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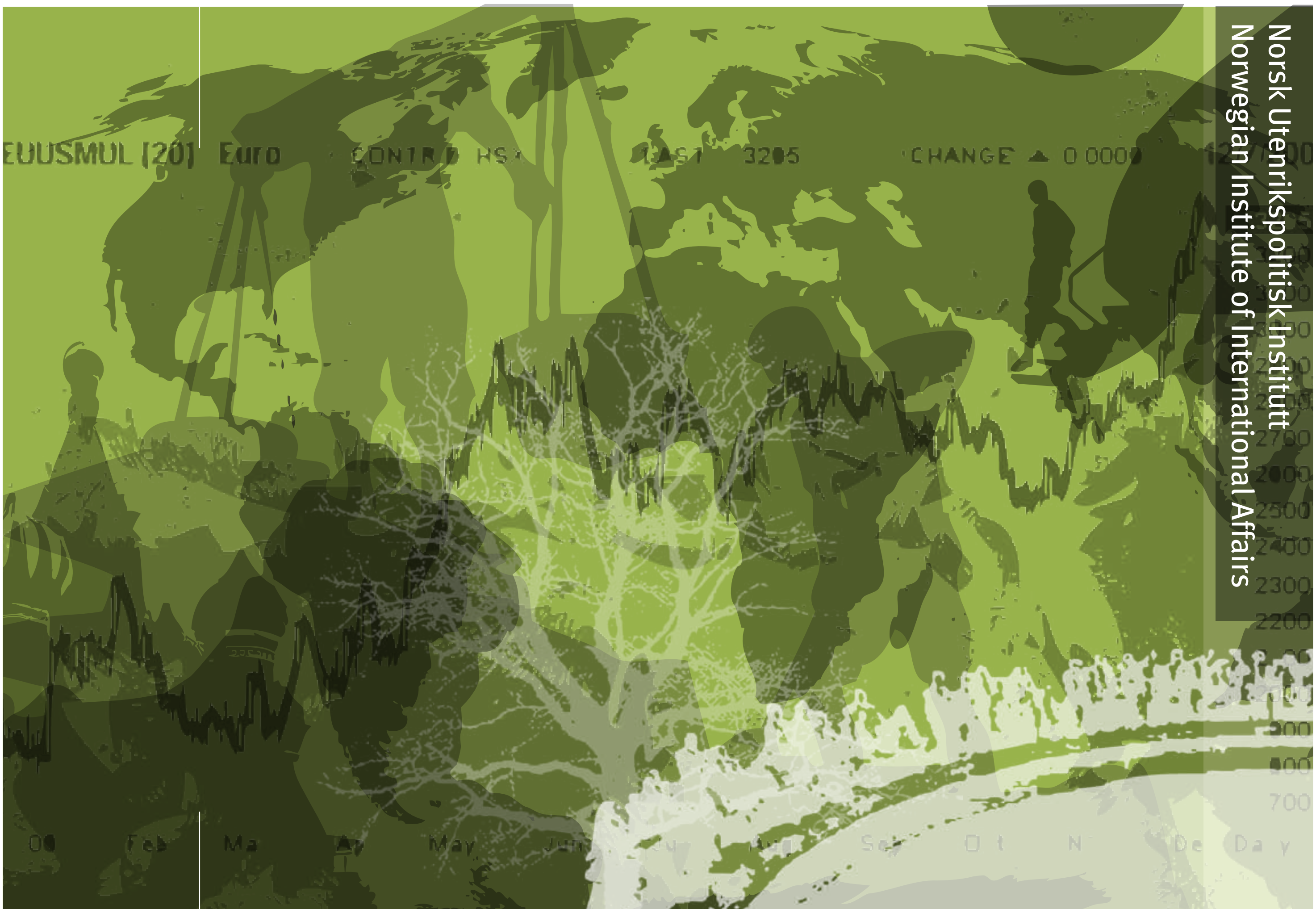

Norsk Utenrikspolitisk Institutt
Norwegian Institute of International Affairs

NUPI Working Paper 775

Department of International Economics

Publisher: Norwegian Institute of International Affairs

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Convergence Islands in Oceans of Divergence

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Abstract
In their influential study on productivity growth at the sector-level, Bernard and Jones (1996, BJ) observed convergence of aggregate labor productivity levels in 14 highly developed countries in 1970-1987. They also found evidence that this could be attributed to convergence in services productivity rather than in manufacturing. The main question this paper addresses is whether this result can be generalized to a broader set of countries. Several strands of growth theory suggest that thresholds with regard to a variety of issues can lead to multiple growth regimes, which are likely to lead to very heterogeneous patterns of convergence and divergence. To analyze this, we use econometric techniques that explicitly allow for identification of parameter heterogeneity (quantile regressions and quantile smoothing splines), both with regard to initial conditions and to performance conditional on these initial productivity levels. BJ's data are extended in several dimensions. The recently developed sectoral dataset we use spans the period 1970-2004 and covers 49 countries, including many developing countries. Overall, our findings suggest that convergence as found by BJ only applies to limited groups of country-sectors ('convergence islands'), whereas the biggest parts of our sample spaces can be considered as 'oceans of divergence'.

JEL: C14, O47
Keywords: sectoral productivity, convergence, parameter heterogeneity, quantile regression.

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1. Introduction

In their pioneering study on productivity convergence and divergence, Bernard and Jones (1996, BJ) brought analyses of these phenomena to the level of sectors, instead of following a large literature that had focused on the performance of national economies. The limited availability of good sector-level data led them to study sectors in a very small set of countries, which could hardly be seen as 'representative' of the world, i.e. 14 of the richest OECD countries. In this sense, their main finding of convergence of labor productivity levels in the services sectors resembles the situation that emerged in the early stages of analyzing convergence and divergence at the level of countries.

Baumol's (1986) seminal paper originally pointed out the existence of a convergence pattern within the club of more advanced economies. DeLong (1987), however, noted that Baumol's convergence result was not robust to the inclusion of other countries in the analysis; if the growth figures of initially equally rich but eventually poorer countries were added to the sample, divergence prevailed. Both Baumol (1986) and DeLong (1987) searched for a single convergence or divergence pattern that could describe their entire samples. Hence, it is as if Baumol did not see anything else than the 'island of convergence' he stood on. On the other hand, DeLong can be viewed as having sailed 'oceans of divergence', neglecting any islands of convergence. In a similar vein, we currently do not know if BJ's results of convergence in services productivity should be taken as an indicator of 'global' convergence in this sector, or rather as depicting the situation on an island of convergence.

This paper proposes empirical approaches focusing on the discovery of parameter heterogeneity in processes of sectoral convergence and divergence. Several growth theories propose thresholds of various kinds that could demarcate coexistent regimes of convergence and divergence.[1] We aim to provide more insights into the relative importance of both regimes (do we find convergence islands in oceans of divergence, or lakes of divergence in a Pangea of convergence?), explicitly taking into account that productivity growth patterns in, for instance, agriculture and services are unlikely to be characterized by similar patterns. Our new dataset contains labor productivity figures for the same six broad sectors as studied by BJ, for as many as 49

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1 See, for example, Abramovitz (1986), Azariadis and Drazen (1990), and Galor (1996), and section 2 of this paper.

countries in the period 1970-2004.[2] In what follows, we will use the term 'country-sectors' to denote the observations in our samples (i.e. the Dutch agricultural sector, or the Indonesian manufacturing sector).

We take the parameter heterogeneity issue as our starting point and propose estimation methods that are able to reconcile the standard convergence specification with the heterogeneity aspect. We use quantile smoothing splines (Koenker *et al*. 1994), which provides us with a richer view of the distributional dynamics of productivity. We obtain a characterization of relative productivity dynamics that allows for varying parameters along two dimensions. First, several regimes related to thresholds in initial conditions can be identified. We thus account for what we call 'X-heterogeneity'. Second, it allows for parameters that vary across the broad spectrum bounded by 'growth miracles' and 'growth disasters'. Such country-sectors attained productivity growth rates well above and well below what could be expected given their initial situation, respectively. We label this 'Y-heterogeneity'. For each sector, we thus determine regions in the space spanned by the values of X (initial labor productivity level) and Y (labor productivity growth) characterized by convergence and divergence, respectively.

The remainder of this paper is structured as follows. Section 2 presents a brief review of the recent growth literature that focuses on the emergence of thresholds and the interactions among determinants of growth. Section 3 introduces the estimation methods, while Section 4 describes the data set. Section 5 re-examines the productivity convergence hypothesis by using the standard OLS regression approach, and reassesses the results that were previously obtained by BJ in the context of advanced economies only. Section 6 then tackles the heterogeneity issue by using quantile regressions and quantile smoothing splines in the enlarged dataset. Section 7 concludes and summarizes the main results.

2 See Timmer and De Vries (2009) for details on construction and coverage. The data set is downloadable from www.ggdc.net.

2. Heterogeneity and Convergence

The convergence hypothesis has attracted a great deal of attention in growth theory. The standard formulation of the convergence mechanism implies that countries that start from a lower initial level of economic development (e.g. GDP per capita or some indicator of productivity) will experience higher long-run growth rates than already rich economies. This may be due either to decreasing returns to capital accumulation (the neoclassical interpretation, e.g. Mankiw *et al*., 1992), or to the non-immediate international diffusion of advanced technologies (the technology-gap interpretation, e.g. Fagerberg, 1994).

