UNIVERSITÀ DEGLI STUDI DI FERRARA
DIPARTIMENTO DI ECONOMIA ISTITUZIONI TERRITORIO
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Decomposing productivity patterns in a conditional convergence framework

Rosa Bernardini Papalia   Silvia Bertarelli

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Rosa Bernardini Papalia[1]

Silvia Bertarelli[2]

Abstract:
In this study we examine regional data on per worker GDP, disaggregated at sectoral level, by focusing our interest on the role of differences in the sectoral composition of activities, and in productivity gaps that are uniform across sectors, in explaining the catching-up process, which is realized through physical and human capital as well as technological knowledge accumulation. Our objective is to investigate how much of the interregional inequality in aggregate productivity per worker is imputable to each component. A methodology for identifying and analyzing sources of inequality from a decomposed perspective is developed in the growth framework by combining a shift-share based technique and a SUR model specification for the conditional-convergence analysis. The proposed approach is employed to analyze aggregate interregional inequality of per worker productivity levels in Italy over the period 1970-2000. With respect to the existing empirical results, our approach provides a more comprehensive and detailed examination of the contribution of each identified component in explaining the regional productivity gaps in Italy. It is argued that region-specific productivity differentials, uniform across sectors, explain a quite large share of differences in productivity per worker. However, sectoral composition plays a non negligible role, although decreasing since the end of '80s, and very different productivity patterns emerge within geographical areas.

Keywords: conditional convergence, shift-share decomposition, SUR estimation.

JEL classification: C13, C21, C23, O18, O47

[1] Dipartimento di Scienze Statistiche, Università di Bologna,Via Belle Arti, 41 - 40126 Bologna, tel.: +39 051 2098275, fax: +39 051 232153, e-mail: rossella.bernardini@unibo.it.
[2] Corresponding author: Dipartimento di Economia Istituzioni Territorio,Università di Ferrara, Via Voltapaletto, 11 – 44100 Ferrara, e-mail: silvia.bertarelli@unife.it.

1. Introduction

Most studies on economic convergence explain the catching-up process through physical and human capital as well as technological knowledge accumulation. It is also recognized that this process is influenced by several factors connected to the industrial structure of a country. First of all, labor reallocation from low to high capital intensive sectors may be a key factor for explaining heterogeneous productivity patterns (Paci and Pigliaru, 1997). Second, technological change and hence growth are favored by the transmission of ideas and innovations between firms. Such knowledge spillovers may arise as a result of a high degree of both concentration and differentiation of economic activities. More specifically, a high concentration of firms of the same industry within a region facilitates intra industry knowledge externalities, while diversity among firms is beneficial for inter industry knowledge spillovers.
From a theoretical point of view, there exist several models highlighting the importance of sectoral composition in the convergence process. In the exogenous growth framework changes in sectoral weights may influence the capital accumulation process (Uzawa, 1961, 1963), while in endogenous growth models structural change may be associated to technological catching-up (Abramovitz, 1986; Barro and Sala-i-Martin, 1997; Howitt, 2000). In the latter case, because of the specific role of national (or regional) production structures for convergence, as well as human capital, infrastructure, and social factors, the accumulation of technological knowledge is (partially) characterized as a localized process and may be linked to industry mix differences. In the endogenous growth literature (Romer, 1986; Lucas, 1988), it is also argued that innovation occurring in one firm increases the productivity of other firms located in the same region and/or technologically close to each other. More specifically, when dynamic externalities originate from other firms within the same industry, MAR externalities (Marshall, 1891; Arrow, 1962; Romer, 1986) and Porter externalities (Porter, 1990) may emerge, while, when knowledge spillovers occur between firms operating in different sectors, Jacobs externalities may arise (Jacobs, 1969). With MAR externalities, specialization positively affects growth through the exchange of ideas or, indirectly, through movements of qualified workers. However, profits may increase more when firms adopt strategies of innovation, rather than strategies of imitation, and supply differentiated products. In this case, the incentive to innovate is higher in the presence of monopolistic firms. Like MAR externalities, Porter externalities are more likely to occur in specialized, geographically concentrated industries. However, they differ on the role of competition. For Porter (1990) local competition rather than monopoly is better for growth because competition stimulates firms to innovate. When the variety of the industrial structure rather than the geographical specialization of a region stimulates innovation and growth, as for Jacobs externalities (Jacobs, 1969), diversity enhances growth, and local competition induces faster transmission of ideas and information. There is a growing number of empirical studies (for a brief survey see Bun and El Hakhlouf, 2007), which analyzes the relationship between knowledge externalities and economic development. The majority of these studies measures economic activity by employment and the sectoral perspective is introduced to take account of sector specific characteristics, which affect local historical industrial conditions. Most of the empirical evidence tests whether knowledge spillovers come from firms operating within the same industry or from firms operating in different industries, confirming Jacobs and Porter theories, while results on MAR externalities are mixed.
With the objective of analyzing the catching-up process along the sector composition dimension, in this study we examine regional data on per worker GDP, disaggregated at sectoral level, by focusing our interest on the role of differences in the sectoral composition of activities, and in productivity gaps that are uniform across sectors. Moreover, by using data decomposed by sector we are able to analyze the role of structural change and capital deepening in a convergence analysis, and to study the relationship between knowledge spillovers and regional economic development. The idea is to identify the main determinants of the convergence process by analyzing the potential determinants of GDP per worker differentials and the relative importance

