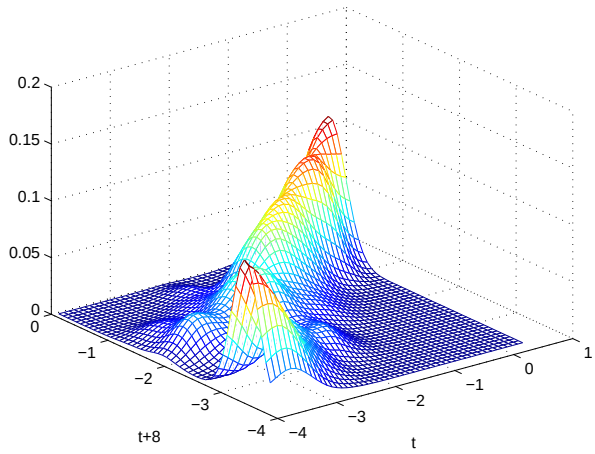


(c) Ergodic distribution

Figure 15: High Technology: Absolute Convergence



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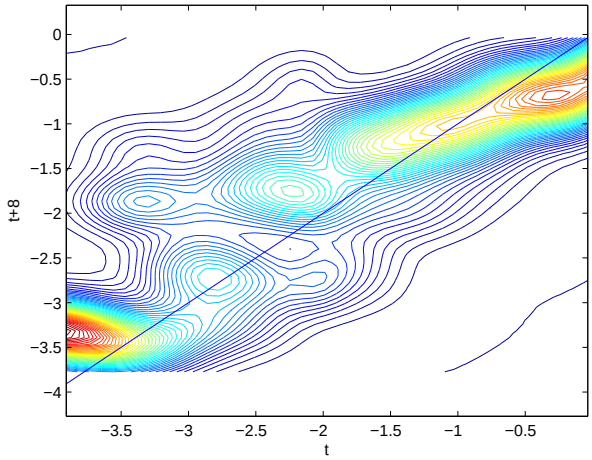

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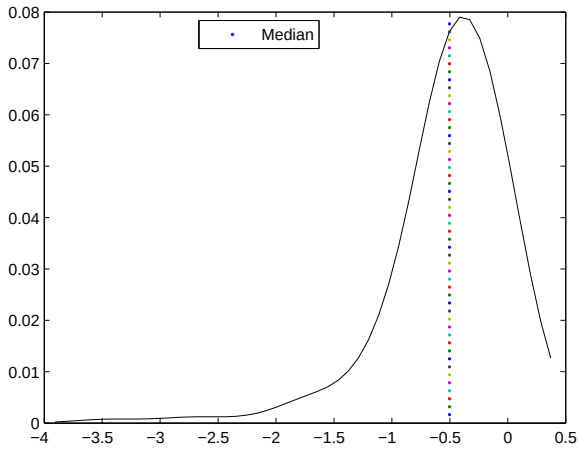
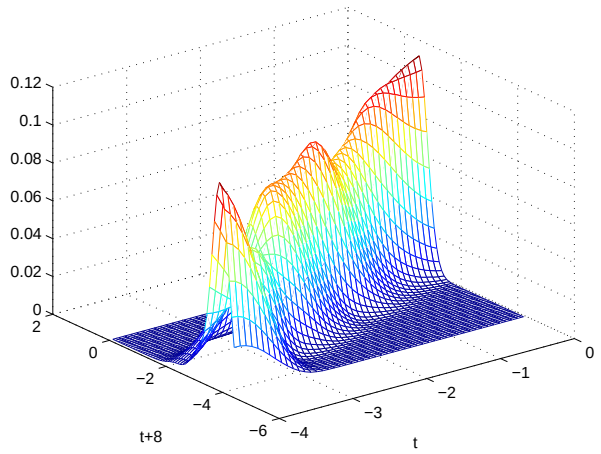
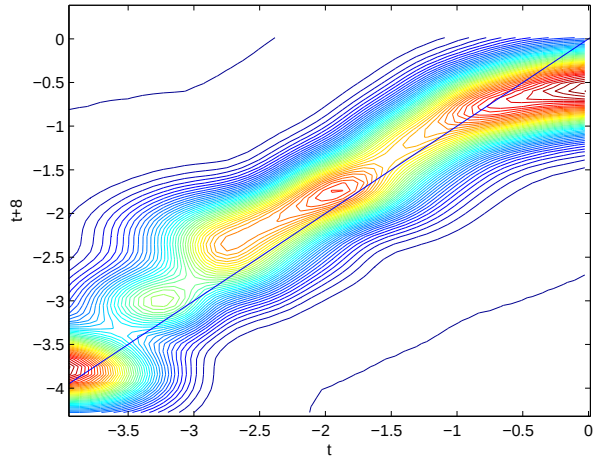