Recently, numerous applied growth studies have reconsidered the convergence hypothesis and criticized its standard formulation by focusing on the heterogeneity issue (see overviews in Temple, 1999, and Durlauf *et al*., 2005). Countries differ greatly in terms of their growth performance as well as the underlying set of economic and institutional factors that may explain it. Hence, it is questionable whether a single convergence regression may provide a reasonable representation of the dynamics of a large set of remarkably different economies (Harberger, 1987).

Empirical findings on polarization and non-linearities in the growth process have inspired a class of theoretical models that seek to understand the mechanisms causing the existence of groups of countries with different growth patterns. Which factors could cause thresholds between growth regimes and how could interactions between characteristics of economies play a role? Broadly speaking, most theories focus on two or more of the following factors: technological progress, population growth, and human capital formation. Below, we will briefly discuss some of these theories, which provide justifications for our empirical analysis in the next sections.

A seminal study in the field is the multiple equilibria model proposed by Azariadis and Drazen (1990). This model augments the neoclassical growth model with a new feature that produces multiple growth paths, threshold externalities in the accumulation of human capital. The threshold property and non-linearity of the model are explained by the mechanism through which individual agents accumulate human capital. Individual investments in education are assumed to depend on two factors: the time invested in human capital formation by each individual, and the private yield on education. The latter factor, in turn, is assumed to be a positive function of the average (aggregate) level of human capital in the economy. This formalization generates threshold externalities because the private incentives to invest in education increase rapidly above a certain threshold level of aggregate human capital, whereas below this given threshold low private yields cause stagnant growth of aggregate human capital and, hence, economic growth. In this model, different initial conditions in terms of human capital levels may therefore explain long-run dynamics of national economies that cannot be defined by a single set of parameters.

Galor and Moav (2000) presented a model in which non-linearities in the growth process are determined by the interaction of human capital and technological change. The basic idea is that an increase in the rate of technical progress tends to raise the relative demand for skilled labor and, hence, to increase the rate of return to private investments in education. The subsequent increase in the supply of educated individuals, in turn, acts to push technological change further. It is such a dynamic interaction between the processes of skill formation and technological upgrading that is at the heart of the cumulativeness of aggregate growth trajectories.

A related idea was proposed by Galor and Weil (2000) and Galor (2005), whose 'unified growth theory' models seek to explain the long-run transition of national economies from backward to more advanced stages of development. These models identify three main development stages – a 'Malthusian', 'post-Malthusian' and a 'modern growth regime' – and study the mechanisms explaining the transition across these long-run phases. In particular, a key insight of these studies is the observation that during the post-Malthusian phase a demographic transition occurred. The faster pace of technological change progressively increased the returns to human capital accumulation. This determined a change in parental attitude towards children's education, favoring a shift from quantity to quality, i.e. a higher preference for a small number of well-educated children. The resulting slowdown in population growth, in combination with the acceleration in human capital and technological accumulation, thus led many economies into a modern growth regime characterized by stable growth of per capita incomes. In this development stage framework, the existence of different country groups is explained as the outcome of different timing of transitions experienced by national economies in the shift from the post-Malthusian to the modern growth regime. Again, the emergence of thresholds implies that multiple sets of parameters are needed to describe the convergence processes correctly.

The model by Galor and Tsiddon (1997) is also consistent with this view, but it refines the multiple equilibria analysis by studying the interactions between technological progress, intergenerational earnings mobility and economic growth. In this overlapping-generations model economic agents live two periods. In the first of these, they must decide in what sectors to work and the level of education they seek to achieve in the future. As opposed to the previously discussed models, economic agents' human capital dynamics depends here on two main factors: their individual ability and their parental sector of employment (since empirical evidence indicates that earnings possibilities for a worker are higher if there is a close match with the parents' sector of employment). In periods of sustained technological progress, individual ability stands out as the more crucial factor for a worker's success, and high-skills agents tend to cluster in more technologically advanced sectors. This introduces greater inter-generational mobility in the economic system, and the concentration of talented individuals in high-tech branches fosters technological change and human capital even further. The cross-country implication of this cumulative dynamics is that initial differences in human capital endowments (and in the distribution of human capital across sectors) may lead to diverging dynamics of national economies.

Howitt (2000) and Howitt and Mayer-Foulkes (2005) refined the Schumpeterian growth model by arguing that cross-country differences in the rates of return to investments in human capital may shape the dynamics of absorptive capacity (see Abramovitz (1986) and Basu and Weil (1998) for related expositions) and thus generate three distinct convergence clubs: an *innovation*, an *implementation* and a *stagnation* group. The first is rich in terms of both innovative ability and absorptive capacity. The second is characterized by a much lower innovative capability, but its absorptive capacity is developed enough to enable an imitation-based catching up process. The stagnation group is instead poor in both aspects, and its distance *vis-à-vis* the other two groups tend to increase over time. Recently, Acemoglu *et al*. (2006) refined this type of model by arguing that a crucial source of dynamics for countries in the *innovation* group is constituted by the availability of a skilled pool of managers and entrepreneurs. The competition and selection process through which skilled managers emerge represents a crucial growth mechanism for countries that are already close to the technological frontier.

A different explanation for the existence of multiple growth paths is provided by Durlauf (1993) and Kelly (2001). Their formalizations focus on the dynamics of industrial sectors and the importance of intersectoral linkages to sustain the aggregate dynamics of the economic system. The main idea of Durlauf's (1993) model is that when intersectoral linkages among domestic industries are sufficiently strong, the growth of leading sectors propagates rapidly to the whole economy, whereas if such technological complementarities are not intense enough the aggregate economy follows a less dynamic growth path. Kelly (2001) refined this framework by building up a Schumpeterian quality-ladder model in which economies evolve by continuously producing new goods and progressively becoming more complex over time. Intersectoral linkages tend to become more complex and intense as new products are introduced in the economy, and threshold externalities thus emerge as the result of different degrees of complexity that characterize different groups of national economies.

This brief survey indicates the relevance of the heterogeneity issue and its implications for the convergence process. The literature clearly suggests that X- and Y-heterogeneity may be seen as complementary aspects of the convergence process. The literature discussed above indicates that different initial development levels may lead to situations in which multiple parameter sets are needed to correctly describe the relationship between productivity growth and initial productivity levels (X-heterogeneity). Furthermore, the interactions between initial productivity and a host of variables that often cannot be included in sector-level convergence regressions will lead to Y-heterogeneity. A country-sector employing much more human capital than most of its foreign counterparts with a similar initial labor productivity level is likely to end up as a growth miracle if lack of data prevents researchers to include human capital as an explanatory variable. For country-sectors with large stocks of unobserved human capital, convergence to the productivity leader might exist, while country-sectors with a similar initial labor productivity level but smaller stocks of unobserved human capital might fail to do so. The overview of the literature thus shows that the growth performance of growth miracles is probably very different from the growth performance of modal growers or growth disasters.[3]

Therefore, our paper provides an attempt to simultaneously consider these various sources of heterogeneity in the convergence process. First, we consider sectoral heterogeneity by explicitly focusing on the sector-level and by comparing the convergence patterns that we observe in different branches of the economy. Secondly, we employ an econometric methodology (quantile smoothing splines), which is able to simultaneously model X- and Y-heterogeneity by searching for threshold levels and non-linearities in the convergence process for different quantiles of the conditional growth distribution. Such an approach is novel in sector-level convergence studies: Dollar and Wolff (1988), Broadberry (1993) and BJ all related sectoral productivity growth to initial productivity levels by estimating a single equation without paying attention to potential parameter heterogeneity.

3 The terms ‘growth miracle’ and ‘growth disaster’ were coined by Temple (1999). See also Los and Timmer (2005). If our argument is taken to the extreme, the difference between ‘growth miracles’ and ‘growth disasters’ is only due to differences in unobserved variables.

3. Reconsidering Bernard and Jones (1996): A New Dataset

This section re-examines the findings by BJ for sectoral convergence in productivity levels. BJ focused on convergence in a sample of 14 OECD countries, for the period 1970-1987.[4] They found significant productivity convergence in services, public utilities, and construction. They did not find evidence for convergence in agriculture and manufacturing. This suggested that convergence as observed for total economies was driven by convergence in services and 'other industries'. In this section, we briefly introduce a comparable dataset that broadens BJ's country coverage and replicate BJ's analysis to assess the robustness of their results.

Our data set comprises 49 countries for the period 1970 to 2004. The countries are spread over various continents (only Africa is not represented) and feature very different initial labor productivity levels. Annual sectoral data for value added and employment for developing countries are obtained from the GGDC 10-sector database (Timmer and de Vries, 2007). The source for developed countries is the EU KLEMS database (see O'Mahony and Timmer, 2009). The database covers the ten main sectors of the economy as defined in the International Standard Industrial Classification, Revision 2 (ISIC rev. 2).[5] Together, these ten sectors make up the national economies of the countries included.