(weight) of each source of regional productivity differential within a growth theory framework. We proceed by formalizing an extended conditional convergence equation to explicitly account for a decomposition of per worker GDP (productivity) which is derived on the basis of a modified (log) version of the shift-share approach proposed by Esteban (2000). To assess the role of these determinants in a convergence framework we then describe the behaviour of these components as a system of seemingly unrelated regression equations.
A quantitative measure of productivity differences across countries and regions with the introduction of the sector composition dimension, has been proposed, among others, by Paci and Pigliaru (1997), Esteban (2000), Kamarianakis and Le Gallo (2003), and Caselli and Tenreyro (2005). In Paci and Pigliaru (1997), some sector components have been considered to measure the contribution of sector composition to the convergence process. Esteban (2000) introduces a decomposition of European regional per worker productivity differential with the aim of disentangling differences in productivity levels due to differences in sector composition from differences in productivity levels that are uniform across sectors. Kamarianakis and Le Gallo (2003) estimate seemingly unrelated regressions to study the evolution of the impact of the same components on the productivity gap of EU regions. Caselli and Tenreyro (2005) revisit Western Europe's labor-productivity convergence with the objective of extrapolating its implications for the future path of Eastern Europe along two margins. One margin (between industries) is connected to the reallocation of labor from agriculture to manufacturing and services. The other margin (within industry) reflects capital deepening and technology catch-up at the industry level. We take a step forward by using analogous decomposed data on productivity per worker with the purpose of disentangling the convergence process along three different margins, though maintaining a unified framework for the analysis (the conditional convergence regression). In addition, results on disaggregated processes may be used to draw some conclusions on the aggregate convergence process. The proposed approach is employed to analyze aggregate interregional inequality of per worker productivity levels in Italy by using information at regional level for fourteen sectors covering a thirty year period (1970-2000).
The paper is organized as follows. In section 2 the productivity decomposition into basic components is presented. In section 3 we discuss an extended version of the traditional convergence equation with regional heterogeneity, which allows for the productivity decomposition. In section 4 we present the results of the empirical application to the Italian database. Section 5 concludes.

2. A multi-sectoral analysis of interregional inequality

Following the work of Esteban (2000) a shift-share based analysis is proposed with the aim of identifying the causes of the interregional aggregate productivity differentials. The basic idea used in the shift-share analysis[3], is to investigate if the difference in growth between each region and the national average is due to the region performing uniformly better than the average on all industries or to the fact that the region happens to be specialized in fast growing sectors.
Since aggregate average productivity per worker can be viewed as the weighted average of the productivities at the sectoral level, a particular region can have an aggregate productivity per worker above the mean because of two reasons, region-specific productivity differentials and industry mix, or a combination of both. In order to quantify and isolate their contribution we compare each region with a benchmark region, which presents sectoral productivities and industry mix equal to the national average. The regional productivity differential with respect to the national mean is then decomposed into three components: structural, differential and allocative.

[3] Originally proposed by Dunn (1960) as a forecasting technique for regional growth, it has usually been based on employment data.

A *structural* (*or sectoral*) *factor* is identified by recognizing that if a region is specialized in the most productive sectors, the regional aggregate productivity would result above the mean even if there are no differences in the productivity of each sector across regions. In this case, we expect that history and local advantages are the main determinants. A *differential* (*or regional*) *factor* depends on sector-by-sector productivity differentials to the average, assuming that the sectoral composition of the regional industry is equal to the mean sectoral composition of the aggregate. In this second component we expect that previous investment in technology, human capital, and public infrastructure may represent the main determinants. Finally, an *allocative factor* indicates the degree of efficiency of each region in allocating the resources over the sectors; it is a combination of the first and the second factors. This component is positive (negative) if the region is specialized in sectors whose productivity is above (below) the national average.
The decomposition of per worker GDP in logs requires to extend the shift share analysis, proposed by Esteban (2000), in terms of log variables. Formally, our approach can be formulated as follows (henceforth, t subscripts are suppressed for sake of simplicity).

Let $p_i^j = \frac{L_{ij}}{L_i}$, be the sector j's employment share in region i, (so that $\Sigma_j\ p_i^j = 1$ for all region i), where L_{ij} is the employment in region i and industry j. In the same way, with reference to the national economy, we denote $p_.^j = \frac{L_{.j}}{L_.}$ sector j's employment share at the national level, where $L_{.j}$ is the employment in industry j in the national economy. Thus, we also have $\Sigma_j\ p_.^j = 1$.

Departing from Esteban (2000), we assume that the aggregate average productivity per worker y_i of the i-th region is measured by means of a weighed geometric mean of the productivity per worker in sector j and region i, with weight for each j-th sector equal to employment shares of the j-th sector[4],

$$y_i = \prod_j \left(\frac{VA_{ij}}{L_{ij}}\right)^{\frac{L_{ij}}{L_i}},$$

where VA_{ij} is the value-added in sector j and region i. Similarly, for the same variable at the national level, we assume:

$$y_. = \prod_j \left(\frac{VA_{.j}}{L_{.j}}\right)^{\frac{L_{.j}}{L_.}}$$

where $VA_{.j}$ is the value-added in sector j at national level.
Therefore, taking logs of the aggregate productivity per worker, relative to region i, and national economy, we can write:

$$\ln y_i = \sum_j \frac{L_{ij}}{L_i} \ln\left(\frac{VA_{ij}}{L_{ij}}\right),$$

$$\ln y_. = \sum_j \frac{L_{.j}}{L_.} \ln\left(\frac{VA_{.j}}{L_{.j}}\right) \qquad (1)$$

The gap between logs of regional and national average productivities is then decomposed into the three components as follows:

$$\ln y_i - \ln y_. = s_i + g_i + m_i \qquad (2)$$

[4] Since per worker productivity levels tend to be log-normally distributed, the geometric mean is a good measure as it averages ratios and rates of change. It is also demonstrated that for lognormal distribution the variance of the geometric mean is always smaller than that of the arithmetic mean.