(c) Ergodic distribution

Figure 16: Manufacturing: Absolute Convergence



(a) Kernel density



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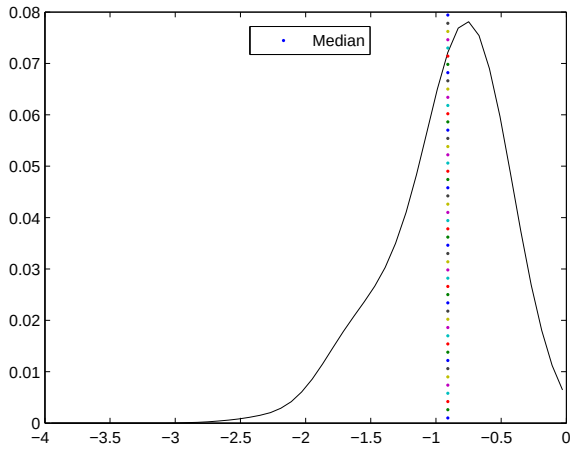
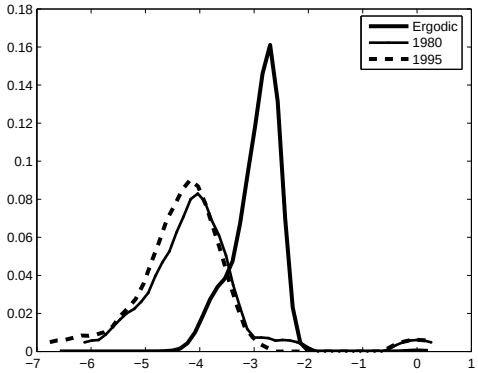
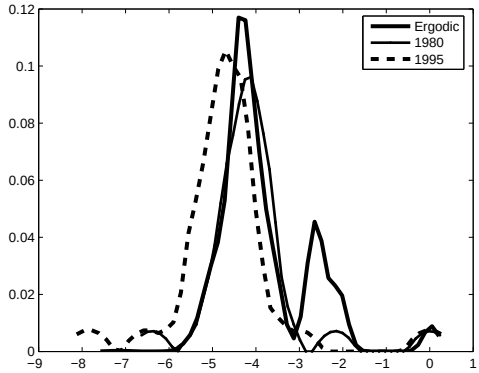


(c) Ergodic distribution

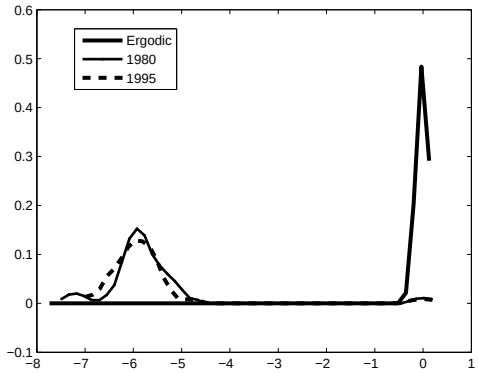
Figure 17: Accumulation dynamics: log relative capital stock per worker by sector