We measure labor productivity by gross value added per full-time equivalent. Sectoral employment figures include self-employed. To compare sectoral productivity levels across countries, we converted value added in national currencies to US dollars using GDP PPPs. First, we multiplied the sectoral shares of GDP in 1990 at current prices by GDP in 1990 Geary Khamis US dollars.[6] Next, we extrapolated sectoral value added in US dollars by the value added volume

4 The 14 countries in BJ's sample are Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom, the United States, and West Germany.

5 The main sectors are: agriculture, mining, manufacturing, public utilities, construction, wholesale and retail trade, transport storage and communication, financial services, and non-market services (community social and personal services, and government services).

6 Geary Khamis US$ 1990 GDP is available from the GGDC Total Economy database (The Conference Board, 2009).

series.[7] Appendix Table A1 reports average annual labor productivity growth rates by country and sector for the period 1970-2004.
To provide some evidence on the properties of our dataset, we start by analyzing the subsample of country-sectors studied in BJ, also considering the same time period (1970 to 1987). The model we estimate is

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i, \qquad i = 1, \ldots, n \qquad (1)$$

where Y_i is the labor productivity growth rate in country-sector i, X_i is the log of its initial sectoral labor productivity level and n is the number of countries for which we have observations for the sector under consideration. Of particular interest are the values and signs of β_1 in the equation. According to the simplest formulation of the β-convergence hypothesis, productivity convergence prevails if ordinary least squares regression yields a significant negative value for β_1. Table 1 shows this first set of estimation results.

Unlike BJ, we cannot report estimates for the total private sector, since our data does not allow us to isolate government activities. Nevertheless, their basic convergence result for the total private sector (second column, second last row in Table 1) is resembled in our almost identical result for the total economy (first columns, bottom row).

Table 1. Sectoral productivity convergence, OLS results, OECD sample

	1970-1987		1970-1993	
	β(CLdV)	β(BJ)	β(CLdV)	β(S)
Agriculture	-0.023**	-0.012	-0.024**	na
Mining	-0.039*	-0.029	-0.044**	na
Manufacturing	-0.047**	-0.026	-0.041**	-0.026*
Services	-0.034**	-0.024*	-0.032**	-0.024*
Utilities	-0.039**	-0.021*	-0.040**	na
Construction	-0.036**	-0.023*	-0.037**	na
Total private sector	na	-0.030**	na	-0.026**
Total economy	-0.035**	na	-0.032**	-0.025*

Note: Estimated coefficients relate to equation (1); 14 observations.
CLdV indicates our results; BJ refers to Bernard and Jones (1996); S refers to Sørensen (2001, Fig. 2, numerical data obtained via private communication).
** denotes significance at 1%, * denotes significance at 5%. na: not available. 14 observations.

7 Ideally, the appropriate conversion factor for productivity comparisons at the sectoral level should be based on a comparison of output prices by industry, rather than on expenditure prices. Expenditure PPPs exclude exports, include imports, take account of differences in trade and transport margins, include indirect taxes between countries, and they do not cover intermediate products. Because of limited availability of sectoral output PPPs, we do not use producer-price based PPPs and follow BJ and Mulder and de Groot (2007) in this respect.

In contrast to BJ, we find productivity convergence in all sectors, including agriculture and manufacturing. Two reasons can be held responsible for this. First, BJ used the OECD intersectoral database, whereas we use the recently constructed EU KLEMS database. The latter is a balanced panel, whereas the OECD intersectoral database is unbalanced for some countries (Australia, Belgium, Italy and the Netherlands). Second, and more importantly, BJ used a different PPP conversion. Their conversion is based on 1980 GDP PPPs as opposed to the 1990 GDP PPPs we use. Sørensen (2001) argued convincingly that the use of different base years is very likely to affect the estimates for β. He found that choosing a later base year tends to increase the significance of convergence in manufacturing productivity.[8] The right panel of Table 1 compares the results that Sørensen obtained for the BJ database if 1990 GDP PPPs had been applied for the period 1970-1993 and our results for this period.[9] In a qualitative sense, the results for our data are similar to those of Sørensen (2001). Convergence is found for both manufacturing and services. Although the coefficients are somewhat larger (in an absolute sense), which is most probably due to the use of OECD GDP PPPs by Sørensen and our use of The Conference Board (2009) GDP PPPs, these results lend some credibility to the part of our dataset covering BJ's countries and period.

In Table 2, we focus on a larger sample of 38 countries, of which 9 Latin American, 10 Asian, and 19 developed countries. We still consider the period studied by BJ, 1970-1987. Since we consider the 1990 PPP conversion for all countries, results in Table 2 can be directly compared with findings in the left panel of Table 1.

8 In a reply to Sørensen , Bernard and Jones (2001) argue that this systematic finding is a consequence of the Balassa-Samuelson effect. In countries with high labor productivity growth in manufacturing, relative manufacturing prices tend to decline rapidly; hence initial value added in manufacturing is underestimated in high productivity growth countries if GDP PPPs associated to a later base year are used to deflate its value added, leading to a tendency to find β-convergence. The use of sector-specific PPPs is to be preferred (see Sørensen and Schjerning, 2008; van Biesebroeck, 2009; and Inklaar and Timmer, 2009 for analyses for OECD countries based on such PPPs), but the required underlying data are lacking for our dataset containing developing countries.

9 We thank Anders Sørensen for making his undocumented estimates using 1990 GDP PPPs available to us.

Table 2. Sectoral productivity convergence (1970-1987), OLS results, large sample

	β
Agriculture	0.001
Mining	-0.033**
Manufacturing	-0.020**
Services	-0.006
Electricity/gas/water	-0.019*
Construction	-0.008
Total economy	-0.004

Note: Estimated coefficients relate to equation (1). ** denotes significance at 1%, * denotes significance at 5%. 38 observations.

After including developing countries, we find that convergence still holds for some sectors, but not for others. For mining, manufacturing, and public utilities we obtain a significant negative estimate of β, implying that there has been catch-up in labor productivity during this period. However, we do not find evidence for convergence in agriculture, services, and construction anymore. Thus, adding more countries to the regression affects the results in a qualitative sense. Our findings suggest that BJ's convergence results for services are not robust. In a sense, this key result of Bernard and Jones (1996) appears to be as sensitive to heterogeneity and selection bias as Baumol's (1986) result for total economies.

A conclusion that services sectors around the world are characterized by labor productivity divergence, however, would not pay justice to the strong convergence found for this sector the sizable subsample of countries analyzed in Table 1. Apparently, part of the sample is characterized by productivity convergence, while divergence prevails in other parts of the sample. The use of quantile regressions and quantile smoothing splines as introduced in the next section will allow for a richer analysis of sectoral convergence patterns in samples with substantial parameter heterogeneity.

4. Methods

Our empirical strategy will be as follows. First, we propose to use quantile regression analysis, which explicitly accounts for heterogeneity in conditional productivity growth rates (Y-heterogeneity).[10] This type of analysis allows for parameter heterogeneity across the conditional distribution of growth rates, but assumes that the parameters are identical for all values of the independent variable(s). Second, we argue that quantile smoothing splines enable us to consider Y-heterogeneity and X-heterogeneity simultaneously. This methodology also makes it possible to detect parameter heterogeneity between country-sectors with high or low *levels* of initial productivity. According to the theories reviewed in Section 2, such heterogeneity is likely to emerge.

4.1 Quantile regression

Quantile regression was pioneered in Koenker and Bassett (1978).[11] Quantile regression does not consider distributions of growth rates as such, but distributions of growth rates conditional on the values of covariates. In the context of the present paper, sectoral productivity growth rates are said to belong to the τth quantile if the conditional growth was higher than the proportion τ of the full set of growth rates, and lower than the proportion (1 - τ).

Median regression estimates (τ = 0.5) are obtained as the solution to the problem of minimizing the sum of absolute residuals. For other quantiles, a sum of asymmetrically weighted absolute residuals is minimized. Different weights are attached to positive and negative residuals. The minimization problem is:

$$\min_{\beta^{\tau} \in \Re} \sum_{i=1}^{n} \rho_{\tau}(Y_i - \beta_0^{\tau} - \beta_1^{\tau} X_i). \tag{2}$$

10 This approach, which does not collapse conditional distributions of productivity growth rates into their means would be able to address the main criticism against the β-convergence concept raised by Quah (1993). If the estimated convergence parameter were more or less uniform over the entire conditional distribution, the type of mobility between productivity classes emphasized by Quah would be limited. By contrast, indications of the probabilities of country-sectors moving from one productivity class to another (the transition probabilities in Quah's Markov chain setting) could be derived from estimates relating to several parts of the conditional productivity growth distributions.

11 See Koenker (2005) for an extended exposition.

In this equation, the loss function, ρ_τ, associated with differences between actual and predicted values is defined as

$$\rho_\tau(\varepsilon_i) = \varepsilon_i(\tau - I(\varepsilon_i < 0)), \tag{3}$$

where I represents the indicator function, equal to one if $\varepsilon < 0$ and zero otherwise ($\varepsilon_i = Y_i - \beta_0^\tau - \beta_1^\tau X_i$). By varying the parameter τ on the (0,1) interval, we can generate several quantile regressions and thus obtain a representation of the conditional growth distribution Y_i given initial productivity levels X_i.