The decomposition in (2) reduces to the productivity difference between two time periods, introduced by Baily *et al*. (1992) and improved by Haltiwanger (1997), if we reformulate our analysis of the regional productivity gaps by measuring the productivity growth between periods (t -1) and t (by exchanging country average variables with time (t -1) values).
The industry-mix component s_i of region i measures the differential in productivity per worker between region i and the national average due to the specific sectoral composition of its industry. Here it is assumed that the productivity per worker in each sector is the same across all regions and is equal to the national average. It is defined as follows:

$$s_i = \sum_j \left(p_i^j - p_.^j\right) \ln y_.^j \qquad (3)$$

where $\ln y_.^j = \ln\left(\frac{VA_{.j}}{L_{.j}}\right)$, $p_i^j = \frac{L_{ij}}{L_i}$, and $p_.^j = \frac{L_{.j}}{L_.}$.

This component takes positive values if the region is specialized in sectors with a higher productivity with respect to the national average level.
The productivity differential component g_i focuses on productivity differentials due to region i's sector by sector productivity differential, assuming that the region's industry mix coincides with the national one. It is defined as follows:

$$g_i = \sum_j p_.^j \left(\ln y_i^j - \ln y_.^j\right) \qquad (4)$$

where $\ln y_i^j = \ln\left(\frac{VA_{ij}}{L_{ij}}\right)$, $\ln y_{ITA}^j = \ln\left(\frac{VA_{.j}}{L_{.j}}\right)$, and $p_.^j = \frac{L_{.j}}{L_.}$.

This component singles out intra-industry differences and takes positive values if productivity at the industry level is higher than the corresponding national aggregate.
The allocative component m_i is a combination of the previous components and is an indicator of the efficiency of each region in allocating its resources over different industrial sectors. This component can also be viewed as measuring the covariance between sectoral and productivity advantages. It is defined as follows:

$$m_i = \sum_j \left(p_i^j - p_.^j\right)\left(\ln y_i^j - \ln y_.^j\right) \qquad (5)$$

where, again, $p_i^j = \frac{L_{ij}}{L_i}$, $p_.^j = \frac{L_{.j}}{L_.}$, $\ln y_i^j = \ln\left(\frac{VA_{ij}}{L_{ij}}\right)$, and $\ln y_.^j = \ln\left(\frac{VA_{.j}}{L_{.j}}\right)$.

This component takes positive values if the region is more specialized, relative to the national average, in sectors where regional productivity is above the national average.

3. The extended conditional-convergence specification

The influence of physical and human capital as well as technological knowledge accumulation on growth depends on several factors connected to the industrial structure of a country. Factor reallocation across sectors may be a key factor for explaining heterogeneous productivity patterns and technological change may be favored by the transmission of ideas and innovations between firms. In the growth literature there exist neoclassical and non-neoclassical models highlighting the importance of sectoral composition in the convergence process[5]. In the exogenous growth

[5] See for a brief survey Paci and Pigliaru (1997). Other theoretical frameworks where sectoral composition influences convergence can be considered, as suggested by Caselli and Tenreyro (2005), with reference to the theory on structural transformation (Lewis, 1954; Imbs and Wacziarg, 2003) and to trade models on comparative advantage.

framework changes in sectoral weights may accompany the capital accumulation process in a two-sector model (Uzawa, 1961, 1963), producing heterogeneous capital deepening effects on the convergence process, which depend on the sector composition of economic activities. In endogenous growth models, structural change may be associated to technological catching-up (Abramovitz, 1986; Barro and Sala-i-Martin, 1997; Howitt, 2000). In the latter case, because of the specific role of regional production structures for convergence, as well as human capital, infrastructure, and social factors, the accumulation of technological knowledge is (partially) characterized as a localized process and may be linked to industry mix differences. In the endogenous growth literature (Romer, 1986; Lucas, 1988), it is also argued that innovation occurring in one firm increases the productivity of other firms located in the same region and/or technologically close to each other. Widespread agreement emerges on the importance of such knowledge spillovers for growth. However, there is no consensus about on whether knowledge spillovers come from firms operating within the same industry (MAR and Porter externalities) or from firms operating in different industries (Jacobs externalities).
With the objective of explaining the convergence process - realized through physical and human capital as well as technological knowledge accumulation - we analyze the role of industry composition by separating its contribution from productivity gaps that are uniform across sectors. From this decomposed perspective, as a first step a generalization of the conditional convergence relation relative to all components is required. The theoretical discussion on conditional convergence is derived from the transitional dynamics of Solow-type neoclassical models, which allow us to introduce a simplified description of the growth process. In this view, we are interested in finding $\{c_t, k_{t+1}\}_{t=0}^{\infty}$ so as to maximize utility:

$$\max \quad U_0 = \sum_{t=0}^{\infty} \rho^t u(c_t), \tag{6}$$

subject to the resource constraint of the economy, and taking initial k_0 as given:

$$\begin{aligned} & c_t + k_{t+1} \le (1-\delta-n)k_t + f(k_t) \\ & c_t \ge 0, \quad k_{t+1} \ge 0, \\ & k_0 > 0 \quad \textit{given} \end{aligned} \tag{7}$$

where c_t is consumption, ρ is the discount factor in the utility function, $0 < \rho < 1$, $u(.)$ is a well-behaved utility function; f is a well-behaved production function expressed in intensive form ($f(k) = F/AL$, where A states the level of technology, L is labor), and k_t is capital in intensive form, which is assumed to depreciate at a constant rate δ, $0 < \delta < 1$. Labor supply grows at a constant rate n. By solving the Bellman equation associated with the dynamic programming problem it is possible to find the steady state capital, k^*, and the steady state income, y*. As already shown by Mankiw, Romer and Weil (1992), we can write a convergence equation as a linearization around the steady state y^* in the following way:

$$\ln y_{it} - \ln y_{it-1} = (1+\beta^y)(\ln y_{it-1} - \ln y^*), \tag{8}$$

The next step requires the approximation of the steady state output y^* by a set of region-specific controls X, which include the investment rates in physical and human capital, the labor supply growth rate, etc, to take account of possible differences on fundamentals (convergence towards different steady-states). Technological diffusion effects favored by knowledge spillovers are also considered, in terms of MAR externalities (Marshall, 1891; Arrow, 1962; Romer, 1986), Porter externalities (Porter, 1990), and Jacobs externalities (Jacobs, 1969). It is possible to introduce the generalized conditional-convergence regression expressed in levels as

$$\ln y_{it} = \beta^y \ln y_{it-1} + \beta^{x}{}' \ln X_{it-1} + u_{it} \tag{9}$$

