Productivity Growth across Industries and Regions: A Production-Frontier Approach Applied to the Spanish Case*

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Abstract

This paper decomposes labor productivity growth into components attributable to technological change (shifts in the frontier), technological catch-up (movements towards the frontier), capital deepening and human capital accumulation. For that purpose, we employ a production-frontier approach applied to Spanish data disaggregated along two dimensions: regional and sectoral. Our main findings show that (1) technological change is clearly nonneutral, showing more intensity at high levels of capitalization; (2) capital deepening is the primary contributor to labor productivity growth, closely followed by human capital accumulation and technological change; (3) wide-spread efficiency losses appear to substantially impede productivity growth; (4) simple convergence regressions as well as analyses of the cross-region distribution of labor productivity in terms of the quadripartite decomposition support the existence of convergence in labor productivity, mainly driven by the higher efficiency losses exhibited by rich regions; (5) analysis of sectoral data shows marked differences in productivity performance as well as in the contribution of the four components across sectors; (6) aggregate productivity growth is mainly driven by intrasectoral productivity dynamics rather than structural change (sectoral shifts).

1 Introduction

Since the seminal work of Färe et al. (1994), there has been a long-standing debate over the role of technology versus physical capital deepening in explaining labor productivity

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improvements across countries.[1] Two main reasons are responsible for this interest. First, the different predictions of Neoclassical growth theory pioneered by the work of Solow (1956) and Cass (1965), and endogenous growth theory regarding the primary source of growth. While the former considers exogenous technological progress as the source of permanent growth changes, endogenous growth models like those of Romer (1986) and Lucas (1988) point to physical and human capital accumulation as the main engines of growth.[2] Second, the increasing availability of cross-country datasets such as the Penn World Table (Summers and Heston (1991)) has allowed the empirical analysis of these issues over relatively long periods.[3]

Using a nonparametric frontier approach, some studies have attempted to determine the relative contributions to growth of technological change, technological catch-up and factor accumulation for different samples of countries. Färe et al. (1994) focus on a sample of 17 industrialized countries over the period 1979−1988, finding that U.S. productivity growth is slightly higher than average, all of which was driven by technological change. In addition, Japan exhibited the highest productivity growth, with half of it being caused by efficiency gains.

Employing similar deterministic nonparametric frontier methods, Kumar and Russell (2002) find that both growth and international income polarization are driven primarily by capital deepening (i.e. changes in the physical capital to labor ratio) in a wide sample of 57 countries over the period 1965−1990. Henderson and Russell (2005) further extend Kumar and Russell (2002) study by adding human capital as an additional input into production. Their analysis indicates that 1) labor productivity growth is driven predominantly by physical and human capital accumulation, and 2) international polarization is caused primarily by technological catch-up via efficiency changes. In stark contrast stand the results by Hall and Jones (1999) who, employing a parametric growth accounting exercise, find that physical and human capital accumulation do not account for a large proportion of productivity differences across countries.

Despite this considerable effort to investigate these issues at the aggregate level, not much work has been conducted at the sectoral level within a specific country or across countries. Margaritis et al. (2007) constitute a clear exception. By decomposing labor productivity growth into technological change, efficiency changes and capital deepening for a panel of 19 OECD countries over the period 1979−2002, they find physical capital accumulation and technological change to be the first and second growth engines, respectively. Their analysis of the contribution of productivity growth within industries and sectoral composition indicates that aggregate productivity changes are predominantly driven by

[1] Throughout the text, we will interchangeably use labor productivity and productivity.

[2] Subsequent models like those of Romer (1990) and Grossman and Helpman (1991) have attempted to endogenize technological progress by making it directly depend on the resources devoted to innovate through research and development (R&D). Other theoretical models like Nelson and Phelps (1966), Barro and Sala-i Martín (1997) and empirical models like Benhabib and Spiegel (1994) have emphasized the role of technology diffusion -leading to catching-up on the part of the lagging economies to the productivity levels of the best-practice frontier economy- as the main source of growth and convergence over extended periods of time.

[3] For an authoritative review of the empirics behind the different theories of growth and the main problems encountered, see Temple (1999).

within sectoral effects with very little contribution resulting from structural change, i.e. sectoral shifts.

In the parallel literature of convergence, the role of technology has been largely ignored. Quoting Bernard and Jones (1996c), "to the extent that the adoption and accumulation of technologies is important for convergence, the empirical convergence literature to date is misguided." They then called for future work on growth and convergence placing more emphasis on technology. In addition, they point out the need to move to sectoral level analysis to examine convergence.[4] As they note, the analysis of the manufacturing sector should be particularly relevant given that most R&D and international trade takes place in this sector. Unexpectedly however, Bernard and Jones (1996b) find no evidence of labor productivity convergence in the manufacturing sector across 14 OECD countries from 1970 to 1987. This contrasts with the finding of convergence in the services sector and the aggregate. These results carry over to the analysis of convergence in multifactor productivity as shown by Bernard and Jones (1996a).[5]

The objective of this paper is to develop a nexus between two important literatures: the deterministic frontier production function literature based on the pioneering work of Farrell (1957) and the investigation of the sources of aggregate labor productivity growth by disaggregating the data along two dimensions: at the sectoral and regional levels. Hence, to the best of our knowledge, this is the first study applying the production frontier approach of Färe et al. (1994) and Kumar and Russell (2002) to examine the sources of aggregate labor productivity growth using this double level of disaggregation. More specifically, we will focus on the Spanish economy over the period 1980−2003 as a laboratory for the analysis of labor productivity dynamics. Unlike the case of most industrialized countries, with the possible exception of the United States, we have access to consistent and detailed data series for the private productive sector on gross value added at factor cost, employment, physical capital stocks and several proxies for human capital stocks across both important dimensions: regional and sectoral.[6] The advantage of using this nonparametric production frontier approach is that is a purely data-driven method, which does not require specification of any particular production function technology (e.g. Cobb-Douglas or CES), nor it does not require the existence of perfectly competitive markets or Hicks-neutral technological change. Unlike the standard regression-based growth accounting literature, this framework allows us to distinguish between catching-up (movements towards the frontier) and technological change (shifts in the frontier).

[4] Kumar and Russell (2002), in their concluding section, also called for a more disaggregated analysis of convergence and growth sources.

[5] Earlier studies like Barro and Sala-i Martín (1991) and Barro and Sala-i Martín (1992) also emphasized the importance of sectoral specialization for conditional convergence, since economies specialized in less productive sectors will be characterized by a lower steady state.

[6] Escribá and Murgui (2001) also investigate the dynamics of growth and convergence in productivity across the Spanish regions over the period 1980−1995 using sectoral level data, but through conventional growth accounting techniques. They find multifactor productivity (TFP) changes to be the main determinant of convergence in labor productivity. Within sectoral dynamics appear to explain 56% of convergence in TFP, while the rest is explained by sectoral shifts leading to structural change. However, it is important to point out that this approach cannot distinguish between technological change (caused by technological innovation) and efficiency changes (caused by technological catch-up).

Our analysis will allow us to provide insights into several issues: (i) the contribution to labor productivity growth in total industry (sum of all sectors), five sectors and 17 regions attributable to 1) technological change leading to upward shifts in the nation-wide or sector-specific production frontiers, 2) technological catch-up resulting from movements toward or away from the frontier, 3) (physical) capital deepening and 4) human capital accumulation; (ii) whether intrasectoral productivity dynamics accord with aggregate productivity changes, (iii) whether structural change -explained by shifting sectoral shares of employment- has affected regional and aggregate labor productivity performance.

A related paper that focuses on the effect of efficiency changes on convergence of labor productivity rather than on the sources of productivity growth is that of Maudos et al. (2000). Applying a Data Envelopment Analysis to Spanish regional data for five sectors over the period 1964−1993, they find that efficiency variations due to structural change in productive specialization across regions as well as intra-sector efficiency gains were a significant source of convergence for most of the period analyzed. Our paper differs from the former in several respects (beyond the analysis of a different time period and the use of a more consistent dataset). First, our analysis not only calculates efficiency scores per se at the sectoral level for each region, but also tries to investigate other sources of labor productivity growth such as technological change, capital deepening and human capital accumulation. This allows us to provide the relative growth contribution attributable to each component. Second, we try to shed some light on the effect of each factor on productivity convergence not only through simple cross-sectional regressions, but also by examining the evolution of the entire cross-section distribution and the degree to which each of the four components of productivity change accounts for such productivity dynamics. This is done through the strategy of constructing counterfactual labor productivity distributions to isolate the effect of each component and comparing it with the actual distribution.[7] This is because, as noted by Quah (1993), Quah (1996a) and Quah (1996c), empirical exercises solely based on the first moments of the distribution can yield misleading inferences regarding convergence dynamics.

Our results indicate that (1) technological change is clearly not Hicks-neutral; (2) capital deepening is the primary contributor to labor productivity growth, closely followed by human capital accumulation and technological change; (3) wide-spread efficiency losses appear to substantially inhibit productivity growth; (4) simple convergence regressions as well as the examination of the cross-region distribution of labor productivity in terms of the quadripartite decomposition support the existence of convergence in labor productivity, mainly driven by the higher efficiency losses exhibited by rich regions relative to poor ones; (5) analysis of sectoral data shows marked differences in productivity performance as well as in the contribution of the four components across sectors; (6) aggregate productivity growth is mainly driven by intrasectoral productivity dynamics -primarily in manufacturing and agriculture- rather than structural change (sectoral shifts); (7) for both total industry and the five sectors separately, productivity dynamics during the subperiod 1980−1994 appear to predominantly drive the outcome for the whole period. This in turn underlines the fact that the subperiod 1995−2003 constitutes a lost decade in terms of

[7] See Jones (1997) for an analysis of cross-country disparities by examining the world income distribution.

labor productivity growth since productivity has slightly regressed due to efficiency losses, zero technological change and very low contribution from capital deepening.

The rest of the article is structured as follows: Section 2 briefly reviews the literature and describes the data. Section 3 presents the statistical methods behind the nonparametric frontier approach of Henderson and Russell (2005), the quadripartite decomposition of labor productivity into its components and the comparison of unknown densities. Section 4 presents the results for total industry and Section 5 does so for the five sectors considered. It also sheds some light on the proportion that intra-sectoral dynamics and sectoral shifts explain aggregate labor productivity growth. Section 6 summarizes the main findings and then concludes.

2 Data Issues and Brief Literature Review

2.1 Brief Literature Review

The great availability of regional and sectoral data for the Spanish economy explains the existence of some previous studies investigating, from other perspectives, growth and convergence issues in Spain. As a matter of fact, Tortosa-Ausina et al. (2005) use distribution dynamics techniques to investigate convergence across the Spanish provinces over the past decades. Their results indicate the existence of convergence in labor productivity, TFP and capital intensity, while the convergence patterns in per capita income are less marked. Using a similar approach, Hierro and Maza (forthcoming) find evidence of convergence at the provincial level for Spain over the period 1996−2005, with foreign-born internal migration exerting a strong influence on income convergence.

Applying a distribution dynamics approach to the analysis of income disparities at the level of the regions of the European Union, López-Bazo et al. (1999) find that the process of income convergence has come to a halt in the late 1970s. This has led to income polarization as held by the "twin-peaks" hypothesis of Quah (1996b) and Quah (1996c). The same pattern is found for the Spanish regions. These findings are corroborated by Ezcurra et al. (2005) using a similar distributional approach. They also find that specific institutional characteristics of countries (i.e. the country effect) condition regional growth dynamics within a country (see also Quah (1996b)), while the production mix does not appear to affect significantly income disparities.[8]

Estimating a descriptive growth model that allows for factor accumulation, technological diffusion, rate effects from human capital and unobserved regional factors, de la Fuente (2002) find evidence that technological catch-up, the equalization of educational levels and the redistribution of the labor force explains most of the fall in regional disparities in Spain over the period 1955−1991. The unexplained TFP differentials across regions

[8]Fingleton (1999) emphasizes the role of spillovers among adjacent regions in convergence across the EU regions using spatial econometrics techniques. See also Cheshire and Carbonaro (1996), Esteban (2000) and Le Gallo (2004) for analyses of income disparities across the European regions using conventional regression and spatial econometrics techniques.

led him to call for additional work on a more disaggregated analysis using sectoral-level data.

2.2 Data Description

The dataset employed for gross value added at factor cost (GVA hereafter), employment and net physical capital stock series is BD.MORES.2000 (see Dabán et al. (2002) and de Bustos et al. (2008)). This database provides magnitudes expressed in 2000 Euros for 17 regions (*comunidades autónomas*) following the sectoral classification R-17. We keep up with the extant literature by focusing on the private productive sector, i.e. excluding the housing and public sectors. Hence, we exclude (1) imputed rents (*alquileres imputados*) and non-market services (*servicios no destinados a la venta*) from GVA, and (2) residential structures and public capital from the net stock of physical capital. The net stocks of physical capital are estimated using the standard perpetual inventory method using depreciation rates and initial stocks in 1964 specific to each sector. In the estimation, they employ sector-specific deflators for gross fixed capital formation.[9]

Unlike alternative data sources, this dataset employs region-specific and sector-specific deflators to compute the disaggregated GVA figures for the period 1980−2003. In our analysis we follow previous work by aggregating into five main sectors: agriculture (including fishery), manufacturing (excluding the energy sector), energy, construction and market services (henceforth services). The advantages of using this dataset are that: 1) is constructed on the basis of official data sources like the Regional Accounts (with base year 2000) provided by the Spanish Statistical Institute (*Instituto Nacional de Estadística: INE*);[10] and 2) is carefully and consistently constructed on the basis of all available primary information, which provides full comparability across regions, sectors and over time.