If initial productivity only affects the location of the conditional growth distribution (that is, the estimated intercept is higher for high values of τ than for lower values, but the slope estimates are not significantly different), OLS is an appropriate method. In the context of this paper, however, quantile regressions allow us to show that patterns of convergence and divergence for growth miracle country-sectors often deviate strongly from those for growth disasters (Barreto and Hughes, 2004). Quantile regressions thus allow us to include the over-performing agricultural sector of Denmark into the same regression sample as the under-achieving agricultural sector of Venezuela. These country-sectors had similar labor productivity levels in 1970, but showed completely different productivity growth performances and may well have been driven by different 'laws of motion'.[12] Such laws are uncovered by quantile regressions applied to our large samples of heterogeneous country-sectors.

The quantile regression approach has two additional advantages over a standard OLS convergence estimator. First, quantile regressions identify differences between the behavior of successful versus unsuccessful country-sectors, but they do not per se address the question of *why* some country-sectors have been more successful than others. The latter question can only be addressed by including more potentially relevant variables. Differences in estimated regression equations for high and low quantiles can therefore point to omitted variables problems present in OLS estimations. Differences between the growth performances of miracles and disasters could be due to differences in human capital endowments, for example (see Section 2). Omitting human capital variables from OLS regressions can have severe consequences for the parameter estimates. The advantage of quantile regressions, however, is that omitted variables are just reflected in the division of country-sectors over high quantiles and low quantiles. These can be governed by different convergence patterns.

12 In the period 1970-2004, labor productivity growth in Denmark's agricultural sector grew on average by 3.5% per year, while Venezuela's corresponding figure amounted to a tiny 0.2%.

Secondly, quantile regressions also offer advantages over OLS if heteroscedasticity is present (see Koenker and Bassett, 1982). In OLS regressions, the well-known funnel-like scatterplots (see e.g. Baumol, 1986, and Pritchett, 1997), which show much more variability of productivity growth rates for countries with low initial productivity levels than for countries with high initial productivity levels, is only reflected in the structure of the residuals but not in the estimated parameters. As will be shown in the next section, quantile regressions show that convergence prevails for the miracles, while divergence dominates the growth performance of disasters. Consequently, they can offer a richer description of Y-heterogeneity.

4.2 Quantile smoothing splines

Quantile regressions cannot cope with what we call X-heterogeneity, i.e. heterogeneity of convergence patterns with respect to the set of explanatory variables. Hence, critics of cross-country regressions still have a valid point in questioning the usefulness of including, for instance, the agricultural sectors of Peru and Canada in a single quantile regression equation. Even though these country-sectors can be shown to belong to similar quantiles of the conditional growth distribution, threshold effects related to their different initial productivity levels (see Section 2) might well have prevented them from being governed by the same law of motion.[13]

In this paper, initial labor productivity is a natural candidate to use for identifying threshold levels and non-linearities in the growth process (Durlauf and Johnson, 1995). In line with the empirical and modelling literature in the convergence clubs tradition, the initial level of productivity is a commonly used proxy for its overall level of economic, technological and institutional development. Thus, in the context of this paper, X-heterogeneity refers to cross-country differences in sectoral productivity levels at the beginning of the estimation periods.

In order to simultaneously take Y- and X-heterogeneity into account, we rely again on work by Roger Koenker. Koenker *et al*. (1994) introduced quantile smoothing splines. For each quantile of the conditional growth distribution (Y-heterogeneity), the smoothing splines estimation method identifies threshold levels for the initial productivity (X-heterogeneity) and provides estimates of the convergence parameter for subsamples of observations above and below these thresholds.
A brief formal presentation of the method is as follows. He and Ng (1999) define ‘fidelity’ to the data as

[13] In 1970, the labor productivity level in the Canadese agricultural sector amounted to approximately 25,500 1990 US$ per worker, while this figure for Peru did not exceed 2,500 1990 US$ per worker.

$$\text{"fidelity"} = \sum_{i=1}^{n} \rho_\tau (y_i - g(x_i)) \ , \tag{4}$$

in which g is a smooth function, and measure ‘roughness’ as:

$$\text{"roughness"} = V(g') = \sum_{i=1}^{n-2} | \, g'(x_{i+1}) - g'(x_i \,) \, | \tag{5}$$

The τth quantile linear smoothing spline is the solution to:

$$\min_{g} \ \text{"fidelity"} + \lambda \, \text{"roughness"}. \tag{6}$$

The smoothing parameter λ in equation (6) is determined as the outcome of a trade-off between the fidelity of the fitted function to the data and its roughness. For λ = 0, the smoothing spline interpolates all observations. In that case, the fit is perfect but it is unlikely that any patterns common to a number of country-sectors can be discovered. For large values of λ, the smoothing spline produces a linear fit, without differences between coefficients for endogenously determined subsamples.

If there are no two observations with the same values for the covariates, the number p_λ of linearly interpolated y_is is at least 2 and at most the number of observations n. Hence, the convergence results depend on the choice for a particular value of λ. The number of linear segments in the fitted function associated with the smoothing parameter λ equals (n - p_λ + 1). Koenker *et al*. (1994) propose to base the value of λ on minimization of equation (7), which can be interpreted as a Schwarz Information Criterion for quantile smoothing splines:

$$SIC(p_\lambda) = \log\left[n^{-1} \sum_{i=1}^{n} p_\lambda \{ y_i - \hat{g}(x_i) \} \right] + \frac{1}{2} n^{-1} p_\lambda \log n \,, \tag{7}$$

in which $\hat{g}(x_i)$ indicates the estimated function. Equation (7) represents a trade-off between fit as measured by the log-likelihood value (captured by the first term), and parsimony as measured by the number of linearly interpolated y_is (captured by the second term). In our empirical applications of quantile smoothing splines, we choose the smoothing parameter λ such that the SIC criterion in (7) reaches its global minimum.

5. X- and Y-heterogeneity: Empirical Results

In line with a distance-to-frontier interpretation of the convergence equation (see, e.g. Fagerberg, 1994, and Aghion and Howitt, 2006), we now specify the regression equation in relative terms. X_i refers to the logarithm of the ratio of relative initial labor productivity levels (of follower and leader), whereas Y_i refers to relative labor productivity growth rates (follower minus leader). Further, we consider growth rates for three sub-periods, 1970-1982, 1982-1993, and 1993-2004. We consider these periods of 12 years as sufficiently long to reveal sources of long-run productivity change rather than to be driven by short-run business-cycle effects. We pool all observations. This procedure yields samples of 125 observations. The sample is slightly unbalanced due to the absence of Eastern European countries in the early subperiods.

5.1 Quantile regression analysis: accounting for Y-heterogeneity

We first contrast quantile regression results with those obtained from OLS regressions. In Table 3, OLS results are displayed first. Subsequently, three quantile estimates are presented, for $\tau = 0.25$, 0.5, and 0.75.[14]

[14] In view of the limited number of observations we do not produce regressions for 'extreme' percentiles (such as $\tau = 0.1$ and 0.9).

Table 3. Sectoral productivity convergence (1970-2004), OLS and quantile regression results, larger sample. Pooled subperiods.

			β	R^2
Agriculture	OLS		-0.001	0.002
	Quantile	0.25	0.001	0.001
		0.50	0.000	0.000
		0.75	-0.005	0.004
Mining	OLS		-0.029**	0.136
	Quantile	0.25	-0.019**	0.031
		0.50	-0.013*	0.040
		0.75	-0.032**	0.074
Manufacturing	OLS		-0.011*	0.041
	Quantile	0.25	-0.002	0.002
		0.50	-0.011	0.014
		0.75	-0.017*	0.045
Services	OLS		-0.007	0.029
	Quantile	0.25	0.001	0.000
		0.50	-0.004	0.010
		0.75	-0.019**	0.108
Public Utilities	OLS		-0.013**	0.064
	Quantile	0.25	-0.006	0.008
		0.50	-0.015**	0.052
		0.75	-0.016**	0.052
Construction	OLS		-0.009	0.026
	Quantile	0.25	0.001	0.001
		0.50	-0.015*	0.031
		0.75	-0.016*	0.047
Total economy	OLS		-0.008**	0.069
	Quantile	0.25	-0.002	0.001
		0.50	-0.011**	0.051
		0.75	-0.014**	0.114

Note: ** denotes significance at 1%, * indicates significance at 5%.
Significance indicators are based on *t*-tests using standard errors as suggested in Koenker and Basset (1982). For quantile regressions, the reported R^2 is the pseudo-R^2: (1-sum of weighted deviations about estimated quantile + sum of weighted deviations about raw quantile). The samples contain 125 observations.