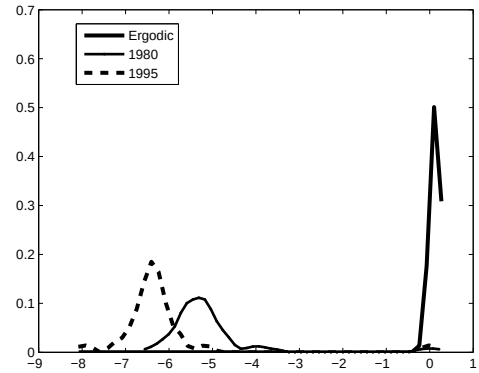
(a) Resource Based



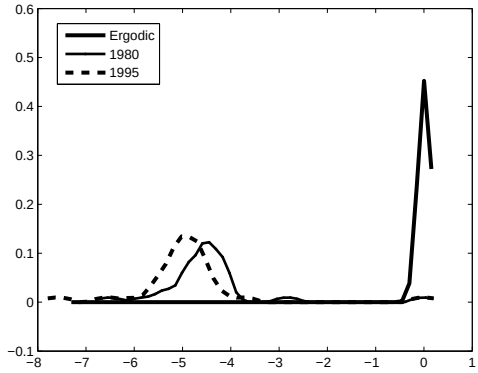
(b) Low Technology



(c) Medium Technology

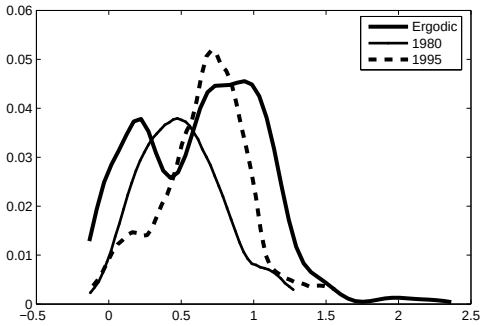


(d) High Technology

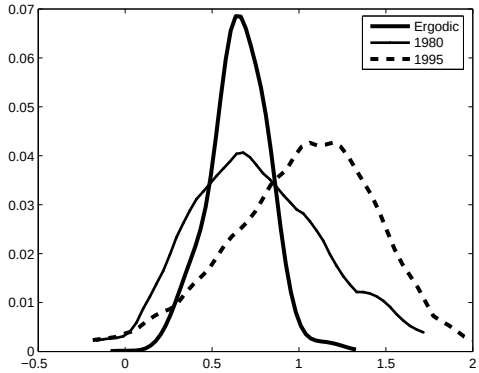


(e) Manufacturing

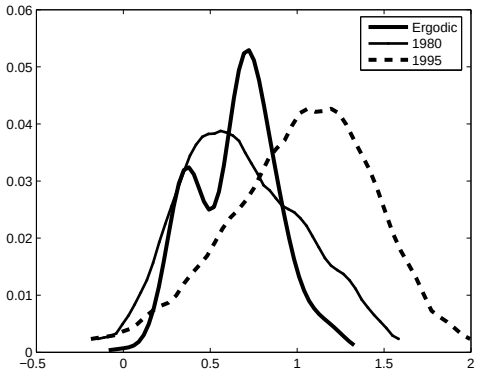
Figure 18: Technological dynamics: TFPgap interacted with schooling by sector