As a measure of human capital for aggregate (total industry), regions and sectors, we employ the average years of schooling in the employed population provided by the Valencian Institute for Economic Research (*IVIE*) in collaboration with Bancaja (see Serrano and Soler (2008)). The length of each schooling cycle is that associated with the educational law called LOGSE (see page 25 of Serrano and Soler (2008) for more details). In addition, we adopt the Hall and Jones (1999) procedure and the Psacharopoulos (1994) survey of wage equations evaluating the returns to education to transform these average years of schooling data into a human capital index. In particular, let ϵ_t^j represent the average number of years of education of the adult population in country j at time t and

[9] According to Dabán et al. (2002), the net stock of private productive physical capital provided by the BD.MORES.2000 dataset appears more in line (than several alternative physical capital stock estimates for the Spanish economy) with the estimates in international databases like the Business Sector Database (OECD).

[10] As noted by de Bustos et al. (2008), the BD.MORES.2000 provides series which are compatible at the aggregate and sectoral level with the official Regional and National Accounts in both current and constant prices. The BD.MORES.2000 provides data mainly from 1980, which is the first year in which INE began supplying official Regional Accounts series on GVA, employment, gross fixed capital formation and other basic variables for the 17 Spanish regions.

define labor in efficiency units in country j at time t by

$$\widehat{L}_t^j = H_t^j L_t^j = h\left(\epsilon_t^j\right) L_t^j = e^{\phi\left(\epsilon_t^j\right)} L_t^j \tag{1}$$

where ϕ is a piecewise linear function, with a zero intercept and a slope of 0.134 through the fourth year of education, 0.101 for the next four years, and 0.068 for education beyond the eighth year. Clearly, the rate of return to education (where ϕ is differentiable) is

$$\frac{d \ln h\left(\epsilon_t^j\right)}{d\epsilon_t^j} = \phi'\left(\epsilon_t^j\right) \tag{2}$$

and $h(0) = 1$.

An alternative human capital proxy only available for each region (but not at the sectoral level) is the series labelled as "human-capital equivalent", which is computed following the approach proposed by Mulligan and Sala-i Martín (2000). They measure the human capital of a worker as a function of the number of "zero-skill workers" (with no education or experience) that would be necessary to attain the worker's productive capacity, measured by accumulated experience and education. The rationale behind this measure is the fact that firms, when paying workers, are indirectly paying for the services provided by the human capital supplied. Hence, relative wages are employed to capture the human capital endowment of a worker, given her experience (proxied by age) and schooling level, to the wage of a 20-year-old man with no schooling.

Taken as a whole, the data employed can be thought of as the richest dataset allowing for an analysis of the sources of growth and convergence with such a high degree of detail (sectoral and regional), which would not be feasible for any other country, excepting probably the U.S. economy.

3 Methodology

3.1 Data Envelopment Analysis

Following (the nonparametric approach of) Henderson and Russell (2005), we construct Spain's production-frontier and the associated efficiency levels of individual regional economies (distances from the frontier) by using Data Envelopment Analysis.[11] The basic idea is to envelop the data in the smallest convex cone, where the upper boundary of this set represents the "best practice" production-frontier. One of the major benefits of this approach is that it does not require prior specification of the functional form of the technology. It is a data driven approach, implemented with standard mathematical programming algorithms, which allows the data to tell the form of the production function (see Kneip et al. (1998) for a proof of consistency for the Data Envelopment Analysis estimator, as well as Kneip et al. (2008) for its limiting distribution).

[11] A fully general exposition of this approach, aimed primarily at economists, can be found in Färe et al. (1985); the management science approach to essentially the same methods began with the paper by Charnes et al. (1994), who coined the evocative term "Data Envelopment Analysis".

Our technology contains four macroeconomic variables: aggregate output and three aggregate inputs – labor, physical capital, and human capital. Let $\langle Y_{it}, K_{it}, L_{it}, H_{it}\rangle$, $t = 1, 2, \ldots, T$, $i = 1, 2, \ldots, N$, represent T observations on these four variables for each of the N regions. We adopt a standard approach in the macroeconomic literature and assume that human capital enters the technology as a multiplicative augmentation of physical labor input, so that our NT observations are $\langle Y_{it}, K_{it}, \hat{L}_{it}\rangle$, $t = 1, 2, \ldots, T$, $i = 1, 2, \ldots, N$, where $\hat{L}_{it} = L_{it}H_{it}$ is the amount of labor input measured in *efficiency* units in region i at time t. The constant returns to scale technology for the world in period t is constructed by using all the data up to that point in time as

$$\mathcal{T}_t = \left\{ \begin{array}{c} \left\langle Y, \hat{L}, K \right\rangle \in \Re^3_+ \mid Y \leq \sum\limits_{\tau \leq t} \sum\limits_i z_{i\tau} Y_{i\tau},\ \hat{L} \geq \sum\limits_{\tau \leq t} \sum\limits_i z_{i\tau} \hat{L}_{i\tau}, \\ K \geq \sum\limits_{\tau \leq t} \sum\limits_i z_{i\tau} K_{i\tau},\ z_{i\tau} \geq 0\ \forall\ i, \tau \end{array} \right\}, \tag{3}$$

where $z_{i\tau}$ are the activity levels. By using all the previous years data, we preclude implosion of the frontier over time. It is difficult to believe that the technological frontier could implode. Thus, following an approach first suggested by Diewert (1980), we chose to adopt a construction of the technology that precludes such technological degradation.

The Farrell (1957) (output-based) efficiency index for province i at time t is defined by

$$E(Y_{it}, \hat{L}_{it}, K_{it}) = \min \left\{ \lambda \mid \left\langle Y_{it}/\lambda, \hat{L}_{it}, K_{it} \right\rangle \in \mathcal{T}_t \right\}. \tag{4}$$

This index is the inverse of the maximal proportional amount that output Y_{it} can be expanded while remaining technologically feasible, given the technology and input quantities. It is less than or equal to unity and takes the value of unity if and only if the it observation is on the period-t production-frontier. In our special case of a scalar output, the output-based efficiency index is simply the ratio of actual to potential output evaluated at the actual input quantities.

3.2 Quadripartite Decomposition

To decompose productivity growth into components attributable to (1) changes in efficiency (technological catch-up), (2) technological change, (3) capital deepening (increases in the capital-labor ratio), and (4) human capital accumulation, we again follow the approach of Henderson and Russell (2005). We first note that constant returns to scale allows us to construct the production-frontiers in $\hat{y} \times \hat{k}$ space, where $\hat{y} = Y/\hat{L}$ and $\hat{k} = K/\hat{L}$ are the ratios of output and capital, respectively, to effective labor. By letting b and c stand for the base period and current period respectively, we see, by definition, that potential outputs per efficiency unit of labor in the two periods are given by $\overline{y}_b(\hat{k}_b) = \hat{y}_b/e_b$ and $\overline{y}_c(\hat{k}_c) = \hat{y}_c/e_c$, where e_b and e_c are the values of the efficiency indexes in the respective periods as calculated in (4) above. Accordingly,

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_b(\hat{k}_b)}. \tag{5}$$

Let $\tilde{k}_c = K_c/(L_cH_b)$ denote the ratio of capital to labor measured in efficiency units under the counterfactual assumption that human capital had not changed from its base period and $\tilde{k}_b = K_b/(L_b H_c)$ the ratio of capital to labor measured in efficiency units under the counterfactual assumption that human capital were equal to its current-period level. Then $\overline{y}_b(\tilde{k}_c)$ and $\overline{y}_c(\tilde{k}_b)$ are the potential output per efficiency unit of labor at $\tilde{k}_c$ and $\tilde{k}_b$ using the base-period and current-period technologies, respectively. By multiplying the numerator and denominator of (5) alternatively by $\overline{y}_b(\hat{k}_c)\overline{y}_b(\tilde{k}_c)$ and $\overline{y}_c(\hat{k}_b)\overline{y}_c(\tilde{k}_b)$, we obtain two alternative decompositions of the growth of $\hat{y}$

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_b(\hat{k}_c)} \cdot \frac{\overline{y}_b(\tilde{k}_c)}{\overline{y}_b(\hat{k}_b)} \cdot \frac{\overline{y}_b(\hat{k}_c)}{\overline{y}_b(\tilde{k}_c)}, \tag{6}$$

and

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_b)}{\overline{y}_b(\hat{k}_b)} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_c(\tilde{k}_b)} \cdot \frac{\overline{y}_c(\tilde{k}_b)}{\overline{y}_c(\hat{k}_b)}. \tag{7}$$

The growth of productivity, $y_t = Y_t/L_t$, can be decomposed into the growth of output per efficiency unit of labor and the growth of human capital, as follows:

$$\frac{y_c}{y_b} = \frac{H_c}{H_b} \cdot \frac{\hat{y}_c}{\hat{y}_b}. \tag{8}$$

Combining (6) and (7) with (8), we obtain

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_b(\hat{k}_c)} \cdot \frac{\overline{y}_b(\tilde{k}_c)}{\overline{y}_b(\hat{k}_b)} \cdot \left[\frac{\overline{y}_b(\hat{k}_c)}{\overline{y}_b(\tilde{k}_c)} \cdot \frac{H_c}{H_b}\right] \\ &\equiv EFF \times TECH^c \times KACC^b \times HACC^b, \end{aligned} \tag{9}$$

and

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\hat{k}_b)}{\overline{y}_b(\hat{k}_b)} \cdot \frac{\overline{y}_c(\hat{k}_c)}{\overline{y}_c(\tilde{k}_b)} \cdot \left[\frac{\overline{y}_c(\tilde{k}_b)}{\overline{y}_c(\hat{k}_b)} \cdot \frac{H_c}{H_b}\right] \\ &\equiv EFF \times TECH^b \times KACC^c \times HACC^c. \end{aligned} \tag{10}$$

These identities decompose the growth of labor productivity in the two periods into changes in efficiency, technology, the capital-labor ratio, and human capital accumulation. The decomposition in (6) measures technological change by the shift in the frontier in the output direction at the current-period capital to effective labor ratio, whereas the decomposition in (7) measures technological change by the shift in the frontier in the output direction at the base-period capital to effective labor ratio. Similarly, (9) measures the effect of physical and human capital accumulation along the base-period frontier, whereas (10) measures the effect of physical and human capital accumulation along the current-period frontier.

These two decompositions do not yield the same results unless the technology is Hicks neutral. In other words, the decomposition is path dependent. This ambiguity is resolved by adopting the "Fisher Ideal" decomposition, based on geometric averages of the two measures of the effects of technological change, capital deepening and human capital accumulation and obtained mechanically by multiplying the numerator and denominator of (5) by $\left(\overline{y}_b(\hat{k}_c)\overline{y}_b(\tilde{k}_c)\right)^{1/2}\left(\overline{y}_c(\hat{k}_b)\overline{y}_c(\tilde{k}_b)\right)^{1/2}$:

$$\begin{aligned}\frac{y_c}{y_b} &= EFF \times (TECH^b \cdot TECH^c)^{1/2} \\ &\quad \times (KACC^b \cdot KACC^c)^{1/2} \times (HACC^b \cdot HACC^c)^{1/2} \\ &\equiv EFF \times TECH \times KACC \times HACC.\end{aligned} \tag{11}$$

3.3 Comparison of Unknown Densities

Our analysis of the change in the productivity distribution exploits nonparametric kernel methods to test formally for statistical significance of differences between (actual and counterfactual) distributions. Specifically, we follow Kumar and Russell (2002) and choose the test developed by Li (1996) which tests the null hypothesis $H_0 : f(x) = g(x)$ for all x, against the alternative $H_1 : f(x) \neq g(x)$ for some x.[12] This test, which works with either independent or dependent data is often used, for example, when testing whether income distributions across two regions, groups or times are the same. The test statistic used to test for the difference between two unknown distributions (which goes asymptotically to the standard normal, as shown by Fan and Ullah (1999)), predicated on the integrated square error metric on a space of density functions, $M(f,g) = \int_x (f(x) - g(x))^2 \, dx$, is

$$J = \frac{Nb^{\frac{1}{2}}M}{\widehat{\sigma}} \sim \text{Normal}(0,1), \tag{12}$$

where

$$M = \frac{1}{N^2 b}\sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N}\left[K\left(\frac{x_i - x_j}{b}\right) + K\left(\frac{z_i - z_j}{b}\right) - K\left(\frac{z_i - x_j}{b}\right) - K\left(\frac{x_i - z_j}{b}\right)\right],$$

$$\widehat{\sigma}^2 = \frac{1}{N^2 b \pi^{\frac{1}{2}}}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[K\left(\frac{x_i - x_j}{b}\right) + K\left(\frac{z_i - z_j}{b}\right) + 2K\left(\frac{x_i - z_j}{b}\right)\right],$$

K is the standard normal kernel and b is the optimally chosen bandwidth.[13]

4 Analysis of the Total Industry

4.1 Efficiency Analysis

Figure 1 superimposes the estimated production frontiers, also presenting scatter plots of $\hat{y}$ (output per efficiency units of labor) versus $\hat{k}$ (capital per efficiency units of labor) for

[12] The explanation that follows assumes that $\{x\}$ and $\{z\}$ are two equally sized samples of size N, taken from f and g respectively. The extension to unequal sample sizes is trivial.