For the total economy, the results reported in the bottom part of Table 3 indicate that the β-convergence pattern observed in the OLS regression is driven by the observations around or above the median of the conditional growth distribution. For the lower tail ($\tau = 0.25$), we find no indications of convergence. This result carries over to most sectors as well. The only sector, for which we find significant convergence at the lower end of the growth tail as well, is mining. By contrast, if we consider the upper tail (τ=0.75), we find convergence results that are broadly in line with those of OLS regressions. In manufacturing, for example, the OLS-result hinting at convergence appears to be driven completely by the 'growth miracles'. The results in Table 3 for services and construction also reveal that OLS-results indicating that convergence is absent might hide interesting distributional aspects. The quantile regressions give a more precise characterization of the productivity dynamics in these sectors, indicating opposite effects for the 25th and 75th percentiles of the conditional growth distributions.

Table 4. Tests for equality of individual coefficients estimated by the quantile regressions, 1970-2004 (Koenker and Xiao, 2002).

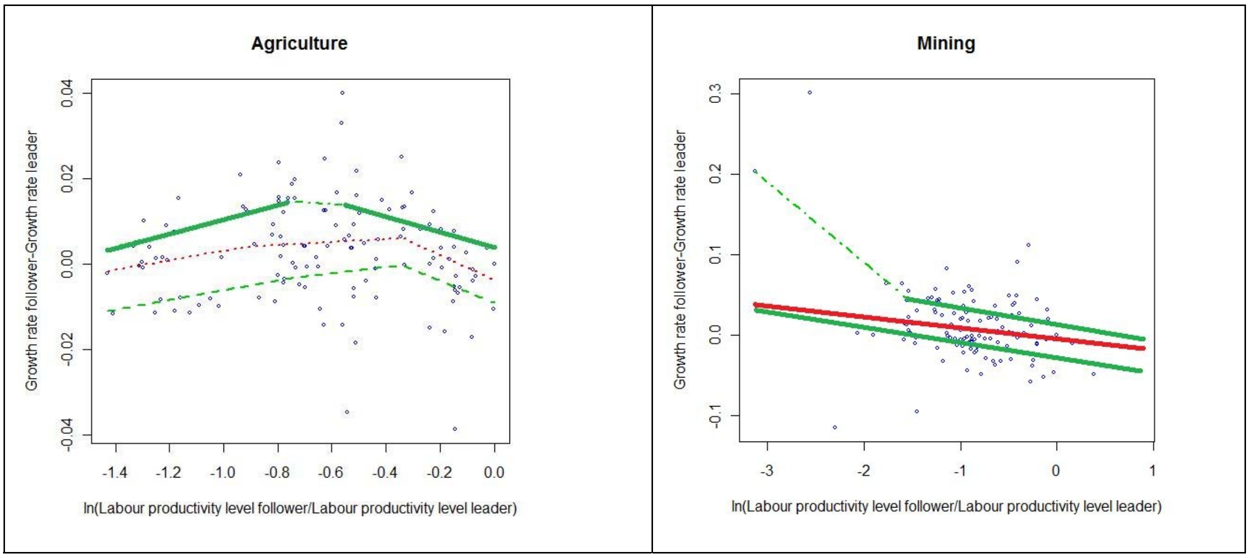
	Hypothesis	*F*-statistic	*p*-value
Agriculture	$\beta(0.25) = \beta(0.50)$	2.25	0.14
	$\beta(0.50) = \beta(0.75)$	1.33	0.25
	$\beta(0.25) = \beta(0.75)$	0.01	0.93
Mining	$\beta(0.25) = \beta(0.50)$	0.24	0.63
	$\beta(0.50) = \beta(0.75)$	0.14	0.70
	$\beta(0.25) = \beta(0.75)$	0.29	0.59
Manufacturing	$\beta(0.25) = \beta(0.50)$	0.44	0.51
	$\beta(0.50) = \beta(0.75)$	2.41	0.12
	$\beta(0.25) = \beta(0.75)$	3.33	0.07
Services	$\beta(0.25) = \beta(0.50)$	4.53	0.04
	$\beta(0.50) = \beta(0.75)$	1.84	0.18
	$\beta(0.25) = \beta(0.75)$	6.13	0.01
Electricity/gas/water	$\beta(0.25) = \beta(0.50)$	0.29	0.59
	$\beta(0.50) = \beta(0.75)$	1.57	0.21
	$\beta(0.25) = \beta(0.75)$	1.44	0.23
Construction	$\beta(0.25) = \beta(0.50)$	3.43	0.07
	$\beta(0.50) = \beta(0.75)$	1.06	0.31
	$\beta(0.25) = \beta(0.75)$	5.17	0.25
Total economy	$\beta(0.25) = \beta(0.50)$	2.69	0.10
	$\beta(0.50) = \beta(0.75)$	3.66	0.06
	$\beta(0.25) = \beta(0.75)$	11.32	0.00

To assess whether the differences between point estimates across quantiles are statistically significant, we perform a non-parametric test for the individual coefficients (Koenker and Xiao, 2002). This procedure tests the 'location shift' null hypothesis under which the β coefficient is constant across the conditional growth distribution, against the alternative hypothesis that β coefficient varies across the conditional growth distribution. Results from the Koenker-Xiao test are reported in Table 4. The differences between the estimates for the lower and higher tails for manufacturing and services as reported in Table 3 are significant, which implies that the dynamic patterns for 'miracle' country-sectors are sharply different from those for 'disasters' indeed. We find a similar result for the total economy sample.

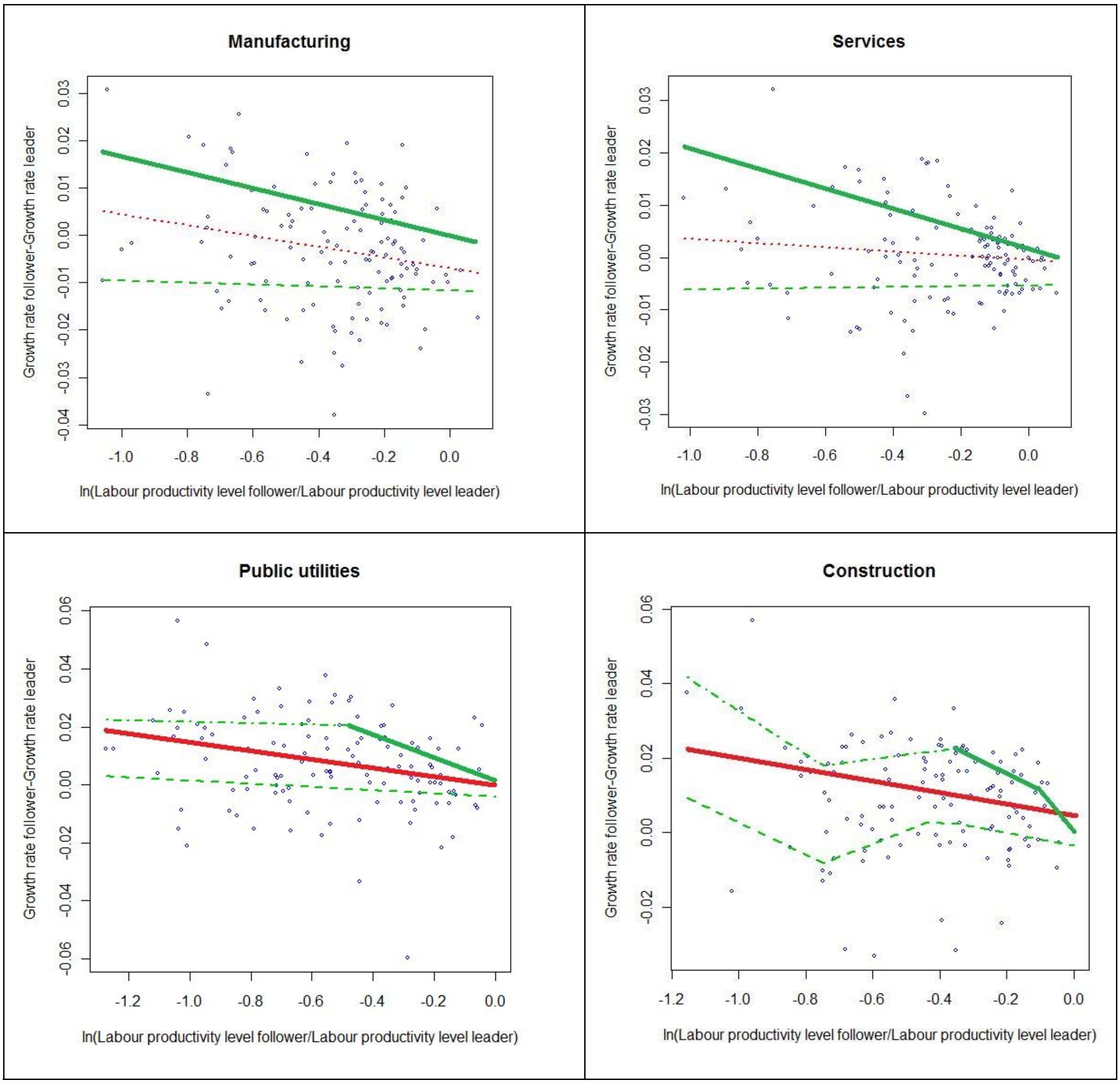
5.2 Quantile smoothing splines: accounting for X- and Y-heterogeneity