Here, a negative value for β^y reflects local diminishing returns. Such local diminishing returns occur in exogenous as well in endogenous growth models. Time effects control for the presence of a common (time trend and stochastic trend) component of technology.
The previous equation can also be expressed in terms of differences from the national mean to eliminate time effects:

$$Z_{it} = \beta^y Z_{it-1} + \beta^{x}{}' \tilde{X}_{it-1} + u_{it} \tag{10}$$

$$Z_{it} = \ln y_{it} - \ln y_{.t} \qquad Z_{it-1} = \ln y_{it-1} - \ln y_{.t-1} \qquad \tilde{X}_{it-1} = \ln X_{it-1} - \ln X_{.t-1} \tag{11}$$

where $\ln y_{.t}$, $\ln y_{.t-1}$, and $\ln X_{.t-1}$ refer to national averages. We then proceed by decomposing regional per worker productivity differential Z_{it}, following the methodology presented in the previous section.
According to the three components decomposition (2), at time t, we can write

$$Z_{it} = s_{it} + g_{it} + m_{it} \tag{12}$$

so we can reformulate the conditional-convergence regression (10) for the regional productivity per worker differential as

$$(s_{it} + g_{it} + m_{it}) = \beta^y Z_{it-1} + \beta^{x}{}' \tilde{X}_{it-1} + u_{it} \tag{13}$$

Our purpose is to disentangle the regional convergence process along three different margins: "convergence in sectoral composition", "within industry convergence", and "inter sectoral productivity convergence". If we had a movement of workforce to the higher productivity sectors, we would have a *convergence in sectoral composition* of the labor force. In this case we refer to s component. If the productivity of a sector converged to the productivity of the same sector in the country, we would state the *within industry productivity convergence*. To assess this movement we refer to the second component g. Finally, if there was a generalized convergence of the productivity of the sectors in which a region had a disproportionate share of the labor force to the national mean productivity of the average industry mix of the country, we would have *inter-sectoral productivity convergence*. The latter movement may be detected by using factor m.

$$\begin{aligned} s_{it} &= \beta_s^y Z_{it-1} + \beta_s^{x}{}' \tilde{X}_{it-1} + u_{it}^s \\ g_{it} &= \beta_g^y Z_{it-1} + \beta_g^{x}{}' \tilde{X}_{it-1} + u_{it}^g \\ m_{it} &= \beta_m^y Z_{it-1} + \beta_m^{x}{}' \tilde{X}_{it-1} + u_{it}^m \end{aligned} \tag{14}$$

with:

$$\begin{aligned} \beta^y &= \beta_s^y + \beta_g^y + \beta_m^y \\ \beta^x &= \beta_s^x + \beta_g^x + \beta_m^x \\ u_{it} &= u_{it}^s + u_{it}^g + u_{it}^m \end{aligned} \tag{15}$$

In this way, we are able to introduce different patterns of convergence connected to structural, sectoral and allocative sources of regional differential productivity, without missing information on the convergence process from an aggregate perspective.
Finally, to empirically evaluate the convergence process in this perspective we introduce a SUR analysis which treats the relationship describing the behaviour of each component as a system of seemingly unrelated regression equations (Zellner, 1962), and accounts for any underlying correlation between the identified components. More specifically, we proceed by specifying a system of three equations, one for each component - $c = s, g, m$ - as a system of seemingly unrelated regression equations (Zellner, 1962), which allows for covariance between the disturbances across different components and assumes that unknown parameters may differ from equation to equation.
The c-th model (equation), relative to the c-th component ($c = s, g, m$), is given by:

$$Y_c = X_c \beta_c^* + \varepsilon_c \tag{16}$$

where Y_c and ε_c are of dimension (NT×1), X_c is (NT×K_c) - including lagged (aggregate) dependent variable Z_{it-1} and regional control variables $\tilde{X}_{it-1}$ - and β_c is (K_c×1), where N is the total number of regions (i = 1,.., N), and T is the total number of time periods (t = 1,.., T).
The system approach considers three equations, of the form (16), relative to the three components as:

$$Y = X\beta^* + \varepsilon$$

$$Y \equiv \begin{bmatrix} s \\ g \\ m \end{bmatrix} \qquad X \equiv \begin{bmatrix} X_s & 0 & 0 \\ 0 & X_g & 0 \\ 0 & 0 & X_m \end{bmatrix} \tag{17}$$

$$\beta^* \equiv \begin{bmatrix} \beta_s \\ \beta_g \\ \beta_m \end{bmatrix} \qquad \varepsilon \equiv \begin{bmatrix} \varepsilon_s \\ \varepsilon_g \\ \varepsilon_m \end{bmatrix}$$

where Y and ε are each of dimension (3NT×1), X is a block diagonal matrix of dimension (3NT×K) with K = Σ K_c and $\beta^* = (\beta_s, \beta_g, \beta_m)'$ is an unknown vector of dimension (3K×1).
We also assume that the equation errors are contemporaneously correlated, but uncorrelated over time. Consequently, the covariance matrix for ε may be written as:

$$\Phi = \Psi \otimes I_{NT} \tag{18}$$

where Ψ is a (3×3) positive definite symmetric matrix, $\otimes$ is the Kronecker product operator and I_{NT} is an identity matrix of dimension NT.
Within this context, the Generalized Least Squares (GLS) estimator is traditionally used when the covariance matrix for errors is known, while if the error covariance is unknown, consistent estimates of the variance and covariances are used to form the feasible GLS estimator (Zellner, 1962).
Two points of interest should be noted here. By first studying the phenomena (conditional convergence across regions) by means of a decomposed system, we can maintain the traditional aggregate perspective and recover aggregate results for the convergence rate by using expressions (15). Concerning the system approach, another point to be noted here is that it is possible to evaluate the effects of usual conditioning variables on each component separately.