[13] For further details see Fan and Ullah (1999), Li (1996), and Pagan and Ullah (1999).

1980 and 2003. The double kink on the 1980 production frontier indicates the existence of only two efficient regional economies (the Balearic Islands and Madrid). The frontier in 2003 is formed by the 1987 Madrid observation and 1985 Balearic Islands observation.[14] We can also observe that the production frontier shifted up from 1980 to 2003 but not by the same proportion for every value of the level of physical capital measured in efficiency units of labor. This implies that technological change was not Hicks-neutral. Rather, we observe that the largest shifts of the frontier occur at higher degrees of capitalization (from $\hat{k}$ greater than about 18,500 Euros), as implied by Harrod-neutral technological change. Thus, assuming Hicks-neutral technological change as done in most studies using conventional growth accounting methods would be misleading.

[Insert Figure 1 about here]

To assess the efficiency of regional economies, we examine their location relative to the frontier. The efficiency scores for each region in 1980 and 2003 are reported in the first two columns of Table 1. The last two rows present the unweighted and population-weighted averages across regions. Given the importance of weighting the outcome of each region by its size as stressed, among others, by Tortosa-Ausina et al. (2005), we will centre on the results for the weighted average.

On average, we observe that Spanish regional economies move further away from the best-practice production frontier, since the efficiency score falls from 0.77 to 0.62 during the 24-year period. Except for Extremadura, whose efficiency index remains almost unaltered, the other regions experience important reductions in efficiency levels.[15] This indicates that regions are not catching-up to the frontier due to technological diffusion, and even the Balearic Islands and Madrid -that were technological leaders with scores equal to 1 in the initial year- have lost a lot of ground over the period under scrutiny. Despite this fact, Madrid is the least inefficient region with an efficiency score of 0.72 in 2003. Not surprisingly so, Figure 2 shows a prominent shift to the left in the probability mass from a distribution containing a high variability of efficiency scores across regions and centered at about 0.75 to a much more concentrated distribution centered at about 0.60. This supports the results shown in Table 1 pointing to the wide-spread fall in efficiency across regions between 1980 and 2003.

[Insert Figure 2 about here]

4.2 Quadripartite Decomposition

To gain a better understanding of the factors that contributed to the growth performance of the Spanish regions, we decompose labor productivity growth into components

[14] Following the "non-implosion of the technology" argument, we have included all year observations to see who defines the 2003 frontier. Note that none of 2003 observations forms the 2003 frontier. If we had not done so, the technological regress would be imposed as the 2003 frontier (solid kinked line on Figure 1) would lie under the 1980 frontier (the dashed kinked line).

[15] This fact only tells us that Extremadura's relative distance to the frontier did not change.

attributable to (1) efficiency changes, (2) technological change, (3) physical capital deepening and (4) human capital accumulation. The change in labor productivity of each region is reported in the third column of Table 1, while the contributions in percentage terms of changes in the four components appear in columns 4 to 7 of Table 1. These contributions in percentage terms can be easily transformed into indices using the formula $(PERCENTAGE/100 + 1)$ so that Equation 11 holds.[16]

On average, labor productivity in Spain has increased by 36.2% from 1980 to 2003, with efficiency changes impeding growth, on average, by almost 19%. In contrast, the average contributions attributable to technological progress, capital deepening and human capital accumulation amount to 16%, 22% and 20%, respectively. Thus, on average, physical capital accumulation has been the main engine of labor productivity growth in Spain, closely followed by human capital accumulation and technological progress.[17]

[Insert Table 1 about here]

When we use "human-capital equivalent" as the measure of human capital stock, our results appear very close to the above ones. As shown in Table 2, efficiency losses appear to have impeded growth by 18.8%, capital deepening remains the main engine of productivity growth contributing by 22.8%, followed by technological change with 18.8% and then human capital with a contribution of 15.8%.[18]

[Insert Table 2 about here]

4.3 Convergence Analysis

For the sake of completeness, we examine the impact of the four growth components on the convergence of output per worker across regions by regressing the change in labor productivity and its four components on the initial level of output per worker. As shown in Figure 3, regional convergence in labor productivity appears entirely driven by efficiency changes through the higher efficiency losses on the part of rich regions relative to poor ones. Since these preliminary conclusions are based on first-moment characterizations

[16] In order to see this, if we apply such formula to the first row of Table 1, we obtain: $1.339 = 0.830 \times 1.162 \times 1.130 \times 1.228$

[17] It is remarkable that two highly populated regions like Madrid and the Valencian Community exhibit high relative contribution of physical capital accumulation but low attributable to technological change and human capital accumulation. In contrast, in most of the regions with relatively low population like Aragon, the Balearic Islands, Cantabria, Extremadura, Navarra, Rioja and to a less extent the Basque Country, the contribution of physical capital is much lower than that attributable to technological change and human capital. These patterns lead the weighted average contribution of capital deepening to be higher than the unweighted one, occurring exactly the opposite for technological change and human capital accumulation.

[18] For the sake of robustness, we have also redone this quadripartite decomposition in each region for the total industry using an alternative measure of human capital provided by de la Fuente and Doménech (2006) as given by the average years of schooling in the working-age population over 25 based on census data. Remarkably, our main results remain unaltered when we employ this alternative human capital measure. These unreported results are available in an unpublished appendix that can be obtained from the authors upon request (and later will be also made available in the authors´ homepage).

of the productivity distribution and are vulnerable to Quah's critique, we now turn to examine the evolution of the entire cross-section distribution of labor productivity.

[Insert Figure 3 about here]

4.4 Distributional Analysis

The labor productivity distribution obtained from nonparametric kernel-based density estimates appear in Figure 4. The solid and dashed curves represent the distribution of labor productivity in 1980 and 2003, respectively, with their corresponding mean values shown as vertical lines. As noted by, among others, Tortosa-Ausina et al. (2005), if the probability mass is increasingly concentrated around a certain value, there would be evidence of convergence towards that value. By contrast, if the probability mass spreads out increasingly as given by a rise in the distance between the extreme values of the distribution, the outcome would be divergence.

It is evident that the distribution of labor productivity is unimodal both in the starting and ending years. We also observe that the distribution has shifted to the right from a mean value of about 24,000 to a mean value of about 33,000. It is also noticeable that the probability mass has become more concentrated around the new labor productivity mean, and the distance between the extreme values of the distribution has narrowed down. Both facts are consistent with the existence of some evidence of convergence, thus supporting the results from the simple convergence regressions presented above.

[Insert Figure 4 about here]

By using now the quadripartite decomposition of productivity growth, we will be able to explore the role of each of the four components in the transformation of the productivity distribution over the sample period, and in turn their influence on the growth and convergence of regional labor productivity. Towards this end, we follow the methodology of Henderson and Russell (2005) and rewrite Equation 11 as follows:

$$y_c = (EFF \times TECH \times KACC \times HACC) \times y_b \tag{13}$$

Accordingly, the labor productivity distribution in 2003 can be constructed by consecutively multiplying the labor productivity distribution in 1980 by each of the four components. To isolate the impact of each component, we create counterfactual distributions by employing nonparametric kernel methods. In addition, we apply the nonparametric bootstrap test developed by Li (1996) that formally tests for statistical significance of differences between the corresponding distributions. This will allow us to indirectly test for the statistical significance of the relative contribution of the four components of the decomposition of productivity changes to changes in the distribution of labor productivity.

In each panel of Figures 5-6, the solid (dashed) curve is the estimated 1980 (2003) distribution of output per worker and the solid (dashed) vertical line represents the 1980 (2003) mean value of output per worker, whereas the counterfactual distributions are shown as dotted curves (and the corresponding vertical dotted line represents the counterfactual mean). For instance, one can assess the shift of the labor productivity distribution due solely to capital deepening by examining the counterfactual distribution of the variable:

$$y^K = KACC \times y_b \tag{14}$$

assuming no efficiency changes, technological change or human capital accumulation. This is shown in Panel A of Figure 5. We can observe that physical capital accumulation has shifted the probability mass to the right, thus causing an important increase in the average output per worker as reflected in the dotted vertical line. We can also infer that physical capital accumulation has made only some regions much richer as the right tail of the counterfactual distribution now stretches beyond that of 2003 income distribution.

We would then include sequentially more components in the counterfactual distribution to isolate, sequentially, the effects of each component. Hence, when we include human capital in y^K, we have:

$$y^{KH} = (KACC \times HACC) \times y_b = HACC \times y^K, \tag{15}$$

drawn in Panel B of Figure 5, which isolates the joint effect of physical and human capital accumulation on the base period distribution. Besides a significant shift to the right in the distribution from a mean value about 29,000 to almost 35,000, the shape of the counterfactual distribution y^{KH} is almost identical to that in Panel A, thus indicating that human capital accumulation has had no effect on shift in income distribution. The additional effect of efficiency changes on the distribution y^{KH} can be assessed by multiplying by efficiency changes such that:

$$y^{KHE} = (KACC \times HACC \times EFF) \times y_b = EFF \times y^{KH}, \tag{16}$$

drawn in Panel C of Figure 5. In this case, there is a significant shift to the left in the distribution, thus corroborating our previous findings pointing to efficiency losses as the main impediment to growth in labor productivity. This leads to offset the productivity gains obtained from human capital accumulation as reflected in the mean values of y^{KHE} relative to y^K. Interestingly, we also observe a much higher probability mass concentration and lower spread in the counterfactual distribution y^{KHE} than in y^{KH}. This clearly indicates that efficiency change has been the main driver of convergence in productivity over the period 1980−2003, thus corroborating the results from the convergence regressions showing that rich regions experience higher efficiency losses than poor ones. From Panel C we can also indirectly infer the positive contribution of technological change, as the difference between the counterfactual distribution y^{KHE} and the distribution in 2003.

[Insert Figures 5 and 6 about here]

In Figure 6 we change the sequence of introducing the factors. We start with efficiency changes, followed by technological change and capital deepening. Panel A shows that, efficiency changes do not only shift dramatically the distribution to the left from a mean value of output per worker around 33,500 in 1980 to 20,000, but also lead to (higher) probability mass concentration and (lower) spread of the distribution -similar to the distribution in 2003. This, again, supports the fact that efficiency change has been the factor responsible for the observed regional convergence in productivity. Panel B, in turn, shows how the growth impediment from efficiency losses has been slightly higher than the productivity gains from technological progress, as reflected in a lower average output per worker than in the base year. And, finally, Panel C shows the positive contribution of physical capital accumulation to productivity growth and indirectly the same result for human capital accumulation. We have tried other sequences of introducing the factors changes, but the conclusions remain unaltered. In sum, factor accumulation and technological change have positively contributed to productivity growth, while significant efficiency losses have impeded it. In addition, cross-regional efficiency changes appear to be responsible for the existence of some convergence in output per worker.

To complement the analysis of counterfactual distributions, we perform formal tests for testing the statistical significance of differences between the actual and counterfactual distributions. More specifically, we employ the test of Li (1996) as well as the bootstrap procedure of Li (1999) that was designed to calculate critical values for this test. Given the relatively small size of our sample, the computation of bootstrapped critical values will allow us to overcome the caveat associated with low statistical power in small samples. In computing the test we also use the Gaussian kernel function and the Sheather and Jones (1991) procedure to select the optimal bandwidth.

The first test in Table 3 indicates that the distributions in 1980 and 2003 are significantly different at the 1% level. The next four tests compare the actual distribution in 2003 with the counterfactual distribution, assuming that only one of the four components is introduced one at a time. The small *p-values* reflect that efficiency change, technological change and capital deepening alone did not do much to statistically significantly shift the base period distribution towards the 2003 distribution. Regarding human capital accumulation, the rejection of distributional equality is less clear since we only reject at the 10% significance level. However, when we combine the effect of any two of the four components except for efficiency change, we find that the resulting counterfactual distribution is not significantly different from the actual 2003 distribution. Interestingly, when we introduce the effect of efficiency changes, we are again able to reject the null of equality in the distributions, since that factor dramatically shifts the counterfactual distribution towards the base period distribution. Not surprisingly so, we also reject the null of distributional equality when we introduce the joint effect of TECH, KACC and HACC, as there would clearly be overshooting. This indirectly reflects the fact that, if it had not been for the efficiency losses, the base period distribution would have shifted to the right much more over the 24-year period investigated.