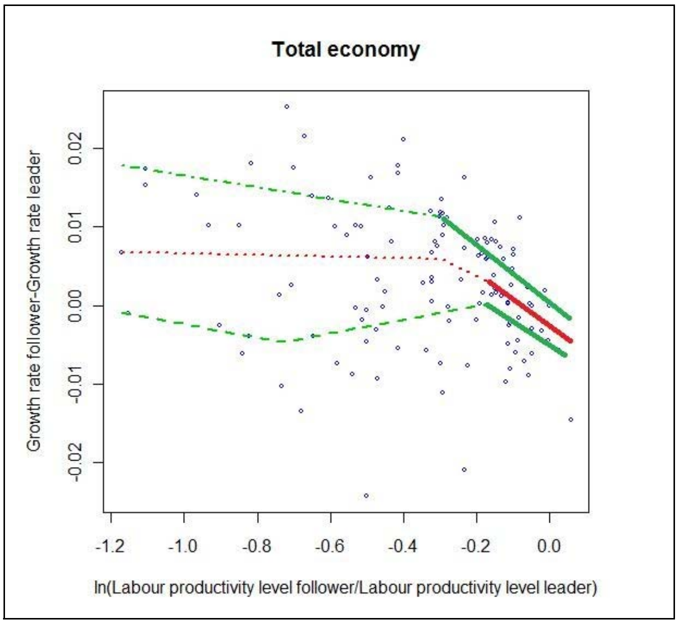
We now combine the analysis of Y-heterogeneity in growth rates with X-heterogeneity in initial labor productivity levels. Figure 1 shows quantile smoothing splines estimations (as introduced in Section 4.2) of convergence equations for each sector and for the total economy.[15] The X-axis displays (the log of) relative initial labor productivity levels, whereas growth rates relative to the leader are shown along the Y-axis. The smoothing parameter, λ, is chosen on the basis of the Schwarz criterion (equation (7)). For each sector and the total economy, we estimate three quantile smoothing splines. These refer to the 75th quantile (the upper dash-dotted line), the median quantile (the dotted line in the middle), and the 25th quantile (the dashed line at the bottom).

Figure 1. Quantile smoothing splines representations of sectoral convergence and divergence.



15 Unconstrained linear quantile smoothing splines were estimated using the COBS package version 1.1-3.5 (He and Ng, 1999).


Manufacturing
Services
Public utilities
Construction
Growth rate follower-Growth rate leader
ln(Labour productivity level follower/Labour productivity level leader)



Note: Solid lines indicate estimates significantly different from zero at 5%.

Our results provide evidence for the existence of threshold effects and non-linearities in the convergence process (X-heterogeneity) for some of the sectors and for the total economy. We will turn to this below, but would like to address the estimates for the slopes first.

A brief glance at the panels of Figure 1 might well lead to the conclusion that convergence prevailed for large ranges of initial productivity gaps, for the medians and the 75th quantiles. Many pieces of lines are downward sloping. If these were not significantly different from zero, however, they would not indicate convergence. Unfortunately, formal tests on model parameters obtained in a quantile smoothing spline estimation framework do not exist. To get reasonable insight into parameter significance, we opted for an informal approach. We ran quantile regressions on subsamples indicated by the splines. For agriculture, for example, the 75th percentile smoothing spline depicted in Figure 1 shows a clear kink for an initial log labor productivity gap of -0.744. Hence, a quantile regression estimate for the τ=0.75 was obtained for the subsample of observations with X_i smaller than or equal to -0.744. In Table 5, both types of estimates are documented. In general, the differences between the quantile smoothing splines estimates (β^{QS}) and the approximate quantile regression estimates for part of the sample (β^{PQR}) are small. This is particularly true for those subsamples for which the quantile regression estimates are found to be significantly different from zero. In Figure 1, these parts of the lines are indicated by solid lines.

We will restrict our discussion of the results in Figure 1 and Table 5 to the sectors that had large shares in total employment in a substantial number of countries (i.e., agriculture, manufacturing and services), and the total economy. For total economies, convergence is only found for countries with small initial gaps. For median and badly performing countries, only countries with initial productivity gaps to the U.S. smaller than those of Japan and Ireland in 1982 proved able to catch-up.[16] For growth miracles, which most probably experienced favorable situations concerning omitted variables (such as human capital stocks), somewhat larger initial gaps still led to convergence. The estimated threshold of -0.296 roughly corresponds to the gaps faced by Finland in 1970 and Singapore in 1982. For countries that were further behind in the initial periods, convergence to the U.S. productivity 'frontier' appeared to be virtually impossible, irrespective of their position in the conditional growth distribution.

X-heterogeneity appears as not to play a role in the convergence patterns of the manufacturing and services sectors. The apparent absence of thresholds implies that the results documented in Table 5 are identical to those in Table 3. For country-sectors in the highest parts of the conditional productivity growth distributions, convergence to the world leader was a global phenomenon. Irrespective of the initial productivity gap, these country-sectors managed to catch up. For the median country-sectors and country-sectors in the lower quantiles, however, divergence prevailed, even if the initial productivity gap was very small. The absence of thresholds in these sectors is rather remarkable, since the interaction effects of schooling, technology and institutional quality as stressed in the growth theories in Section 2 might have been expected to play an important role in these sectors.[17] We interpret the result of lack of convergence for growth disasters with a high initial labor productivity level as evidence that productivity growth by the leading countries in these sectors could only be matched if schooling, technological infrastructure and institutions (and most probably other important omitted factors) are sufficiently well-developed. Even for initially productive country-sectors, 'imitation' requires continuous investment in innovative capabilities.

16 The choice of subperiods implies that the initial productivity gaps correspond to 1970, 1982 and 1993.

17 Appendix B shows that the absence of kinks for manufacturing and services is not due to the value of the parameter λ that follows from adopting the Schwarz Information Criterion (equation (7)).

Table 5. Quantile smoothing splines: Heterogeneity in sectoral productivity convergence

τ=0.25			τ=0.50			τ=0.75		
LP-gap	β^{QS}	β^{PQR}	LP-gap	β^{QS}	β^{PQR}	LP-gap	β^{QS}	β^{PQR}
Agriculture								
>-1.431	0.011	0.001	>-1.431	0.011	0.006	>-1.431	0.016	0.025**
>-0.798	0.008	-0.001	>-0.918	0.004	0.003	>-0.744	-0.005	0.105
>-0.338	-0.026	-0.031	>-0.338	-0.029	-0.041	>-0.559	-0.018	-0.031**
Mining								
>-3.133	-0.019	-0.019**	>-3.133	-0.013	-0.013*	>-3.133	-0.10	-0.104
						>-1.538	-0.02	-0.020*
Manufacturing								
>-1.059	-0.002	-0.002	>-1.059	-0.011	-0.011	>-1.059	-0.017	-0.017*
Services								
>-1.018	0.001	0.001	>-1.018	-0.004	-0.004	>-1.018	-0.019	-0.019**
Public utilities								
>-1.275	-0.006	-0.006	>-1.275	-0.015	-0.015**	>-1.275	-0.002	0.000
						>-0.478	-0.04	-0.038**
Construction								
>-1.156	-0.044	-0.118	>-1.156	-0.015	-0.015*	>-1.156	-0.058	-0.079
>-0.749	0.035	0.059				>-0.749	0.012	0.012
>-0.444	-0.001	-0.204				>-0.348	-0.046	-0.063*
>-0.348	-0.017	-0.018				>-0.179	-0.083	-0.110**
Total economy								
>-1.171	-0.009	-0.017	>-1.171	-0.001	-0.004	>-1.171	-0.008	-0.005
>-0.734	0.009	0.012	>-0.296	-0.022	-0.029	>-0.296	-0.037	-0.040**
>-0.173	-0.03	-0.067*	>-0.173	-0.034	-0.047**			

Notes: LP-gap: Initial relative labor productivity ratio between country-sector and leading country sector (in logs). β^{QS} refers to the slope estimated by means of quantile smoothing splines, β^{PQR} refers to estimates using quantile regressions for subsamples identified by quantile smoothing splines. ** denotes significance at 1%, * indicates significance at 5%.

Agriculture is the only large sector (from a worldwide perspective) for which thresholds like those for total economies are found. Especially for the highest quantiles of its growth distribution, we find strong productivity divergence for country-sectors with low initial productivity levels. The first threshold (-0.798) corresponds to initial gaps similar to those of Denmark in 1970, Mexico in 1982 and Slovenia in 1993.[18] Only for the growth miracles initially rather close to the world leaders, significant convergence is found. The initial gap that demarcates the boundary between divergence and convergence (-0.559) corresponds to gaps like those of Spain in 1982 and the Slovak Republic in 1993. Interestingly, the identified thresholds vary across the conditional distribution of growth rates. Although the slope estimates are not significant at a 5% level, the maximum gaps that allowed for convergence towards the agricultural labor productivity leader are considerably larger for the well-performing country-sectors than for the median and underachieving agricultural country-sectors. Whereas omitted initial conditions of 'growth miracles' allowed for convergence of agricultural country-sectors with a gap smaller (in an absolute sense) than -0.559, country-sectors representing quantiles on the median or below were only in a convergence regime if they had initial gaps closer to zero than -0.338 (this threshold gap roughly corresponds to the situations in Belgium 1970, Ireland 1982 and Norway 1982).