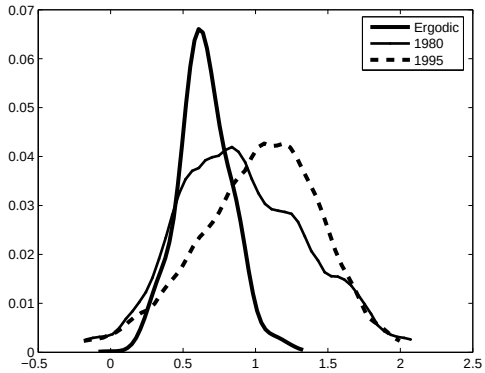
(a) Resource Based



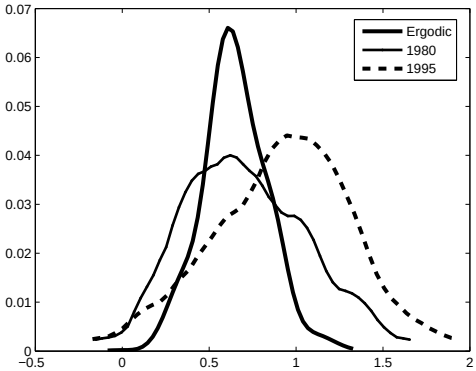
(b) Low Technology



(c) Medium Technology



(d) High Technology



(e) Manufacturing

References

Azariadis, C., and A. Drazen (1990): "Threshold Externalities in Economic Development," *The Quarterly Journal of Economics*, 105(2), 501–526.

Azariadis, C., and J. Stachurski (2004): "Poverty Traps," in *Hanbook of Economic Growth*. Aghion, Philippe and Durlauf, Steven eds.

Barro, R., and J. W. Lee (2000): "Barro-Lee Data Set for a Panel of 138 Countries," Discussion paper, NBER.

Barro, R. J. (1991): "Economic growth in a cross-section of countries," *Quarterly Journal of Economics*, 106(2), 407–443.

Baumol, W. (1986): "Productivity growth, convergence and welfare: what the long run data show," *American Economic Review*, 76(5), 1072–85.

Bennell, P. (1996): "Rates of return to education: does the conventional pattern prevail in sub-Saharan Africa," *World Development*, 24(1), 183–199.

Bernard, A., and C. Jones (1996a): "Comparing apples to oranges: productivity convergence and measurement across indutries and countries," *American economic review*, 86(5), 1216–1238.

——— (1996b): "Technology and convergence," *Economic Journal*, 106, 1037–1044.

Bloom, D., D. Canning, and J. Sevilla (2003): "Geography and Poverty Traps," *Journal of Economic Growth*, 8, 355–378.

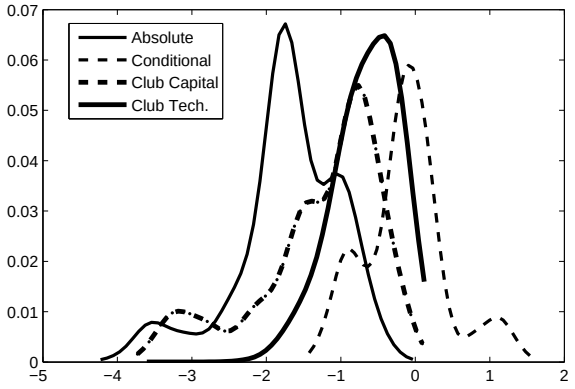
Boheim, M., M. Pfaffermayr, and K. Gugler (2000): "Do growth rates differ in European Manufacturing Industries," *Austrain Economic Quarterly*, 2, 93–104.

Broadberry, S. (1993): "Manufacturing and the covergence hypothesis: what the long-run data show," *The journal of economic history*, 53(4), 772–795.

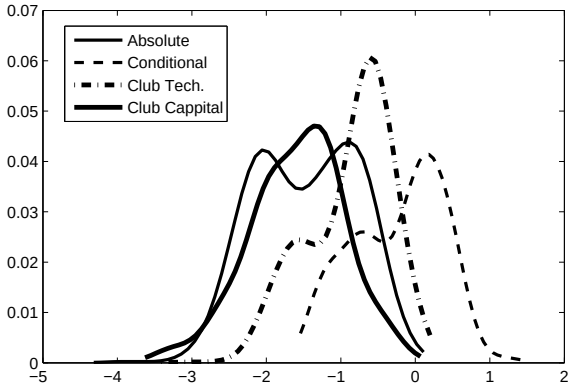
Bruno, R. L., and N. Campos Ferreira (2010): "A systematic review of the effects of Foreign Direct Investment on economic growth in low income countries," *Mimeo, DFID*.