[Insert Table 3 about here]

4.5 Splitting the Sample Period

Now it is interesting to investigate whether there is one particular subperiod driving the results for the whole period. An illustrative way to shed some light on this issue is to plot output per efficiency units of labor against physical capital per efficiency units of labor for each of the 17 regions. This will allow us to determine whether there is a specific year from which regions began producing significantly less output with the same amount of inputs. This may be caused by a fall in efficiency or a reduction in the contribution of technological change to labor productivity growth. In Figure 7, the scatter plots between $\hat{y}$ and $\hat{k}$ show that in nine regions (Canary Islands, Aragon, Castilla-la-Mancha, Extremadura, Andalusia, the Valencian Community, Balearic Islands, Navarra and Madrid) from 1995 onwards, there has been a continuous fall in the amount of output per efficiency units of labor that can be produced relative to the amount of capital per efficiency units of labor. The same is found from 1996 onwards for Cantabria, Castilla-Leon, Catalonia and the Basque Country as well as from 1997 for Asturias and Rioja. The same pattern is found since 1993 and 2000 for Murcia and Galicia, respectively.

[Insert Figure 7 about here]

Given that most of the regions exhibit this fall in $\hat{y}$ relative to $\hat{k}$ in 1995 or adjacent year, we choose to split the sample period into two subperiods: $1980-1994$ and $1995-2003$.[19] The results for both subperiods are presented in Tables 4 and 5, respectively. For the first subperiod, as with the results for the whole period, the Balearic Islands and Madrid are located on the production frontier, with efficiency scores equal to unity. In this case, the average increase in labor productivity is equal to 38.4%, which is slightly higher than that observed for the whole period. This in turn indicates that labor productivity has fallen during the second subperiod. With the exception of Extremadura that exhibits a modest increase in efficiency equal to 15% and Aragon, Cantabria and Castilla-la-Mancha with efficiency gains of about 2.5%, the rest of the regions exhibit efficiency losses, which are substantial in some rich regions like Madrid and the Valencian Community. On average, the efficiency fall amounts to 9.4%. With regard to the contributions to labor productivity attributable to the rest of the components, the highest contribution is found for capital deepening (17.5%) -as with the full period-, closely followed by technological change (16.2%) and human capital accumulation (12,4%).

[Insert Table 4 about here]

As occurred with the full period, simple convergence regressions show evidence of productivity convergence, which is entirely driven by efficiency losses that appear much higher in rich regions than in poor ones. The analysis of the distributions also show that efficiency losses have led to a shift to the left of the productivity distribution as well as to higher probability mass concentration and lower spread of the distribution. This supports the fact that efficiency losses have contributed to the equalization of income disparities across regions.[20]

In stark contrast stand the results for the second subperiod (shown in Table 5), where we find that labor productivity has fallen on average by 2.2%, doing so also for most

[19] This coincide with the finding by Doménech (2008) supporting the change in regime in labor productivity growth from 1995 onwards caused mainly by a sharp fall in TFP growth.

[20] Due to space limitations, we do not report the production frontiers, the convergence scatterplots and the distributional analysis for both subperiods. However, these results are readily available in an unpublished appendix.

of the regions. The main contributor to this reduction in labor productivity has been efficiency losses by 9.7%. Interesting also is the fact that technological change appears to have come to a halt over the period 1995−2003 across all the regions, and that the contribution of physical capital has also been zero for most of the regions, and less than 2% on average. The only factor that has prevented labor productivity from falling further during this period has been human capital accumulation with an average contribution of 6.3%.[21]

[Insert Table 5 about here]

From the analysis of the two subperiods, we observe that the period 1980−1994 -with positive labor productivity growth combined with efficiency losses and positive contributions from technological change, capital deepening and human capital accumulation- appears to predominantly drive the findings for the whole period. Hence, the last subperiod represents a lost decade in terms of labor productivity growth, which has slightly regressed. This has been primarily caused by efficiency losses, zero technological change and extremely low contribution from capital deepening.

5 Sectoral Analysis

Having explored the sources of aggregate labor productivity growth and convergence across the Spanish regions during the period 1980−2003, we now shift the focus to investigate whether individual sectors are responsible for the economic performance of the aggregate private productive sector, and whether the changing mix of industries has contributed to such performance. Towards this end, we calculate efficiency scores as well as the quadripartite decomposition of labor productivity growth in the 17 regions for each sector. For the sake of saving space, we report the weighted average outcomes of such exercises, leaving to the unpublished appendix the detailed results for each region.[22]

Table 6 presents the results for the different sectors in a concise way. Remarkably, we observe that output per worker in agriculture, energy and manufacturing has on average grown much faster than total industry (private productive economy), with average changes over the 24-year period equal to 197.5%, 117.6% and 63.5%, respectively. Hence, the agricultural sector has exhibited a sixfold increase in labor productivity relative to the growth in the total industry; the energy sector has more than tripled the growth performance in total industry and manufacturing has almost doubled aggregate productivity growth. In stark contrast stand the results for the construction and services sectors, whose labor productivity has hardly changed over the 24-year period (only 3% and 4.2%, respectively). The marked sectoral differences in labor productivity underline the importance of analyzing intra-sectoral productivity dynamics and possibly structural change (sectoral shifts) in affecting aggregate productivity performance. Indeed, by observing the labor

[21] Simple convergence regressions also support convergence in output per worker during the second subperiod, which is again driven by efficiency changes.

[22] The appendix also presents the production frontier plots, the convergence scatterplots and the distributional analysis for each sector.

productivity change recorded for the total industry as well as for each individual sector, one can expect that significant sectoral shifts may have occurred from rapidly growing sectors such as agriculture and manufacturing to less productive sectors (in terms of productivity growth) like the services and construction sectors.[23] In fact, as drawn in Figure 8, we observe that the share of employment in agriculture and manufacturing has steadily decreased at the expense of rising shares in construction and services.

[Insert Figure 8 about here]

Regarding the contribution attributable to each of the four components for each sector, we find the following:

Agriculture: The extraordinarily high labor productivity growth has been mainly driven by rapid technological change (with a contribution of 96.6%), followed by capital deepening that contributed by 38% and human capital accumulation by 18.3%. Efficiency losses in this sector have been relatively low (-5%). Even though there were three regions (Cantabria, Castilla-la-Mancha and Navarra) located on the production frontier in 1980, only Castilla-la-Mancha retained an efficiency score equal to 1 in 2003. In this sector, convergence in labor productivity appears to be driven by technological change and capital deepening.

Manufacturing: The main contributor to productivity growth has been human capital accumulation (21,3%), followed by technological change (18.7%), capital deepening (12.4%) and efficiency gains (2.4%). In 1980, Rioja was the most efficient economy with an efficiency score equal to one, while Madrid the most efficient one in 2003. This sector does not show evidence of convergence in labor productivity. This is because the driving forces towards convergence stemming from capital deepening have been cancelled out by those causing divergence as occurs with technological change and human capital accumulation.

Construction: The very poor productivity growth performance is mainly driven by the very high efficiency losses that inhibited growth by 37.5%. Hence, efficiency changes almost offset the positive contribution from technological change (22.6%), human capital accumulation (13.7%) and capital deepening (8.4%). The dramatic fall in efficiency has been wide-spread in all the regions. From a situation in 1980 with three regions (Navarra, Rioja and the Valencian Community) with an efficiency index of unity, we end up in a situation in which the highest efficiency index takes on a value of 0.66 for Asturias. In this sector, convergence in labor productivity is brought about by 1) efficiency changes as given by higher losses in rich regions relative to poor ones, and 2) the neoclassical mechanism associated with diminishing returns exhibited by physical capital accumulation.

Energy: The good growth performance can be attributed to technological change (45%), followed by human capital accumulation (27%), capital deepening (13%) and efficiency gains (7.4%). The frontier economy in this sector in 2003 is the Basque Country, while Canary Islands, Murcia and Rioja in 1980 -whose efficiency levels fell dramatically

[23] It is important to note that the construction sector has experienced an incredible boom over this 24-year period, changing from 1,173.5 to 2,335,2 thousand employees. Likewise, GVA has doubled over the 1980−2003 period (from 28,323 to 57,642 million euros).

during the 24-year period. Convergence in output per worker in this sector is entirely driven by the higher efficiency losses on the part of rich regions relative to lower losses in poor ones.

Services: The stagnation of this sector in terms of labor productivity is caused by the extraordinarily high efficiency losses (-47.6%), which almost offset the positive contributions from capital deepening (54%), human capital accumulation (18.6%) and technological change (9.4%). Interestingly, the efficiency losses have been higher and the contributions of technological change lower than in the other sectors. Given the high weight that this sector has in the Spanish economy, this has constituted an important obstacle to labor productivity growth in total industry. In this sector, efficiency losses have been particularly substantial, with most regions seeing their efficiency levels halved or even further reduced. In fact, the highest efficiency score reached by two regions (Cantabria and the Valencian Community) equals 0.54 in 2003, which sharply contrasts with their unit efficiency indices in 1980. In this sector, convergence in labor productivity is driven by physical capital accumulation which counteracts the statistically significant divergence-promoting effect of technological change.

[Insert Table 6 about here]

Overall, the disparity of outcomes across sectors suggests that sectoral composition plays a relevant role in generating growth and convergence in aggregate labor productivity.

5.1 Analysis of Subperiods: 1980−1994 and 1995−2003

As with the analysis of aggregate labor productivity growth, it is also interesting to examine whether one of the subperiods has also conditioned the sectoral productivity dynamics for the whole period. To ease comparison across sectors and subperiods, Table 6 also presents the efficiency scores and quadripartite decomposition results for total industry and five sectors over the whole period and subperiods.

Remarkably, as occurred with the analysis of total industry, the dynamics of the four components during the first subperiod appear to drive labor productivity growth for the whole period. In addition, labor productivity growth appears significantly reduced in the second subperiod relative to the first one, reaching even a negative value in construction and services. We also find that the contribution attributable to technological progress during the second period is much lower than that of the first subperiod in each of the five sectors. In fact, as with total industry, technological change contributes zero to productivity growth in construction and services, and almost zero in energy. Interesting also is the small contribution of capital deepening during the second subperiod relative to the first one, which is close to zero in agriculture and energy, and even negative for manufacturing and construction. Though lower than in the first subperiod, the contribution of capital deepening in services is still significant (15%), thus partly counteracting the effect of efficiency losses which amounts to −21.4% during the 1995−2003 subperiod.

The contribution of human capital is also considerably lower during the second subperiod in all sectors. Finally, unlike the three other components, we do not find a clear-cut pattern for efficiency changes. On the one hand, there is a worsening in efficiency in manufacturing and construction during the second subperiod. On the other, there is evidence of a clear improvement in efficiency in agriculture and energy that exhibit positive efficiency changes (24.2% and 17.7%) relative to the negative variations during the first subperiod. Likewise, in services the negative contribution of efficiency changes has decreased from −31.4% to −21.4%.

Taken as a whole, the first subperiod usually drives the performance for the whole period, occurring that the contribution of technological change and capital deepening falls dramatically in all sectors in the second subperiod relative to the first one. Likewise, the contribution of human capital accumulation is reduced, but to a less extent than technological change and capital deepening. In addition, efficiency changes exhibit a less clear-cut pattern with improvements in agriculture, energy and services, and worsening in manufacturing and construction.

5.2 Intrasectoral Dynamics or Sectoral Shifts?

Once we have examined the sources of growth for each sector separately, we try to determine the proportion of labor productivity growth in total industry caused by instrasectoral productivity growth and structural change (sectoral shifts). To formalize this intuition, we employ the following expression:

$$\begin{aligned}\frac{GVA_c}{L_c}-\frac{GVA_b}{L_b} \quad = \quad & \sum_{j=1}^{5}\frac{L_{jb}}{L_b}\left(\frac{GVA_{jc}}{L_{jc}}-\frac{GVA_{jb}}{L_{jb}}\right)+\sum_{j=1}^{5}\frac{GVA_{jb}}{L_{jb}}\left(\frac{L_{jc}}{L_c}-\frac{L_{jb}}{L_b}\right)+ \\ & +\sum_{j=1}^{5}\left(\frac{L_{jc}}{L_c}-\frac{L_{jb}}{L_b}\right)\left(\frac{GVA_{jc}}{L_{jc}}-\frac{GVA_{jb}}{L_{jb}}\right), \qquad (17)\end{aligned}$$

where j refers to each of the five sectors, and b and c stand for base (1980) and current (2003) period, respectively. The first component is the (intrasectoral) productivity growth effect which constitutes the contribution of within sector productivity growth for each region, using initial sectoral employment shares as weights (i.e. assuming that sectoral employment structure remains unchanged over the 24-year-period). The second component called the share effect shows the contribution of shifting sectoral composition to aggregate labor productivity growth, considering that sectoral productivity does not change (i.e. assuming that initial levels of sectoral productivity remain unaltered). Those sectors with falling employment shares will exhibit negative share effects. The third component called the interaction dynamic effect shows the contribution of the interaction between the variations in the sectoral share of employment and labor productivity to aggregate productivity growth.