4. The analysis of productivity patterns in Italy

The recent empirical literature analyzing the Italian experience reveals that regional differences in productivity levels are the main reason for regional inequality in per capita income. Moreover, quite different productivity patterns emerge when the analysis is conducted by considering geographical areas (Southern and Center-Northern regions) separately (Paci and Pigliaru, 1995; Di Liberto *et al*., 2007). Differences in productivity levels cannot be motivated by a lack of physical capital per worker and are partially correlated to differences in human capital endowments between North and South. Indeed labor productivity differentials are predominantly explained by TFP differences (Di Giacinto and Nuzzo, 2004; Scoppa, 2007). We change the perspective of the explanation of productivity differentials, to distinguish sectoral composition from productivity gaps that are uniform across sectors. We apply the methodology presented in previous sections to regional data on per worker productivity levels in Italy, disaggregated for 14 sectors and covering a thirty-year period (1970-2000).

4.1 Decomposition of regional inequalities: explorative analyses

The modified shift-share approach, developed in section 2, is employed in order to assess the extent to which industry composition affect regional labor productivity in Italian regions and to study the effects of different industrial structures on regional per worker GDP growth.
The CRENOS data set on 20 Italian regions and 14 sectors for the whole economy covering the period 1970-2000, is utilized (see Appendix A for a description of data). All final data are expressed in logs and are calculated as 5-year averages. Per capita value added figures at constant 1995 prices are used. The s_{it}, g_{it}, m_{it} components are calculated according to (3), (4) and (5), while the log of

regional productivity levels (ln y_{it}) are obtained as a weighted average of logs of sectoral value added per worker, following (2). The same procedure is used for the corresponding log of national productivity per worker (ln $y_{.t}$). The analysis is also conducted by considering two different regimes, A and B, which represent sub-groups of homogenous Italian regions as identified by a mapping analysis (Bernardini Papalia and Bertarelli, 2006a). See table A2 (in Appendix A) for details on groupings.
Our results show how the productivity differential component g_i (t subscript suppressed to simplify notation) is positive for regime A, while it is negative for regime B, showing the (negative) labor productivity gap of the South (see Table 1, reported in Appendix B). The industry mix component, s_i, is positive for regime A and negative for regime B, but both tend to zero, while the allocative component appears to be negative on average for regimes A and B. We also find that industry mix and per worker productivity differential components equally explain the negative gap of Southern regions (Regime B) at the beginning of the period. However, the g-component has increased its relative importance, accounting for 2/3 of Regime B productivity per worker gaps in the second half of '90s. Finally, total labor productivity gaps tend to zero for both regimes, indicating that the gap between rich and poor regions has been shrinking.
According to the decomposition of regional average productivity, $Z_{it} = \ln y_{it} - \ln y_{.t}$, into the sum of three *shift-share* components (*s, g, m*), as in Eq. 2, the role played by each of these factors in explaining interregional differences in productivity per worker emerges by analyzing the share of total variance by components, together with a term collecting the co-variances. We refer to the whole sample of 20 regions (Italy), and to a sub-sample of 12 regions belonging to regime A, and to the remaining sub-sample of 8 regions included in regime B. The results obtained are given in Table 2 (in Appendix B). Most of the observed interregional variance in aggregate productivity per worker is attributable to industry mix (s_i) and productivity differentials (g_i) for Italy and Regime A, while the industry mix has a higher weight than the productivity gap for regime B. It is also worth noting the relevant weight of the co-variances especially for Regime B. For a detailed evolution over time of the variance of the three components, see figures 1, 2 and 3 reported in Appendix B. It is worth noting that Regime B has been showing a g-component variance that is higher than s-component one, since the end of 80s.
In order to have a sharper appreciation of the role played by each component, following Esteban (2000), we first test whether interregional differences in aggregate productivity per worker can be explained by a model including one single component of the *shift-share* decomposition[6]. The results obtained with reference to each model are given in Table 3 (Appendix B), for the whole sample of 20 Italian regions and for regime A and B sub-groups. We can immediately see that the fit, measured by the adjusted R^2, given by the industry mix and the productivity differential components are almost equal, even though for regime B the industry mix component is the most important one. This result tells us that we can have an accurate prediction of the differences in aggregate productivity per worker between any two Italian regions on the basis of both the industry mix and the differential components. However, by considering results relative to regimes, some differences arise given that for regime B besides a major role for the industry mix we also find that the allocative component (m) is not negligible.

4.2 The conditional convergence analysis in a system view

With the objective of explaining heterogeneous productivity patterns in Italian regions, as emerged in previous sections, we now proceed by investigating the importance of physical and human capital as well as technological knowledge accumulation in the regional conditional convergence process, by using decomposed data along the industry-mix, productivity gap, and allocative dimensions and

[6] To this effect we estimate the following three models:
M1: $Z_{it} = a_i^s + b_i^s s_{it} + e_{it}^s$; M2: $Z_{it} = a_i^g + b_i^g g_{it} + e_{it}^g$; M3: $Z_{it} = a_i^m + b_i^m m_{it} + e_{it}^m$.

by analyzing the behavior of these determinants as a system of three seemingly unrelated (SUR) equations. In analyzing conditional convergence across Italian regions by means of the system specification (17) and using the decomposition developed in section 3, we are able to investigate if the decomposition of regional deviations (from the national mean) of per worker value added for the Italian economy has had any effect on growth.