Carree, M. A., L. Klomp, and A. L. Thurik (2000): "Productivity convergence in OECD manufacturing industries," *Economic Letters*, 66, 337–345.

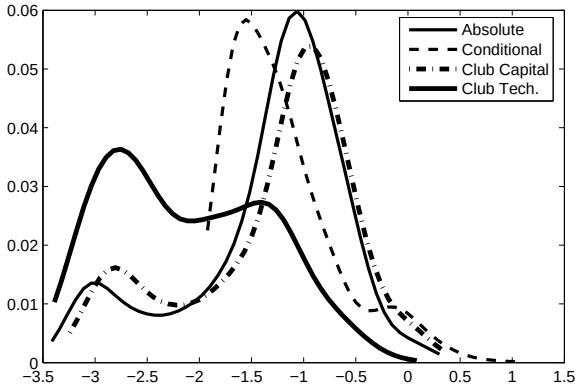
Figure 19: Intra-sectoral long run scenarios



(a) Resource Based

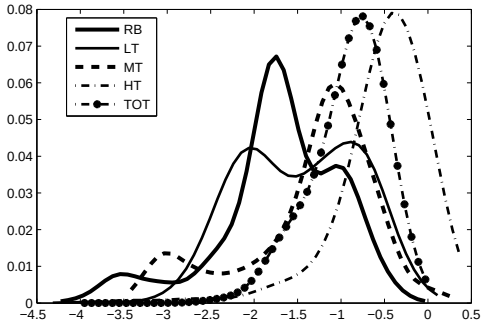


(b) Low Technology

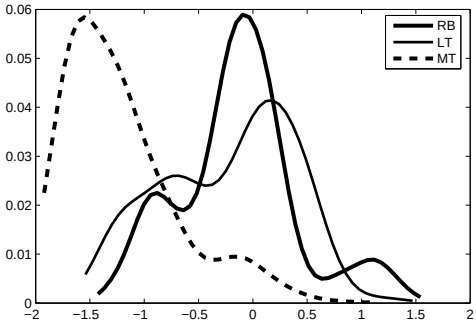


(c) Medium Technology

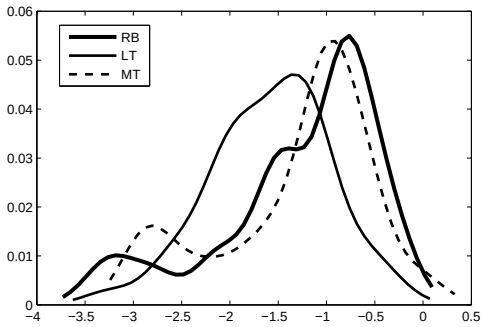
Figure 20: Inter-sectoral long run scenarios