Table 7 reports the three effects both in absolute and percentage terms for each of the regions as well as for Spain as a whole. The results of this *shift-share* analysis indicate that sectoral contributions to aggregate productivity growth for all the regions and Spain are predominantly driven by *within* sector effects.[24] In contrast, we find limited contribution stemming from the static share effect resulting from sectoral shifts from high-productivity sectors gaining employment shares or low-productivity sectors losing shares. Remarkably, the dynamic effect appears negative in all regions except the Balearic Islands, which indicates that the process of economic restructuring is not bringing about higher aggregate productivity growth. Interestingly, the overall effect from sectoral shifts is very low, since the dynamic effect almost cancels out the positive static share effect for many regions and the whole Spain. For other regions (Castilla-la-Mancha, Catalonia, Madrid, Navarra, the Basque Country and Rioja) the dynamic effect is even higher in absolute terms than the share effect. Hence, we can infer that aggregate labor productivity dynamics are primarily driven by intrasectoral productivity dynamics rather than by shifting sectoral composition, as shown in the percentage contribution of the productivity growth effect.

[Insert Table 7 about here]

6 Conclusion

This paper represents the first known analysis of the sources of growth and convergence across two dimensions (regional and sectoral) jointly employing a nonparametric production frontier approach and distribution dynamics methods. The advantages of this frontier approach over standard regression-based growth accounting exercises are that (1) it does not require specification of any particular production function technology nor the existence of perfectly competitive markets or Hicks-neutral technological change, (2) it allows us to distinguish between catching-up (movements towards the frontier) and technological change (shifts in the frontier), (3) it allows for the modelling of inefficiency of regional economies and sectors. The quadripartite decomposition enables us to decompose labor productivity growth into four components attributable to technological catching-up, technological change, capital deepening and human capital accumulation. This together with the examination of the evolution of the entire cross-section distribution and the degree to which the four components of productivity change account for such productivity dynamics allow us to determine the specific role of each of the components in growth and convergence.

Our main results for aggregate productivity indicate that (1) technological change is clearly nonneutral in Hicks sense, (2) capital deepening is the primary contributor to aggregate labor productivity growth, closely followed by human capital accumulation and technological change; (3) wide-spread efficiency losses appear to substantially inhibit productivity growth; (4) simple convergence regressions as well as the analysis of the cross-region distribution of labor productivity in terms of the quadripartite decomposition support the existence of convergence in labor productivity, mainly driven by the higher efficiency losses exhibited by rich regions relative to poor ones. In addition, the sectoral analysis evinces (5) marked differences in productivity performance as well as in

[24]The productivity growth effect in percentage terms for agriculture, manufacturing, construction, energy and services is 35.5, 43, 0.7, 12.8 and 8%, respectively. Hence, manufacturing followed by agriculture are the sectors driving aggregate productivity growth.

the contribution of the four components across sectors; (6) aggregate productivity growth is mainly driven by intrasectoral productivity dynamics -primarily in manufacturing and agriculture- rather than structural change; (7) for both total industry and the five sectors separately, productivity dynamics during the subperiod 1980−1994 appear to predominantly drive the outcome for the whole period. More specifically, we find that technological change has come to a halt since 1995 in total industry and separate sectors. Likewise, the contribution of capital deepening has been reduced dramatically during the period 1995−2003, observing a similar (but less marked) pattern for human capital accumulation. In addition, efficiency changes exhibit a less clear-cut pattern with improvements in agriculture, energy and services, and worsening in manufacturing and construction. Overall, this analysis underlines the fact that the subperiod 1995−2003 constitutes a lost decade in terms of labor productivity that has slightly regressed due to efficiency losses, zero technological change and very low contribution from capital deepening.

The analysis of data with such a high degree of detail (regional, sectoral and over time) has helped us identify the exact sources of the poor labor productivity performance in Spain. Remarkably, efficiency losses appear wide-spread across regions and in three sectors (agriculture, construction and services) for the whole period, with manufacturing also showing efficiency losses during the last subperiod. In addition, the fact that the source of the reduction in disparities across regions is the higher efficiency losses incurred by rich regions relative to lower losses in poor ones appears highly disappointing. Hence, this indicates that rather than converging toward the technological frontier, regional economies are moving away from the frontier. This is particularly the case for rich regions that, over the 24-year-period analyzed, have seen their efficiency scores going down to comparable levels to those characteristic of poor regions. If we add to this the fact that over the period 1995−2003 the contribution attributable to technological change has come to a halt and that of capital deepening has been negligible, we can be nothing but very pessimistic about the prospects that the Spanish economy faces for the coming years.

To reverse this situation, policymakers should make the effort to conduct structural reforms with the aim of bringing efficiency gains by helping regional economies move towards the best-practice frontier. Hence, Spanish regions could boost their growth if they manage to reverse the negative trends in efficiency observed over the whole period. In addition, productivity growth gains can be reaped by promoting capital accumulation and especially technological change, whose contribution has been extremely low or zero over the subperiod 1995−2003.

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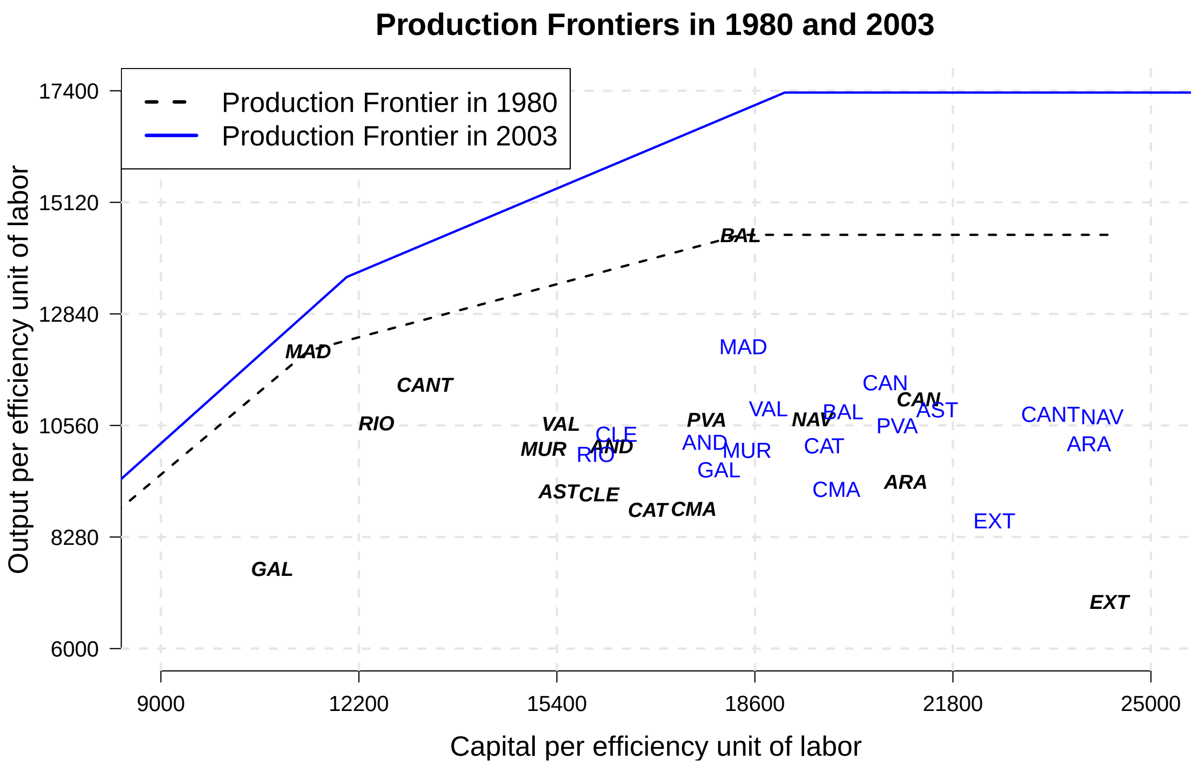


Figure 1: Production frontiers in 1980 and 2003

Notes: The bold italic abbreviations show the 1980 observations and the normal font abbreviations show the 2003 observations. The dotted line represents the 1980 production frontier and the solid line presents the 2003 production frontier.

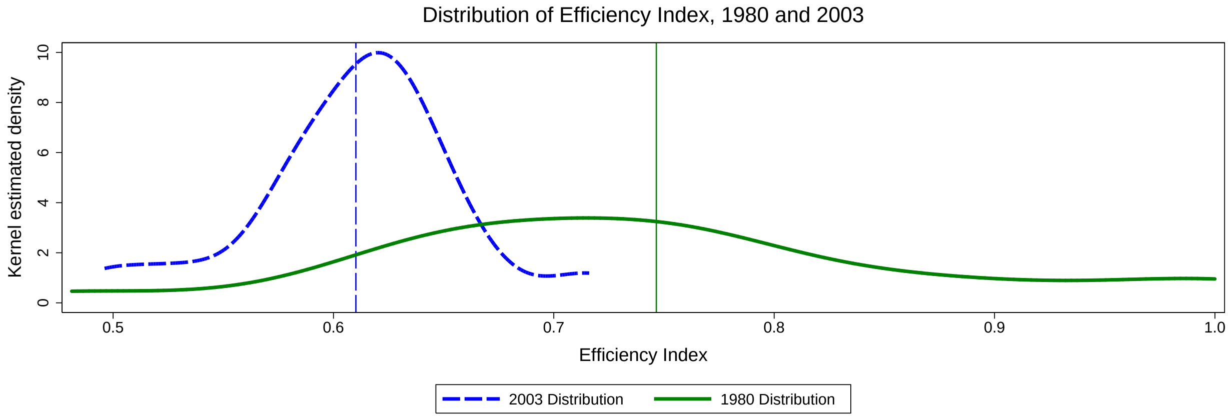


Figure 2: Distributions of efficiency scores in 1980 and 2003

Notes: The solid vertical line represents mean of 1980 efficiency distribution and the the dashed curve is the mean of 2003 efficiency distribution.

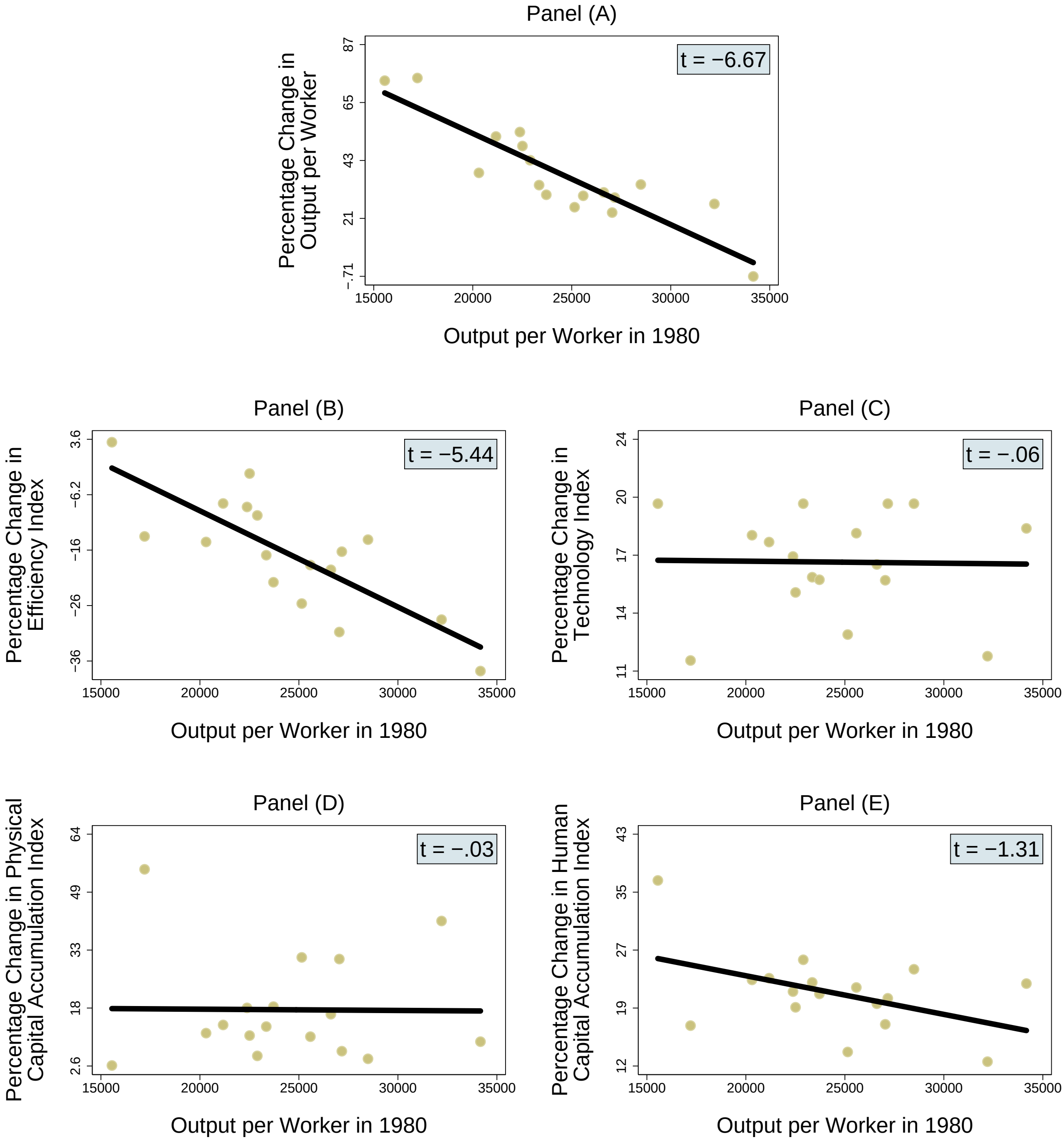


Figure 3: Percentage change (from 1980 to 2003) in output per worker and four decomposition indexes, plotted against output per worker in 1980

Note: Each panel contains a GLS regression line; the topright figure in each panel shows a *t*-statistic of a respective GLS regression.