More specifically, in order to estimate a system of three seemingly unrelated (SUR) equations, relative to the three components (s_i, g_i, m_i) for the period 1970-2000, capital deepening and technological knowledge accumulation effects are introduced. With reference to capital deepening effects, we consider as explanatory variables: the lagged per worker value added (*ly*), and a set of other region-specific explanatory variables suggested by the theory, which determine the steady state per worker productivity as stated in section 3[7]. This set includes the investment in physical capital (*lsk*), the investment in human capital (*lsh*), the sum of the employment growth rate, the exogenous technological growth rate, and the depreciation rate (*lndx*) at $(t-1)$ [8]. The saving rate in physical capital is given by the ratio of investment and aggregate value added, and the investment rate in human capital is the ratio of enrollment in secondary school and population of age 14-19[9]. Moreover, we add to the employment growth rate a constant value of 0.05 to take account of the exogenous technological growth rate and the depreciation rate. Finally, since empirical evidence focusing on Italian regions shows the presence of two homogenous sub-groups of regions (Mauro and Podrecca, 1994; Bernardini Papalia and Bertarelli, 2006b), a dummy variable is introduced with the aim of evaluating potential differences in regimes, A and B, as identified by Bernardini Papalia and Bertarelli (2006b) in a club convergence analysis. See table A2 in Appendix A for details on groupings. The *d_regimeA* variable takes value 1 if region *i* belongs to regime A, and 0 otherwise.

With reference to technological diffusion effects favored by knowledge spillovers, namely MAR-Porter-Jacobs externalities, we consider three explanatory variables, as in Glaeser *et al*. (1992), measuring dynamic externalities in the diffusion of technological innovation with reference to four macro-sectors (*ag, inss, c, ms, nms*; see table A4). With reference to Marshall (MAR) agglomeration spillovers, capturing the positive effects of the agglomeration of firms belonging to the same sector, we consider a sector specialization index computed on industry employment:

$$lspec_{ij} = \frac{L_{ij} \Big/ \sum_j L_{ij}}{L_{.j} \Big/ \sum_j L_{.j}} \qquad \text{with } i = 1, \ldots, 20 \;\; j = ag, inss, c, ms, nms \qquad (19)$$

where L_{ij} is employment in region *i* and industry *j*, and $L_{.j}$ is employment at national level in industry *j*. To account for spillovers created among firms localized in the same geographical area (Porter-type spillovers), a district variable has been introduced (*district*). Specifically we have considered the number of districts, identified by ISTAT, in a region divided by the total number of Italian districts in 1996, as a measure of the local development of firms' networks across Italian regions[10]. Other types of agglomeration economies can arise from the diversity of the regional economic structure, so industrially diversified regions could attract other firms. To measure the so called Jacobs externalities we employ the relative Hirschman-Herfindal index (Henderson *et al*., 1995 among others):

[7] Again, the s_{it}, g_{it}, m_{it} components are calculated according to (3), (4) and (5), while the log of regional productivity levels ($\ln y_{it}$) are obtained as a weighted average of logs of sectoral value added per worker, following (2). The same procedure is used for the corresponding (log of) national productivity per worker ($\ln y_{.t}$).

[8] Per capita value added and other economic aggregates at constant 1995 prices are used. All final data are expressed in logs and are calculated as 5-year averages to eliminate the business cycle component. Other studies have taken averages over 5-*year* periods, like Islam (1995) and Caselli *et al*. (1996) among others. As explained in section 3, all variables are demeaned with respect to the national average to eliminate time effects.

[9] This measure of human capital has been introduced to directly compare to previous results based on secondary school enrolment rates, Mauro and Podrecca (1994), Paci and Pigliaru (1995). Following Di Liberto and Symons (1998) and Di Liberto (2001), further investigation with average years of schooling in the workforce is required.

[10] Cingano and Schivardi (2003) differently consider a local Herfindahl index of concentration computed at the firm level as a measure of local competition.

$$ldiv_{ij} = \frac{H_{ij}}{H_{.j}} \qquad \text{with } i = 1, \ldots, 20 \;\; j = ag, inss, c, ms, nms \qquad (20)$$

where $H_{ij} = \sum_{j^* \neq j} s^2_{ij^*}$, and $s^2_{ij^*} = L_{ij} \Big/ \sum_{j^* \neq j} L_{ij^*}$.

For region *i* and sector *j*, the index is measured over all the industrial sectors except *j* and is decreasing with the relative diversity of the area compared with the national average, that is higher indexes indicate less diversified areas. Provided that economic theory predicts a positive relation between sectoral diversity and labor productivity levels, negative coefficients for such diversity indexes are expected to come out in convergence regressions[11].

Results with feasible GLS estimates have been obtained with reference to four different model specifications and are summarized in table 4 for the period 1970-2000. In addition tables 5-6-7 present feasible GLS estimates for three sub-periods with a time span of ten years: '70s, '80s, and '90s. We start our analysis by estimating the baseline convergence system (Model 1), which includes the lagged per worker value added (*ly*), the investment in physical capital (*lsk*), the investment in human capital (*lsh*) the population growth rate (*lndx*) and a dummy variable that measures potential heterogeneity between Regime A and B regions due to other institutional and social factors (*d_regimeA*). In Model 2 specification the purpose is to evaluate the role of agglomeration spillovers through the geographic distribution of economic activities (*district*). To take account of MAR agglomeration externalities we add specialization measures (Model 3) and for Jacobs's externalities we consider diversity indexes (Model 4). Model 5 considers MAR and Porter spillovers together, while Model 6 introduces MAR and Jacobs spillovers.