It is interesting to compare these results for the agriculture branch with those previously obtained through quantile regression (see Table 4, section 6.1). We find an important difference that confirms the usefulness of the smoothing splines estimation method. Not accounting for X-heterogeneity leads to a different interpretation of Y-heterogeneity. The 25th quantile and the median for agriculture in Table 4 suggested in fact the existence of productivity divergence, whereas the 75th quantile indicated productivity convergence (by construction for the whole range of initial productivity levels). Accounting for X-heterogeneity as done in Figure 2, however, we find productivity divergence for all quantiles at lower relative productivity levels. In addition, we find productivity convergence for all quantiles at higher relative productivity levels.

The sector-specific results show that convergence is rather the exception than the rule. Only the mining sector shows convergent tendencies across the board. In most other sectors, only the productivity levels of 'growth miracles' tend to converge to the world leader. In sectors like public utilities and construction, convergence is only found for the well-performing country-sectors that started out with fairly limited productivity gaps. The simultaneous consideration of X- and

18 In 1970 and 1982, the Netherlands was the productivity leader in agriculture. In 1993, Belgium had surpassed the Netherlands.

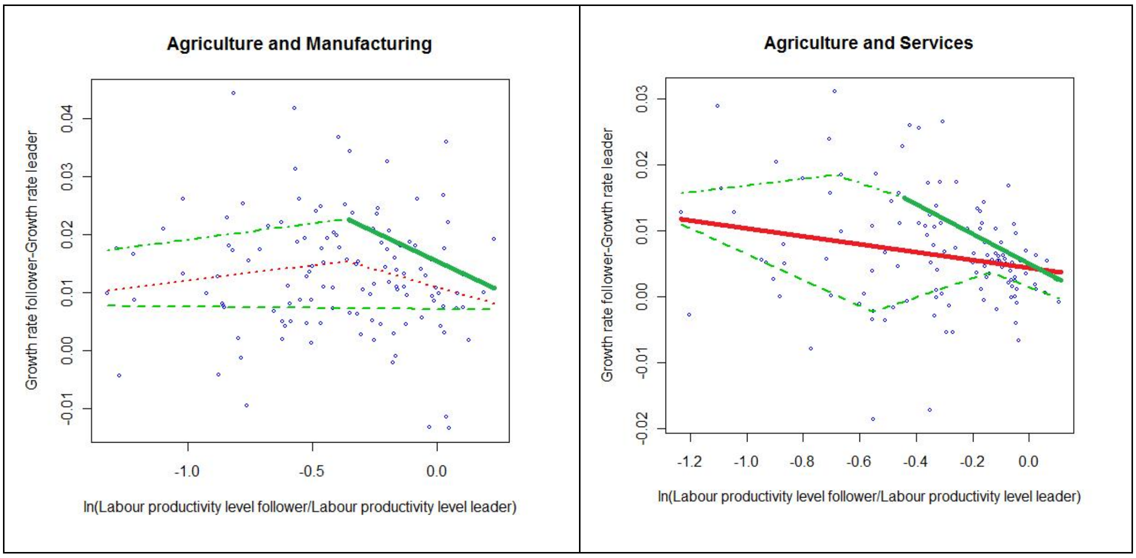
Y-heterogeneity clearly provides a more detailed characterization of the convergence pattern for different groups of country-sectors than OLS-regressions like those presented by BJ did. We feel that the observed patterns are most aptly described by 'convergence islands in oceans of divergence'. Most of these islands can be found in the Northeastern ranges of the map, i.e. country-sectors that were initially rather close to the world productivity leader and performed considerably better than what could be expected given this initial gap.

6. Sectors Driving Aggregate Patterns of Convergence and Divergence

A final question to be addressed is which sectors drove the convergence pattern observed for total economies in the bottom panel of Figure 1. BJ argued that their result (obtained for a limited set of relatively rich countries) of convergence for the total private sector was mainly driven by services. The graphs in Figure 1 clearly show that this result does not carry over to our extended set of countries when parameter heterogeneity is allowed for. A formal way to assess the similarity of detailed convergence/divergence patterns as found by applying quantile smoothing splines is not available, but comparing the total economy pattern in Figure 1 to results for single sectors and smaller aggregates of sectors might be insightful.
‘

Figure 1 indicates that no single industry generated a pattern broadly comparable to the pattern found for total economies. Hence, we have to turn to broader country-aggregates indeed.

Figure 2. Quantile smoothing splines for aggregates of major sectors.



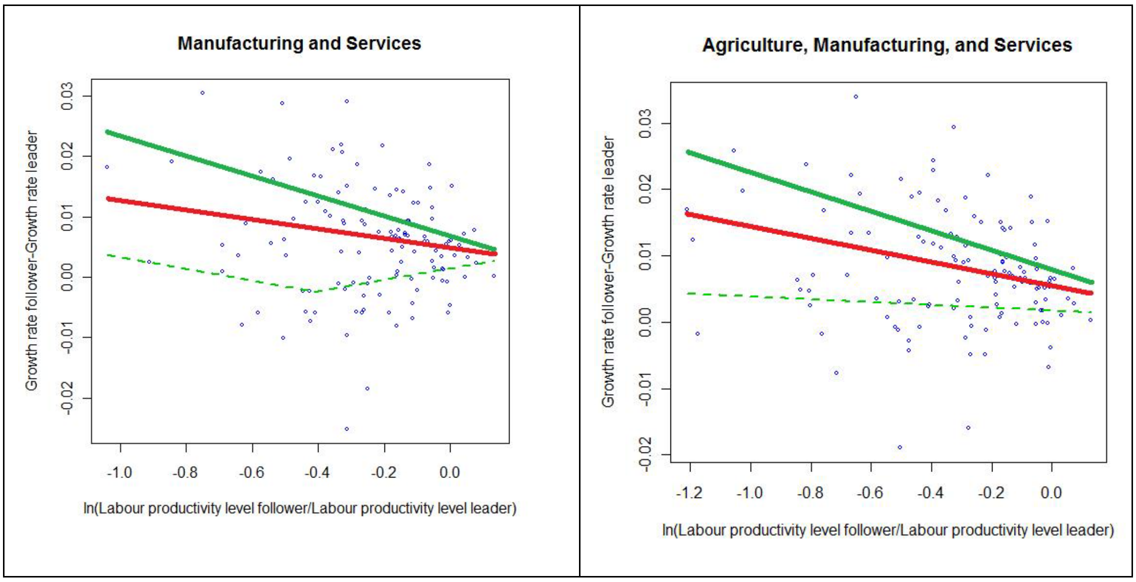
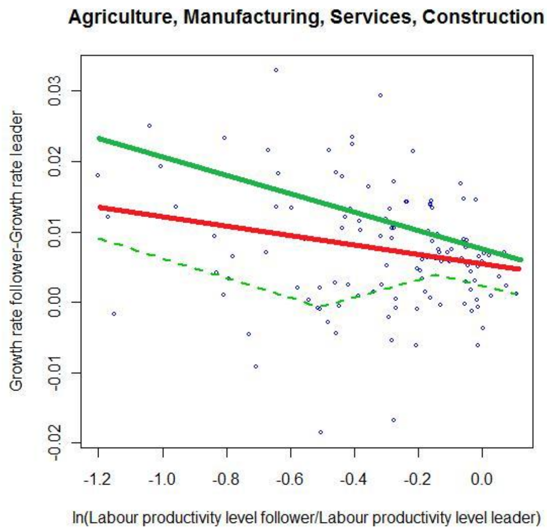


Figure 2 shows that no aggregate of the major sectors agriculture, manufacturing and services yields convergence patterns comparable to the result for total economies that only countries that are initially close to the world leader converge. If only the aggregate agriculture + manufacturing is studied, convergence is only found for growth miracles already close to the leader, country-aggregates in the middle and bottom part of the do not tend to converge. For the other aggregates, which all include services, at least some indication of global convergence is found (when the agriculture + manufacturing + services aggregates are considered, convergence appears as the rule for all country-aggregates except the worst-performing, irrespective of their initial labor productivity gaps).

Figure 3. Convergence pattern for total economies minus mining and public utilities



Finally, Figure 3 shows that even including construction in the broad aggregate does not lead to thresholds for the median and 75th percentile smoothing splines Instead this inclusion yields global convergence for the relatively well-performing country-aggregates. Apparently, even on average relatively small sectors like mining and public utilities play an important role in shaping the complex pattern of convergence and divergence for total economies in our broad set of countries. In this respect, a clear and simple conclusion like BJ drew ('total economy convergence is driven by convergence in services') cannot be drawn if a sample of heterogeneous countries is studied by means of methods that explicitly allow for heterogeneity in the convergence process.

7. Conclusions

This paper studies sectoral labor productivity convergence. Its main aim is to investigate to what extent the main result of the influential article by BJ carries over to a broader range of countries than the developed OECD countries studied by BJ. They found that convergence of productivity levels for the aggregated private sector was mainly driven by the services sector, while manufacturing hardly contributed to convergence.