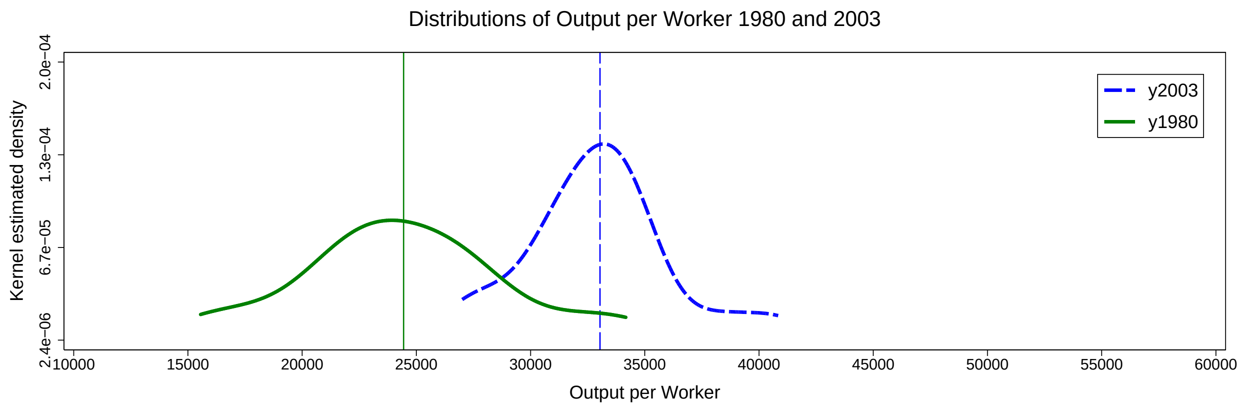


Figure 4: Actual Distributions of Output per Worker

Notes: The solid curve is the actual 1980 distribution and the dashed curve is the actual 2003 distribution.

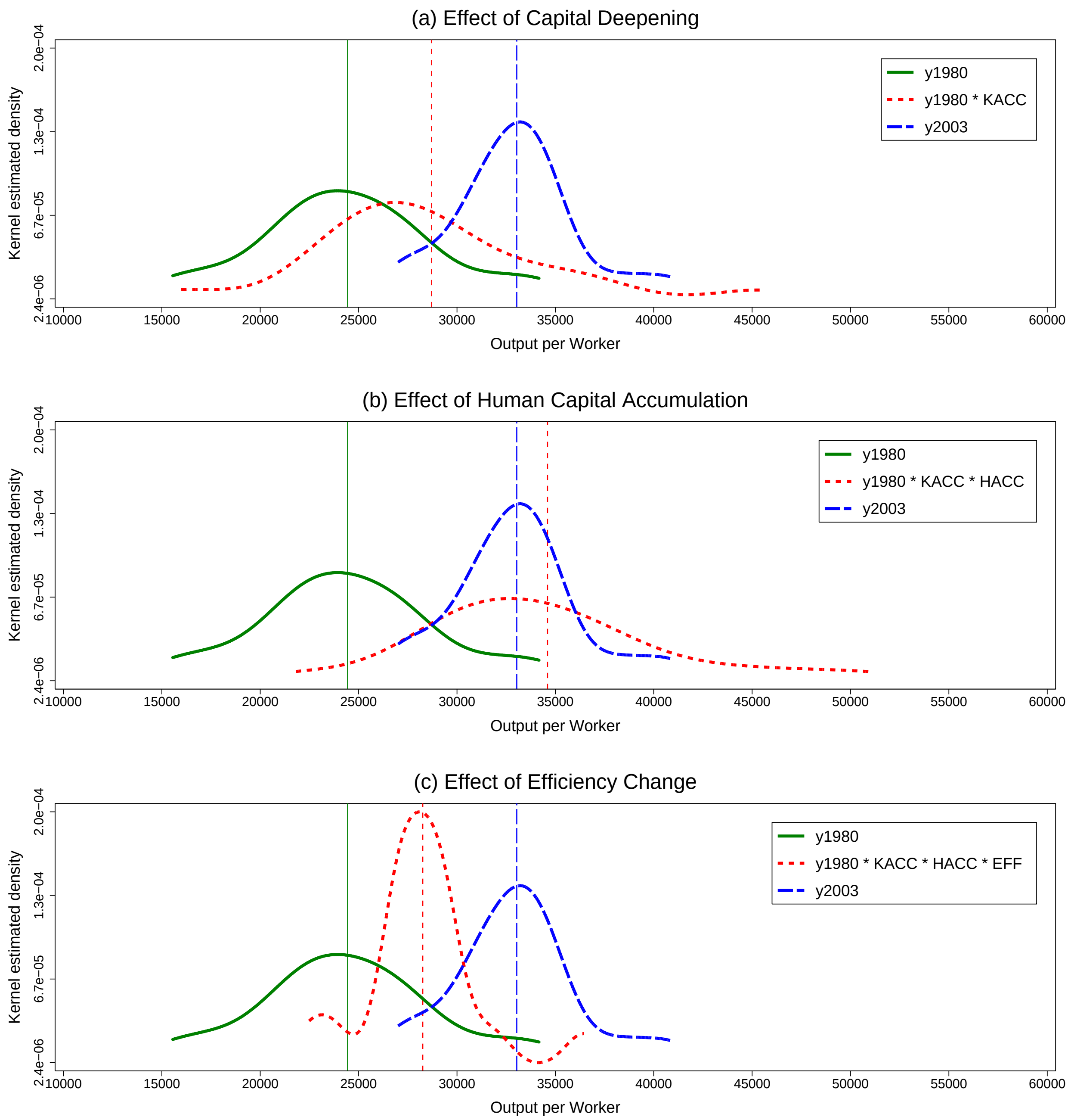


Figure 5: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: KACC, HACC, and EFF

Notes: In each panel, the solid curve is the actual 1980 distribution and the dashed curve is the actual 2003 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of capital deepening, human capital accumulation, and efficiency change on the 1980 distribution.

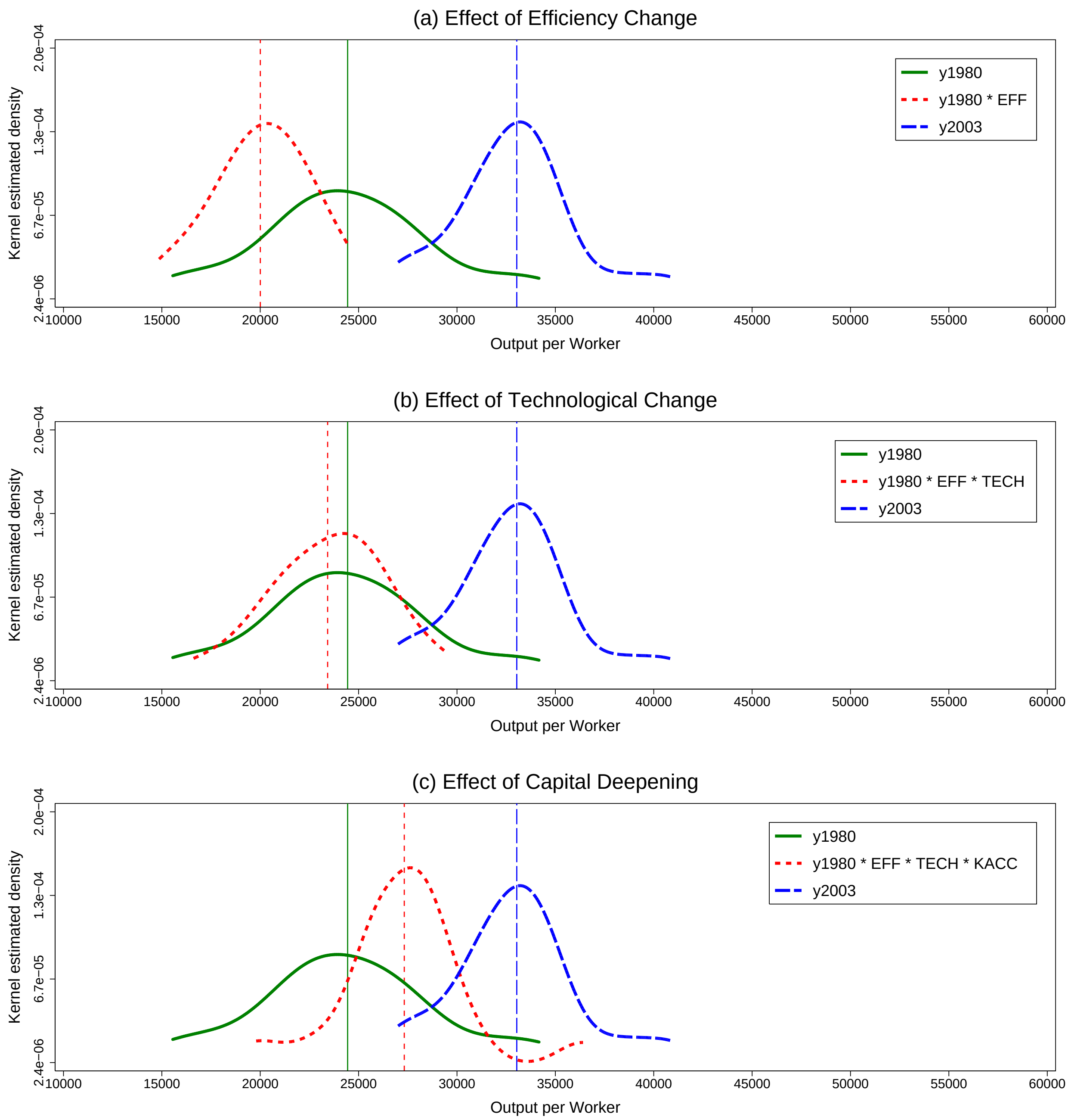


Figure 6: Counterfactual Distributions of Output per Worker. Sequence of introducing effects of decomposition: EFF, TECH, and KACC

Notes: In each panel, the solid curve is the actual 1980 distribution and the dashed curve is the actual 2003 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of efficiency change, technological change, and capital deepening on the 1980 distribution.