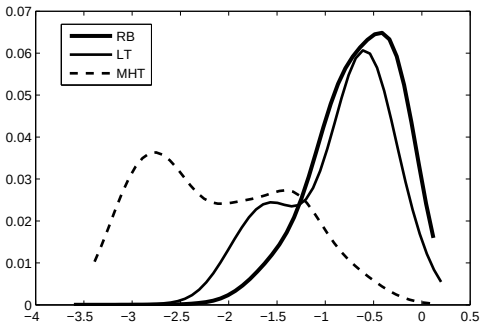
(a) Absolute Convergence



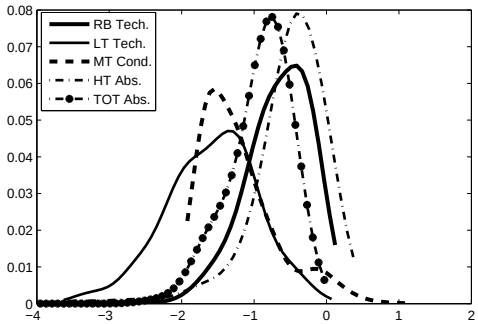
(b) Conditional Convergence



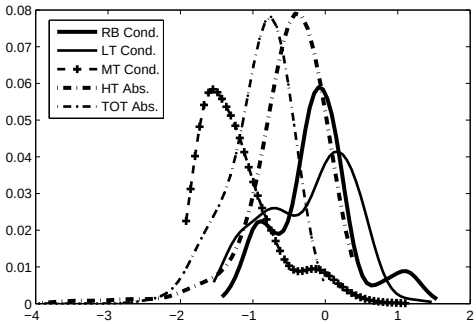
(c) Club Convergence, Capital Stock



(d) Club Convergence, Technology



(e) Relevant convergence prediction



(f) Highest-mean convergence prediction

Caselli, F. (2005): "Accounting for cross-country income differences," in *Handbook of Economic Growth*. Aghion, Philippe and Durlauf, Steven.

Caselli, F., and D. J. Wilson (2004): "Importing technology," *Journal of Monetary Economics*, 51(1), 1–32.

Caves, D. (1982a): "Multilateral comparisons of output, input and productivity using superlative index numbers," *Economic Journal*, 99, 73–86.

Caves, D., L. Christensen, and E. Diewert (1982b): "The economic theory of index numbers and the measurement of input, output and productivity," *Econometrica*, 50(6), 1393–1414.

Chamberlain, G. (1984): "Panel data," *Hanbook of Econometrics*, 2, 1247–1318.

Cohen, W. M., and D. A. Levinthal (1989): "Innovation and Learning: the two faces of R&D," *The Economic Journal*, 99 (397), 569–596.

Dal Bianco, S. (2010): "New Evidence on Classical and Technological Convergence in Manufacturing," *Rivista Italiana degli Economisti*, XV, No.2, 305–336.

Desdoigts, A. (1999): "Patterns of economic development and the formation of clubs," *Journal of economic growth*, 4(3), 305–330.

Desmet, K., and M. Fafchamps (2006): "Employment concentration across U.S. counties," *Regional Science and Urban Economics*, Forthcoming.

Dollar, D., and E. N. Wolff (1988): "Convergence of industrial labour productivity among advanced economies, 1963-82," *Review of Economics and Statistics*, 70, 549–558.

——— (1993): *Competitiveness, convergence and international specialization*. The MIT Press, Cambridge, Massachusetts.

Durlauf, S. N. (1993): "Nonergodic Economic Growth," *The Review of Economic Studies*, 60, No. 2, 349–366.

——— (1996): "On the Convergence and Divergence of Growth Rates," *The Economic Journal*, 106, No.437, 1016–1018.

Durlauf, S. N., and P. A. Johnson (1995): "Multiple Regimes and Cross-Country Growth Behaviour," *Journal of Applied Econometrics*, 10, 365–84.

Durlauf, S. N., P. A. Johnson, and J. R. Temple (2005): "Growth Econometrics," *Handbook of Economic Growth. P. Aghion and S. N. Durlauf (eds.), North-Holland: Amsterdam*, 1A, 555–677.

Durlauf, S. N., and D. Quah (1999): "The new empirics of economic growth," in *Handbook of macroeconomics, Vol.(1.A)*. Taylor, J.B and Woodford, M (eds) North Holland Elsevier Science, Amsterdam.

Galor, O. (1996): "Convergence? Inferences from Theoretical Models," *Economic Journal*, 106, 1056–1069.

Galor, O., and J. Zeira (1993): "Income Distribution and Macroeconomics," *Review of Economic Studies*, 60(1), 35–52.

Gerschnkron, A. (1954): *Economic backwardeness in historical perspective*. Belknap Press.

Graham, B. S., and J. Temple (2006): "Rich nations, poor nations: how much can multiple equilibria explain?," *Journal of Economic Growth*, 11, 5–41.

Griffith, R., S. Redding, and J. Van Reenen (2004): "Mapping the two faces of R&D: productivity growth in a panel of OECD industries," *The Review of Economics and Statistics*, 87, 475–494.

Hansson, P., and M. Henrekson (1994): "What makes a country socially capable of catching-up?," *Weltwirschafliches Archiv*, 130(4), 760–783.