The process of conditional convergence, analyzed from a decomposed perspective, reveals the most important role of the productivity gap component, showed by the highest relative value of the estimated coefficient of the lagged per employed value added in *g* equation for all model specifications, with the exception of Models 1 and 2 where *s* and *g* components are equivalently relevant. Model 1 and 2 results are consistent with the exploratory investigation developed in section 4.1, while other specifications are able to capture a phenomena emerging in Italian regions only in the 90s, that is the increasing importance of uniform-across-sector productivity gaps.

All explanatory variables used as a proxy of the steady state value added influence the productivity gap *g* in the traditional way predicted by growth theory[12], while the evidence for the industry mix component *s* suggests that human and physical capital investment resources have been channeled toward traditional (low productivity) sectors, given that a negative coefficient for the physical and human capital growth rates emerges in almost all specifications. This result departs from the evidence on other developed economies characterized by increasing investments in high productivity sectors. For the allocative component *m*, results display no significant coefficients for the same variables.

By focusing on agglomeration externalities, we observe that MAR externalities have encouraged the regional specialization in high productivity sectors and the increase of uniform across sector productivity gaps (positive coefficient of specialization indexes for the *g* and *s* components), while Jacob's spillovers have provided mixed effects on *s* and *g* across sectors. More specifically, the degree of diversity significantly affects productivity per worker through productivity gap (positively) and industry mix components (negatively) only for some sectors. The evidence confirms a positive sign for the former component and a negative sign for the latter one only for the agriculture sector in Model 5. From Model 6 specification this effect on the *s*-component does not emerge, while the *g*-component seems to be affected positively by agriculture, market and non market services indexes, and negatively by the construction sector one. With reference to the

[11] Sector specialization and Hirschman-Herfindal indexes have been calculated with reference to five macro-sectors (agriculture, industry in the strict sense, construction, market services, and non-market services).

[12] The positive coefficient of the investment in physical capital (*lsk*) is confirmed in almost all specifications (in other cases it is not significant) and the estimated value for regime A dummy variable (*d_regimeA*) is positive, while for human capital (*lsh*) and employment growth rate (*lndx*) we cannot refuse the null hypothesis.

allocative component *m*, MAR and Jacob's externalities have produced negative effects. This result may indicate a loss of efficiency in allocating resources from these knowledge spillovers, mostly concentrated in '70s (with some differences between regimes A and B) and '80s.
Finally, much attention has been devoted to Porter externalities measured by the district variable. The effects of the district variable are quite significant and positive on the productivity gap component *g* and negative on the industry-mix component *s*, while a negligible effect on the allocative component *m* emerges. The presence of districts in a region, that is geographic areas where the economic activity is highly specialized and the average firm dimension is small, guarantees a positive differential from the national productivity level. However, the region with districts tends to be specialized in low productivity sectors[13].
Finally, with reference to the analysis of the rate of convergence from an aggregate perspective, our results support the hypothesis of conditional convergence among Italian regions of 2.8% a year in Model 1 and Model 2. For Model 3 and Model 4, the rate of convergence increases to 3.3%[14]. In addition, by splitting the sample into three groups with a time span of ten years, '70s, '80s, '90s, we obtain diversified results. See tables 5-6-7, respectively. We find lack of convergence during the 70s, due to an important slow down of regime B regions, while in the '80s we observe convergence ranging from 6.9% (Model 6) to 8.9% (Model 4) while in the '90s for the alternative models diversified results for the convergence rate emerge. This evidence is in line with our previous findings (Bernardini Papalia and Bertarelli, 2006 a, b).
In summary, by combining a shift-share based technique and a SUR model specification for the conditional-convergence analysis, our approach has provided a more comprehensive and detailed examination of the contribution of each identified component in explaining the regional productivity gaps. In addition, the role of variables measuring (physical and human) capital accumulation and knowledge diffusion can be studied by testing the heterogeneity of their effects on the productivity gap uniform across sectors, on the industry mix component, and on the degree of efficiency in the allocation of resources.

5. Conclusions

The influence of physical and human capital as well as technological knowledge accumulation on growth depends on the industrial structure of a country. Factor reallocation across sectors may be a key factor for explaining heterogeneous capital deepening effects and technological change may be favored by the transmission of ideas and innovations between firms. In this view, the connection between growth and its determinants has been analyzed assuming a sectoral perspective and focusing the attention on the contribution of the existing differences in the sectoral composition of activities and in the productivity gaps that are uniform across sectors. Knowledge externalities connected to sectoral composition have also been considered and classified into two different classes: specialization and diversity externalities. The first group comprises knowledge spillovers among firms of the same industry (MAR and Porter externalities), while in the second one spillovers are identified by the interaction of firms operating in different sectors (Jacobs externalities). The idea is to separate the effects of technology diffusion due to a high concentration of firms of the same industry within a region (intra industry knowledge externalities), from those relative to diversity among firms that promote the inter industry knowledge spillovers.
A methodology for identifying and analyzing sources of inequality in aggregate productivity per worker across regions has been developed in the growth framework by combining a shift-share

[13] With reference to local labor systems and 10 sectors, positive effects of specialization on TFP growth, while negligible effects of competition and diversity spillovers, have been established by Cingano and Schivardi (2003),

[14] The corresponding rate of convergence is given by $\lambda = -\ln \beta^{y} / T$, with T = 5. Convergence rates seem to be robust in all specifications, when comparing to convergence rates estimates calculated from a convergence equation regression based on aggregate data (see table 8).