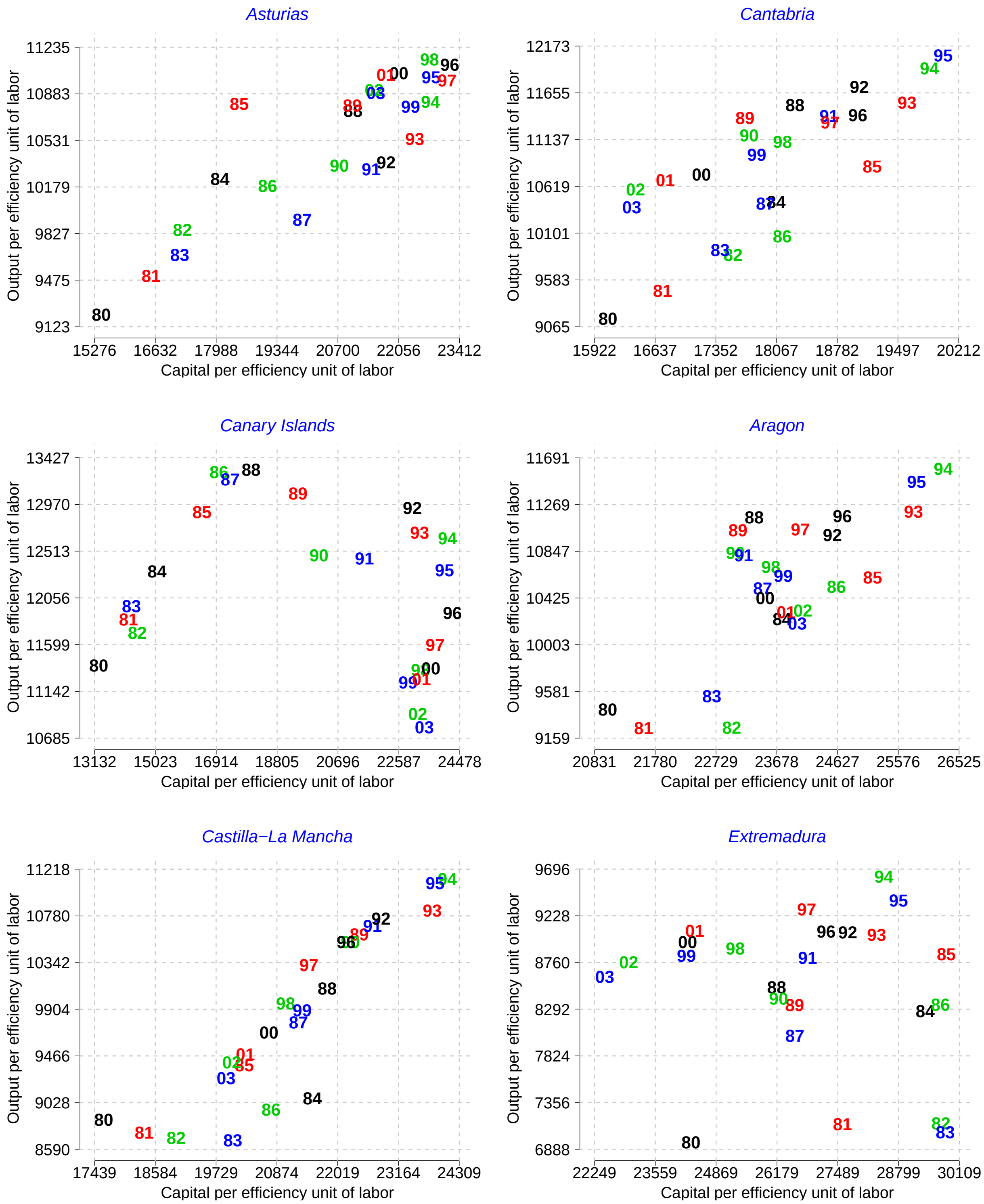


Figure 7: Scatters of $k = K/L/H$ vs. $y = Y/L/H$ on own regional scale

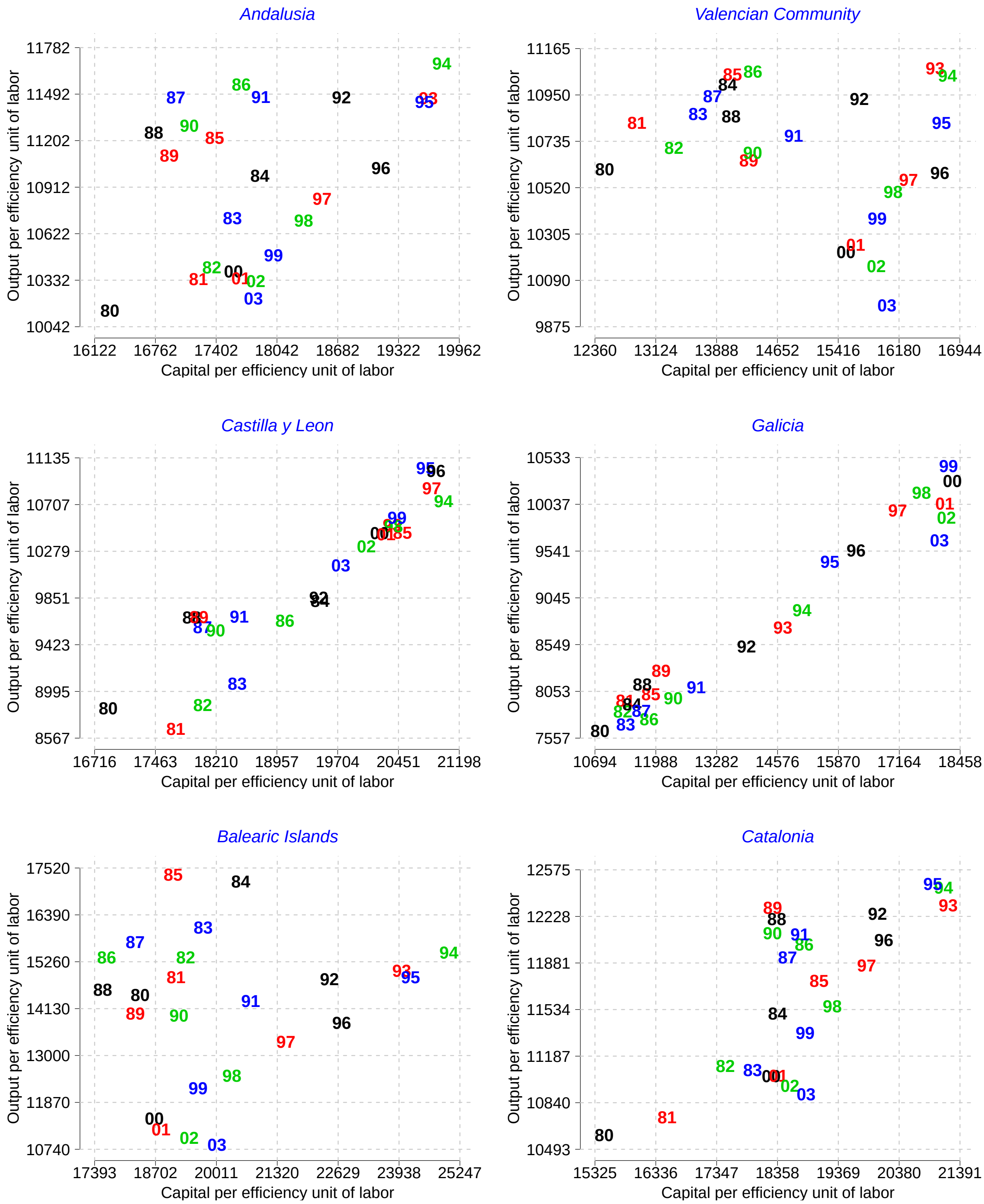
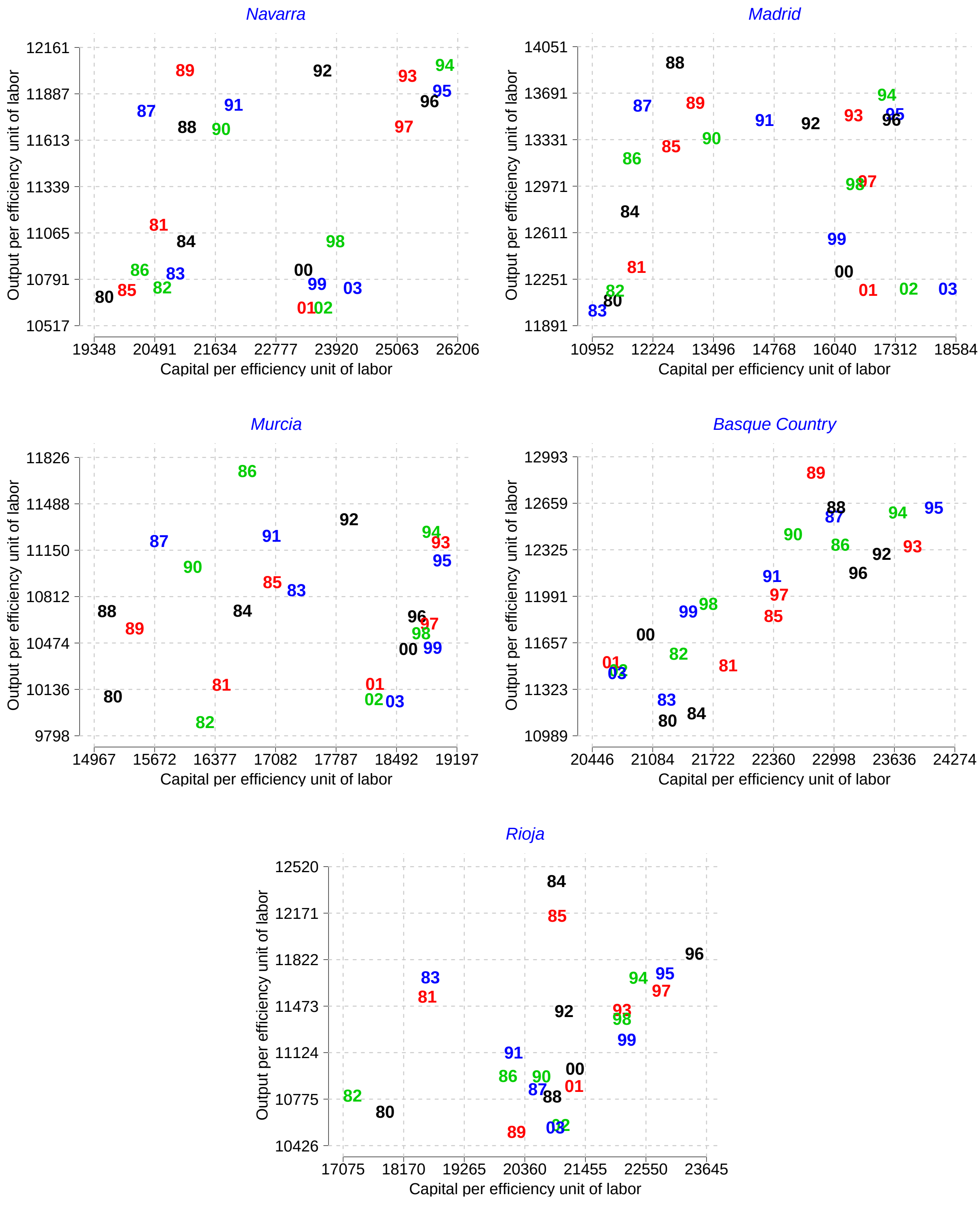


Figure 7 continued...



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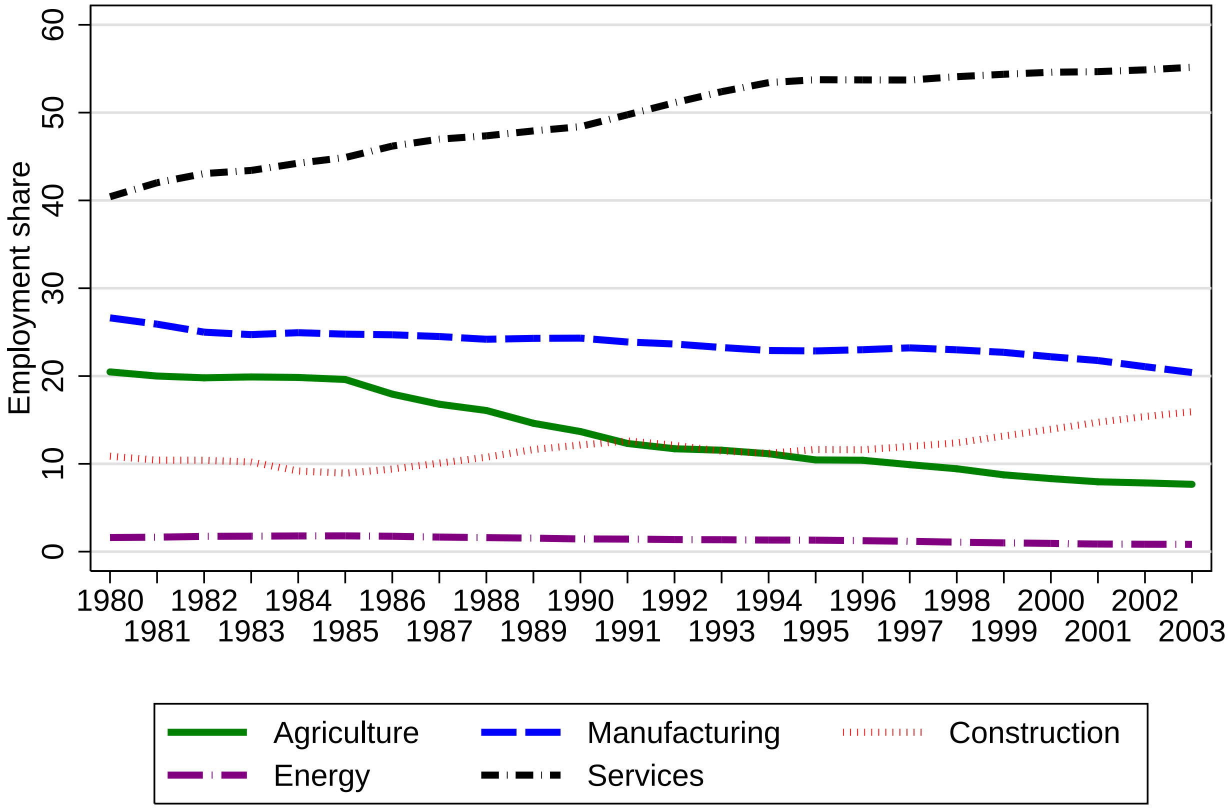

Figure 8: Evolution of Sectoral Employment Shares

Table 1: Efficiency scores and percentage change of quadripartite decomposition indexes, 1980−2003

#	Region	TE_b	TE_c	productivity change	EFF−1 × 100	TECH−1 × 100	KACC−1 × 100	HACC−1 × 100
1	Andalusia	0.74	0.61	34.0	−17.0	16.2	13.0	22.8
2	Aragon	0.65	0.59	43.4	−9.9	20.1	5.3	25.8
3	Asturias	0.68	0.63	54.1	−8.4	17.3	18.0	21.6
4	Balearic Islands	1.00	0.62	−0.7	−37.5	18.8	9.1	22.6
5	Basque Country	0.77	0.66	34.2	−14.2	20.1	4.5	24.5
6	Canary Islands	0.90	0.62	23.5	−30.6	16.0	30.9	17.2
7	Cantabria	0.67	0.65	48.8	−2.5	15.4	10.7	19.5
8	Castilla-La Mancha	0.62	0.53	38.6	−14.6	18.4	11.3	23.1
9	Castilla y Leon	0.63	0.58	52.4	−7.8	18.1	13.5	23.4
10	Catalonia	0.79	0.63	31.2	−19.5	16.9	16.3	19.9
11	Extremadura	0.48	0.50	73.6	3.1	20.1	2.8	36.4
12	Galicia	0.67	0.57	74.6	−13.6	11.8	54.6	17.0
13	Madrid	1.00	0.72	26.8	−28.4	12.0	40.9	12.2
14	Murcia	0.75	0.59	30.3	−21.8	16.1	18.3	21.3
15	Navarra	0.74	0.62	29.2	−16.3	20.1	6.5	20.7
16	Rioja	0.75	0.61	29.9	−18.7	18.5	10.4	22.1
17	Valencian Community	0.85	0.63	25.6	−25.5	13.2	31.3	13.5
	average	0.75	0.61	38.2	−16.7	17.0	17.5	21.4
	weighted average	0.77	0.62	36.2	−18.8	15.9	21.8	19.8

Table 2: Efficiency scores and percentage change of quadripartite decomposition indexes, 1980−2003. Decomposition using Human-Capital Equivalent.