Islam, N. (2003): "What have we learned from the convergence debate?," *Journal of Economic Surveys*, 17, 309–362.

J, C. (1977): *Modern Capitalism: its Growth and Transformation*. Martin Robertson, London.

Johnson, P. A. (2005): "A continuous state space approach to "Convergence by Parts"," *Economics Letters*, 86, 317–321.

Lall, S. (1997): *Learning from the Asian Tigers : Studies in Technology and Industrial Policy*. Palgrave MacMillan.

——— (2000a): "Selective industrial and trade policies in developing countries: theoretical and empirical issues," *QEH Working Paper Series*, 48.

——— (2000b): "The technological structure and performance of developing country manufactured exports, 1985-1998," *Oxford Development Studies*, 28 (3), 337–369.

——— (2001): *Competitiveness, technology and skills.* Edward Elgar, Cheltenham.

Lewis, W. A. (1954): "Economic Development with Unlimited Supplies of Labor," *Manchester School of Economic and Social Studies*, 22, 139–91.

Luenberger, D. G. (1979): *Introduction to dynamic systems.* Wiley, New York.

Maffezzoli, M. (2006): "Convergence Across Italian Regions and the Role of Technological Catch-Up," *The B.E. Journal of Macroeconomics*, 6, Iss.1 (Topics).

Matsuyama, K. (1992): "Agricultural Productivity, Comparative Advantage, and Economic Growth," *Journal of Economic Theory*, 58, 317–322.

Nelson, R., and E. Phelps (1966): "Investment in humans, technological diffusion and economic growth," *American Economic Review*, 56(2), 69–75.

Pack, H., and L. Westphal (1986): "Industrial strategy and technological change: theory versus reality," *Journal of Development Economics*, 22(1), 87–128.

Pavitt, K. (1984): "Sectoral patterns of technical change: towards a taxonomy and a theory," *Research Policy*, 13, 343373.

Quah, D. (1993): "Galton's fallacy and tests of the convergence hypothesis," *The Scandinavian Journal of Economics*, 95(4), 427–443.

——— (1996a): "Convergence empirics across economies with (some) capital mobility," *Journal of Economic Growth*, 1, 95–124.

Quah, D. T. (1996b): "Twin Peaks: Growth and Convergence in Models of Distribution Dynamics," *The Economic Journal*, 106, No.437, 1045–1055.

Rogers, M. (2003): *Knowledge, technological catch-up and economic growth.* Edgward Elgar.

Sala-i Martin, X. (1996): "The Classical Approach to Convergence Analysis," *Economic Journal*, 106, 1019–1036.

——— (2006): "The World Distribution of Income: Falling Poverty...and Convergence," *Quarterly Journal of Economics*, 121 (2), 351–281.

Sala-I-Martin, X., G. Doppelhofer, and R. Miller (2004): "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach," *American Economic Review*, 94(4), 813–835.

Scarpetta, S., and T. Tressel (2004): "Boosting Productivity via Innovation and Adoption of New Technologies: Any Role for Labor Market Institutions?," *World Bank Policy Research Working Paper*, 3273.

Sims, C. A. (1972): "Money, income, and causality," *American Economic Review*, 62 (4), 540–552.

Singh, L. (2006): "Innovations, High-Tech Trade and Industrial Development. Theory, Evidence and Policy.," *UNU-Wider Research Papers*.

Stockey, N. L., R. E. Lucas, and E. C. Prescott (1989): *Recursive methods in economic dynamics*. Harvard University Press, Cambridge MA.

Summers, R., and A. Heston (1991): "Penn World Tables (Mark 5): an expanded set of international comparisons, 1950-1988," *Quarterly Journal of Economics*, 106(2), 327–368.

UNCTAD (2002): "World Investment Report: Transnational Corporations and Export Competitiveness," Discussion paper.

——— (2003): "World Investment Report: FDI Policies for Development: National and International Perspectives," Discussion paper.

——— (2005): "World Investment Report: TNCs and the Internationalization of R&D," Discussion paper.