In this study, we use a recently constructed sectoral dataset that covers 49 countries, including many countries in Latin America, Asia and a number of countries in Eastern Europe. Paying tribute to Harberger's (1987) famous words about inclusion of very different countries in a single regression equation, the empirical methods we choose emphasize the importance of several sources of heterogeneity. We first show that BJ's results are not robust against inclusion of developing countries. First, total economies (including government services) did not converge to the world leader. Second, at the sectoral level, we find indications of convergence in manufacturing, but not in services. Since our results for the subsample of countries covered in BJ are similar to those in BJ itself, these results warrant investigations allowing for parameter heterogeneity with regard to initial conditions and unobservable variables.

We first focus on Y-heterogeneity (the relation between sectoral productivity growth and initial productivity might be different for 'growth miracles' and 'growth disasters', for example due to unobservable variables), by means of quantile regressions. For most sectors, we find that convergence is only apparent in country-sectors that did very well in comparison to country-sectors with a comparable initial labor productivity level.

Next, we enrich this analysis of heterogeneity and convergence by making use of quantile smoothing splines. This estimation method identifies threshold effects (X-heterogeneity), while the distinction between miracles and disasters is maintained. The results show that the convergence hypothesis represents a useful model to describe the behavior of only a limited group of country-sectors. By contrast, most other observations in our sample, representing under-performing country-sectors and those below a minimum threshold level of initial development, have indeed experienced divergence in the last three-decade period. This result leads us to view the worldwide convergence pattern as ‘convergence islands in oceans of divergence’. This pattern is not driven by one or two sectors like in BJ’s analysis.

The results reported in this paper ask for further research efforts, first of all addressing data issues. Analyses of sectoral productivity dynamics would benefit greatly from data based on sectoral PPPs, to improve the international comparison of productivity levels. Inklaar and Timmer (2009) describe a recently released first dataset based on these preferred conversion factors, but their dataset needs to be expanded to cover less-developed countries. A further disaggregation of our manufacturing and services sectors into low-tech and high-tech sectors might shed light on the somewhat surprising result that we do not find the types of kinked convergence equations for these sectors, although modern growth theories suggest that threshold effects should be apparent in these sectors.

Data at the sector level regarding other variables than just productivity are also needed. Our analyses show that convergence patterns of ‘growth miracles’ are often different from those of ‘growth disasters’. If data on skill levels and institutional differences (just to mention two important candidates suggested by growth theory) were available at the sector level and could be included in analyses like ours, it would be possible to provide a better account of the performance of growth miracles and growth disasters. In this respect, too, some major efforts have produced results that justify some optimism. The EU KLEMS dataset (see O’Mahony and Timmer, 2009) contains information on inputs of low-skilled, medium-skilled and high-skilled labor at a detailed industry-level, while internationally comparable data on issues like trade liberalization have become available for important subsets of industries (see, e.g., Kalirajan, 2000, and Mattoo *et al*., 2006). Inclusion of variables like these might provide a more precise explanation of Y-heterogeneity and could allow for a testing framework that can address the threshold effects predicted by modern growth theories much more directly. This paper should be seen as providing evidence that such efforts could pay off, because estimating a worldwide valid, single convergence equation hides lots of heterogeneity. More efforts are needed to find empirical evidence for the causes that make convergence islands co-exist with oceans of divergence.

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Appendix A

Table A1. Labor productivity growth rates, 1970-2004

	Agriculture	Mining	Manufacturing	Services	Public Utilites	Construction	Total economy
Argentina	0.011	0.013	0.006	0.021	0.002	-0.001	0.002
Australia	0.010	0.006	0.021	0.027	0.011	0.010	0.011
Austria	0.014	0.005	0.016	0.015	0.006	0.005	0.010
Belgium	0.019	0.038	0.019	0.018	0.007	0.003	0.008
Bolivia	0.008	0.006	-0.005	0.004	-0.017	-0.009	-0.002
Brazil	0.016	0.015	0.001	0.029	0.002	-0.006	0.002
Canada	0.006	0.003	0.012	0.016	0.010	0.006	0.007
Chile	0.023	0.017	0.009	0.013	0.004	0.004	0.008
Colombia	0.008	0.011	0.001	0.012	-0.006	0.000	0.003
Costa Rica	0.009	0.013	0.001	-0.002	0.000	-0.003	0.002
Cyprus	0.022	0.036	0.024	0.027	-0.002	0.006	0.010
Czech republic	0.032	0.021	0.018	-0.002	-0.008	0.010	0.012
Denmark	0.035	0.059	0.012	0.014	0.005	0.006	0.009
Estonia	0.029	0.031	0.040	0.018	0.029	0.028	0.031
Finland	0.022	0.029	0.022	0.018	0.002	0.007	0.011
France	0.021	0.100	0.010	0.018	0.005	0.004	0.007
Germany	0.019	0.009	0.010	0.012	0.000	0.004	0.006
Greece	0.011	0.018	0.004	0.014	0.002	0.000	0.005
Hong Kong	-0.001	0.041	0.033	0.038	0.007	0.008	0.016
Hungary	0.034	0.018	0.019	0.006	0.007	0.012	0.015
India	0.004	0.011	0.011	0.017	-0.006	0.016	0.013
Indonesia	0.011	-0.018	0.020	0.018	0.005	0.011	0.013
Ireland	0.006	0.020	0.031	0.019	0.004	0.007	0.013
Italy	0.026	0.014	0.014	0.005	0.004	0.002	0.008
Japan	0.010	0.008	0.015	0.010	0.001	0.009	0.011
Korea	0.016	0.030	0.015	0.020	-0.001	0.016	0.016
Latvia	0.028	0.004	0.007	0.018	-0.003	0.021	0.020
Lithuania	0.032	0.047	0.043	0.036	0.022	0.026	0.035
Luxemburg	0.011	0.021	0.013	0.011	-0.001	0.014	0.011
Malaysia	0.002	0.000	0.000	0.006	-0.013	-0.001	0.000
Malta	0.000	0.026	0.008	0.000	0.000	0.000	0.002
Mexico	0.005	0.017	0.001	0.007	-0.012	-0.006	0.000
Netherlands	0.007	0.012	0.014	0.013	0.001	0.003	0.005
Norway	0.020	0.082	0.007	0.006	0.009	0.006	0.010
Peru	0.005	0.007	-0.001	0.009	0.010	-0.009	-0.003
Philippines	0.014	0.005	0.019	0.033	0.004	0.017	0.017
Poland	0.006	0.017	0.037	0.013	0.019	0.018	0.020
Portugal	0.018	0.017	0.011	0.021	0.007	0.013	0.014
Singapore	0.023	0.027	0.029	0.043	0.011	0.006	0.019
Slovak Republic	0.056	0.032	0.032	-0.001	0.012	0.008	0.018
Slovenia	0.013	0.022	0.027	0.017	0.006	0.009	0.017
Spain	0.028	0.015	0.010	0.017	0.004	0.003	0.008

Sweden	0.014	0.014	0.017	0.012	0.009	0.005	0.008
Switzerland	-0.014	0.007	0.014	0.013	-0.006	-0.002	0.001
Taiwan	0.017	0.029	0.020	0.026	0.009	0.018	0.021
Thailand	0.012	0.048	0.014	0.023	-0.007	0.006	0.017
United Kingdom	0.012	0.038	0.013	0.025	0.007	0.005	0.007
United States	0.021	0.009	0.015	0.001	-0.007	0.004	0.005
Venezuela	0.002	-0.014	-0.001	0.015	-0.015	-0.010	-0.008
Unweighted average	0.015	0.021	0.015	0.016	0.003	0.006	0.010

Notes: growth rates are computed as the coefficient on a time trend in the regression of the log (productivity) on a constant and a trend. Other industries include mining, construction, and public utilities. Market services include wholesale and retail trade, transport, storage and communication, and financial services. Non-market services include community, social and personal services, and government services. For many East European countries, including Cyprus, Malta, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia, data refer to 1995-2004. Switzerland 1990-2000, Norway 1970-2002, Australia 1970-2003, Canada 1970-2003, Bolivia 1970-2003, Hong Kong 1974-2004, Indonesia 1971-2004, Japan 1970-2003, Malaysia 1975-2004, Philippines 1971-2004.
Source: EU KLEMS database, March 2007 release (www.euklems.net) and GGDC 10-sector database (www.ggdc.net).

Appendix B

Section 4.2 in the main text explains the role of λ, which is basically a smoothing parameter for the estimated splines. In our empirical application of quantile smoothing splines, we choose the smoothing parameter λ such that the SIC criterion in (7) reaches its global minimum. The results indicate that X-heterogeneity appears as not to play a role in the convergence patterns of the manufacturing and services sectors.

We checked the vector of SIC criterion evaluated at lambda. For lambda values greater than one in manufacturing, the improvement in the SIC criterion is small. Similarly, for lambda values greater than 1,5, the SIC criterion hardly improves. These values therefore might serve as the lower boundary values to examine the absence of X-heterogeneity (if lambda is equal to zero, all values would be linearly interpolated). Appendix figure B1 shows that results for manufacturing and services are similar using the lower boundary values of lambda.

Figure B1. Quantile smoothing splines for manufacturing and services