#	Region	TE_b	TE_c	produc. change	EFF−1 × 100	TECH−1 × 100	KACC−1 × 100	HACC−1 × 100
1	Andalusia	0.72	0.61	34.0	−15.0	18.3	15.0	15.8
2	Aragon	0.63	0.57	43.4	−10.4	25.2	6.7	19.8
3	Asturias	0.68	0.61	54.1	−10.2	20.4	20.5	18.2
4	Balearic Islands	1.00	0.65	−0.7	−35.1	22.2	8.5	15.3
5	Basque Country	0.77	0.64	34.2	−17.4	25.2	5.9	22.5
6	Canary Islands	0.90	0.63	23.5	−30.5	19.3	30.8	13.8
7	Cantabria	0.67	0.65	48.8	−2.0	17.2	11.7	15.9
8	Castilla-La Mancha	0.62	0.54	38.6	−12.1	21.6	12.1	15.6
9	Castilla y Leon	0.62	0.56	52.4	−9.5	20.8	16.3	19.8
10	Catalonia	0.80	0.64	31.2	−20.5	20.8	17.1	16.6
11	Extremadura	0.46	0.50	73.6	7.8	25.2	2.7	25.3
12	Galicia	0.67	0.58	74.6	−13.1	13.9	54.5	14.1
13	Madrid	1.00	0.71	26.8	−29.2	13.2	43.0	10.7
14	Murcia	0.76	0.60	30.3	−21.4	20.4	18.7	15.9
15	Navarra	0.73	0.61	29.2	−17.2	24.2	7.5	16.8
16	Rioja	0.74	0.60	29.9	−19.5	21.8	11.8	18.4
17	Valencian Community	0.88	0.65	25.6	−26.4	15.6	30.0	13.4
	average	0.74	0.61	38.2	−16.5	20.3	18.4	16.9
	weighted average	0.77	0.62	36.2	−18.8	18.8	22.8	15.8

Table 3: Distribution hypothesis tests (*p-values*)

	H_0: Distributions are equal H_1: Distributions are not equal	Bootstrap *p-value*
1	$g(y_{2003})$ vs. $f(y_{1980})$	0.0004
2	$g(y_{2003})$ vs. $f(y_{1980} \times EFF)$	0.0000
3	$g(y_{2003})$ vs. $f(y_{1980} \times TECH)$	0.0480
4	$g(y_{2003})$ vs. $f(y_{1980} \times KACC)$	0.0060
5	$g(y_{2003})$ vs. $f(y_{1980} \times HACC)$	0.0658
6	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times TECH)$	0.0000
7	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times KACC)$	0.0000
8	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times HACC)$	0.0000
9	$g(y_{2003})$ vs. $f(y_{1980} \times TECH \times KACC)$	0.1702
10	$g(y_{2003})$ vs. $f(y_{1980} \times TECH \times HACC)$	0.8212
11	$g(y_{2003})$ vs. $f(y_{1980} \times KACC \times HACC)$	0.7022
12	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times TECH \times KACC)$	0.0000
13	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times TECH \times HACC)$	0.0082
14	$g(y_{2003})$ vs. $f(y_{1980} \times EFF \times KACC \times HACC)$	0.0000
15	$g(y_{2003})$ vs. $f(y_{1980} \times TECH \times KACC \times HACC)$	0.0122

Notes: We used the bootstrapped (Li96) Tests with 5000 bootstrap replications and the (Sheather,Jones,1991) bandwidth.

Table 4: Efficiency scores and percentage change of quadripartite decomposition indexes, 1980−1994

#	Region	TE_b	TE_c	productivity change	EFF−1 × 100	TECH−1 × 100	KACC−1 × 100	HACC−1 × 100
1	Andalusia	0.74	0.67	40.2	−8.8	17.8	12.9	15.6
2	Aragon	0.65	0.67	45.8	2.5	20.1	2.1	16.1
3	Asturias	0.68	0.62	40.1	−9.0	17.3	15.1	14.0
4	Balearic Islands	1.00	0.89	27.9	−10.8	18.8	6.2	13.7
5	Basque Country	0.77	0.73	35.8	−5.5	20.1	2.1	17.2
6	Canary Islands	0.90	0.73	34.7	−18.7	16.0	26.3	13.1
7	Cantabria	0.67	0.69	54.6	2.6	17.7	12.8	13.5
8	Castilla-La Mancha	0.62	0.64	50.2	2.6	18.4	8.4	14.0
9	Castilla y Leon	0.63	0.62	44.5	−2.4	18.1	10.4	13.6
10	Catalonia	0.79	0.72	38.7	−8.9	17.3	14.6	13.2
11	Extremadura	0.48	0.55	68.8	15.1	20.1	0.0	22.1
12	Galicia	0.67	0.58	39.5	−12.1	10.4	36.5	5.4
13	Madrid	1.00	0.84	32.7	−16.2	11.4	33.3	6.7
14	Murcia	0.75	0.65	30.5	−13.3	16.8	14.9	12.1
15	Navarra	0.74	0.69	34.9	−6.1	20.1	4.5	14.5
16	Rioja	0.75	0.67	32.7	−10.1	18.5	8.2	15.1
17	Valencian Community	0.85	0.68	25.2	−19.7	13.5	26.2	8.7
	average	0.75	0.69	39.8	−7.0	17.2	13.8	13.4
	weighted average	0.77	0.69	38.3	−9.4	16.2	17.5	12.4

Table 5: Efficiency scores and percentage change of quadripartite decomposition indexes, 1995−2003

#	Region	TE_b	TE_c	productivity change	EFF−1 × 100	TECH−1 × 100	KACC−1 × 100	HACC−1 × 100
1	Andalusia	0.66	0.61	−4.0	−7.0	0.0	−0.7	4.0
2	Aragon	0.66	0.59	−3.0	−11.2	0.0	0.0	9.2
3	Asturias	0.63	0.63	6.8	−1.1	0.0	0.0	7.9
4	Balearic Islands	0.86	0.62	−20.5	−27.1	0.0	0.0	9.2
5	Basque Country	0.73	0.66	−2.3	−9.4	0.0	0.0	7.8
6	Canary Islands	0.71	0.62	−6.4	−12.4	0.0	0.0	6.9
7	Cantabria	0.69	0.65	−6.1	−6.1	0.0	−5.1	5.3
8	Castilla-La Mancha	0.64	0.53	−8.5	−16.5	0.0	0.0	9.6
9	Castilla y Leon	0.64	0.58	1.0	−8.1	0.0	0.3	9.6
10	Catalonia	0.72	0.63	−6.5	−11.9	0.0	−0.4	6.5
11	Extremadura	0.54	0.50	5.3	−8.2	0.0	0.0	14.6
12	Galicia	0.61	0.57	16.9	−5.2	0.0	13.6	8.5
13	Madrid	0.82	0.72	−4.4	−13.1	0.0	6.4	3.3
14	Murcia	0.64	0.59	−1.0	−7.7	0.0	1.7	5.4
15	Navarra	0.69	0.62	−4.9	−9.8	0.0	0.0	5.4
16	Rioja	0.67	0.61	−2.8	−9.9	0.0	0.0	7.8
17	Valencian Community	0.67	0.63	1.4	−5.7	0.0	3.0	4.4
	average	0.68	0.61	−2.3	−10.0	0.0	1.1	7.4
	weighted average	0.69	0.62	−2.2	−9.7	0.0	1.9	6.3

Table 6: Efficiency scores and percentage change of quadripartite decomposition indexes, Sectoral Analysis

Region	TE_b	TE_c	productivity change	EFF−1 × 100	TECH−1 × 100	KACC−1 × 100	HACC−1 × 100
			Total Industry				
1980−2003	0.77	0.62	36.2	−18.8	15.9	21.8	19.8
1980−1994	0.77	0.69	38.3	−9.4	16.2	17.5	12.4
1995−2003	0.69	0.62	−2.2	−9.7	0.0	1.9	6.3
			Agriculture				
1980−2003	0.77	0.72	197.2	−5.0	96.6	38.0	18.3
1980−1994	0.77	0.66	126.1	−14.1	80.4	34.8	11.0
1995−2003	0.62	0.72	44.4	24.2	7.2	1.8	5.9
			Manufacturing				
1980−2003	0.83	0.84	63.5	2.4	18.7	12.4	21.3
1980−1994	0.83	0.87	46.0	6.0	13.3	8.2	13.4
1995−2003	0.88	0.84	9.3	−4.8	5.8	−0.2	8.9
			Construction				
1980−2003	0.85	0.58	2.96	−31.49	22.59	8.36	13.72
1980−1994	0.85	0.70	26.91	−16.55	21.30	13.41	11.26
1995−2003	0.70	0.58	−19.2	−18.0	0.0	−5.5	4.2
			Energy				
1980−2003	0.63	0.63	117.6	7.4	44.8	13.1	26.8
1980−1994	0.63	0.55	69.2	−7.9	43.7	9.7	17.9
1995−2003	0.55	0.63	29.0	17.7	0.3	1.6	8.0
			Services				
1980−2003	0.92	0.48	4.2	−47.6	9.4	54.1	18.6
1980−1994	0.92	0.63	10.6	−31.4	7.3	38.0	9.2
1995−2003	0.62	0.48	−6.2	−21.4	0.0	15.1	4.0

Table 7: Sources of Productivity Growth, 1980−2003

Region	Productivity Growth Effect	Share Effect	Dynamic Effect	Total Effect	% Productivity Growth Effect	% Share Effect	% Dynamic Effect	% Total Effect
Andalusia	7529.66	2854.90	−2456.13	7928.43	94.97	36.01	−30.98	100
Aragon	9913.21	2384.58	−2361.92	9935.87	99.77	24.00	−23.77	100
Asturias	10852.80	5287.23	−4028.82	12111.20	89.61	43.66	−33.27	100
Balearic Islands	−2147.94	6571.34	−4676.98	−253.58	847.05	−2591.43	1844.38	100
Canary Islands	5409.72	3086.33	−2138.57	6357.48	85.09	48.55	−33.64	100
Cantabria	9523.31	4533.51	−3072.53	10984.29	86.70	41.27	−27.97	100
Castilla-Leon	10855.79	5303.88	−5060.23	11099.45	97.80	47.79	−45.59	100
Castilla-la-Mancha	7952.08	1840.98	−1951.44	7841.61	101.41	23.48	−24.89	100
Catalonia	8916.66	1551.81	−2171.20	8297.28	107.46	18.70	−26.17	100
Velencian Community	5686.86	2960.58	−2222.61	6424.83	88.51	46.08	−34.59	100
Extremadura	11378.24	3785.94	−3711.16	11453.01	99.35	33.06	−32.40	100
Galicia	9700.29	7661.81	−4520.83	12841.27	75.54	59.67	−35.21	100
Madrid	9376.73	3005.32	−3748.58	8633.46	108.61	34.81	−43.42	100
Murcia	6830.70	2946.68	−2597.23	7180.15	95.13	41.04	−36.17	100
Navarra	9187.22	2821.74	−4077.58	7931.37	115.83	35.58	−51.41	100
Basque Country	11285.38	2099.02	−3647.23	9737.16	115.90	21.56	−37.46	100
Rioja	8639.40	3365.84	−4357.26	7647.97	112.96	44.01	−56.97	100
Spain	8741.66	3486.66	−3083.47	9144.85	95.59	38.13	−33.72	100