based technique and a SUR model specification for the conditional-convergence analysis. The role played by three identified components (structural, sectoral and allocative) in explaining the regional differential productivity – that is the gap between logs of regional and national average productivities – has been explored by specifying a system of three equations where the effects of the main variables, commonly introduced in the classical conditional convergence regression, on the regional specialization and on the uniform productivity gaps have been evaluated. The presented approach contributes to the empirical analysis of regional conditional-growth processes along two main directions. First, the knowledge of the convergence process is enhanced by analyzing three different patterns of regional productivity gaps, which contribute to its determination and interpretation. Second, when we decompose the productivity differentials into its constituents, we can test if: (i) previous investment in technology, human capital, and public infrastructure, for one hand, and/or (ii) history and local advantages for the other hand, represent the main determinants of each component and/or if they produce differentiated effects.
The proposed approach has been employed to analyze interregional inequality in aggregate per worker productivity levels in Italy over the period 1970-2000. The role of variables connected to capital deepening effects and measuring steady state productivity has been confirmed for productivity gaps uniform across sectors, as suggested by growth theory, while the evidence for the industry mix component suggests that human and physical capital investment resources have been channeled toward traditional (low productivity) sectors and a negligible effect on the allocative component emerges. We have also investigated the effects of local advantages in technology diffusion measured by various agglomeration spillovers through their influence on steady states and total factor productivity. The idea has been to study the role played by the agglomeration of firms belonging to the same sector (intra-sectoral spillovers). To this end, (i) a common measure of Marshall externalities (a sector specialization index computed on industry employment, and (ii) a "district" measure which looks at the district's diffusion across Italian regions, have been introduced. Furthermore, in order to capture the effects of agglomeration externalities arising from the diversity of the regional economic structure (inter-sectoral or Jacob's externalities), such as inter-sectoral knowledge spillovers and advantages produced by reduction in transaction costs, the relative Hirschman-Herfindahl index has been used. Positive effects from almost all types of agglomeration externalities generally emerge, though with some loss of efficiency in the allocation of resources. MAR externalities have encouraged the regional specialization in high productivity sectors and the increase of uniform across sector productivity gaps, while for Jacob's spillovers evidence is mixed across sectors. Porter's spillovers connected to districts, characterized by the presence of highly specialized economic activities in low productivity sectors, have certainly favored the increase of uniform across sector productivity gaps.
With reference to the convergence rate, our analysis has confirmed results of other studies showing that the Italian regional convergence process diminished or failed after about 1975 and confirming the existence of the so-called Italian dualism and of a relative slow down of Southern regions in 70s and 80s. In addition, our approach has provided a more comprehensive and detailed examination of the contribution of each identified component in explaining the regional productivity gaps. Differences in productivity per worker have been explained in large part by the existence of region specific productivity differentials uniformly distributed across sectors. However, the industry mix component has also played a non negligible role in explaining the convergence process, although its importance has been decreasing since the end of '80s.

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Appendix A: Description of data

Tab. A1: Description of CRENOS 1970-2000 data set

Code	Description
VA	Total Value Added
VAINSS	VA in industry in the strict sense
VAEN	VA in mining, fuel and power products, ferrous and non-ferrous mineral and metals, chemical products
VAMI*8	VA in minerals and non-metallic mineral products
VAMI*10+11	VA in metal products and machinery and transport equipment
VAMI*12	VA in food, beverages, tobacco
VAMI*13	VA in textiles and clothing, leather and footwear
VAMI*14	VA in paper, and printing products
VAMI*15	VA in wood, rubber and other industrial products
VAC	VA in building and construction sector
VAMS	VA in market services
VAMS18	VA in trade, hotels and public establishment
VAMS19	VA in transport and communication services
VAMS20	VA in credit and insurance institutions
VAMS21	VA in other market services
VANMS	VA in non-market services
INV	Investment
L	Units of Labour in the whole economy
LINSS	Units of Labour in industry in the strict sense
LEN	Units of labour in fuel and power products sector
LMI*8	Units of Labour in minerals and non-metallic mineral products
LMI*10+11	Units of Labour in metal products and machinery and transport equipment
LMI*12	Units of Labour in food, beverages, tobacco
LMI*13	Units of Labour in textiles and clothing, leather and footwear
LMI*14	Units of Labour in paper, and printing products
LMI*15	Units of Labour in wood, rubber and other industrial products
LC	Units of Labour in building and construction sector
LMS	Units of Labour in market services
LMS18	Units of Labour in trade, hotels and public establishment
LMS19	Units of Labour in transport and communication services
LMS20	Units of Labour in credit and insurance institutions
LMS21	Units of Labour in other market services
LNMS	Units of Labour in non-market services
	Enrollment in secondary school
	Population of age 14-19

Source: CRENOS elaboration of disaggregated regional data along NACE Rev.1 classification (original source: Istat).
Note: monetary values in 1995 constant prices and millions of Euro; employment and demographic variables in thousand of units.

Tab. A2: Time intervals – 5-year averages

Time	**Interval**
1975	1970-1974
1980	1975-1979
1985	1980-1984
1990	1985-1989
1995	1990-1994
2000	1995-1999

Tab. A3: Description of Italian regions

Regimes	**Regions**
REGIME A	Piemonte, Val D'Aosta, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna, Toscana, Umbria, Marche, Abruzzo
REGIME B	Lazio, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna

Tab. A4: Description of sectors

Agriculture	*ag*
Industry in the strict sense	*inss*
Mining, fuel and power products sector	EN+ MI7+ MI9
Ferrous and non-ferrous mineral and metals	
Chemical products	
Minerals and non-metallic mineral products	MI8
Metal products, machinery and transport equipment	MI10+MI11
Food, beverages, tobacco	MI12
Textiles and clothing, leather and footwear	MI13
Paper and printing products	MI14
Wood, rubber and other industrial products	MI15
Building and construction sector	*c*
Market services	*ms*
Trade, hotels and public establishment	MS18
Transport and communication services	MS19
Credit and insurance institutions	MS20
Other market services	MS21
Non-market services	*nms*

Appendix B:
Tables and figures

Table 1: Shift share analysis of labor productivity
(14 sectors; average values of s_i, g_i, m_i)

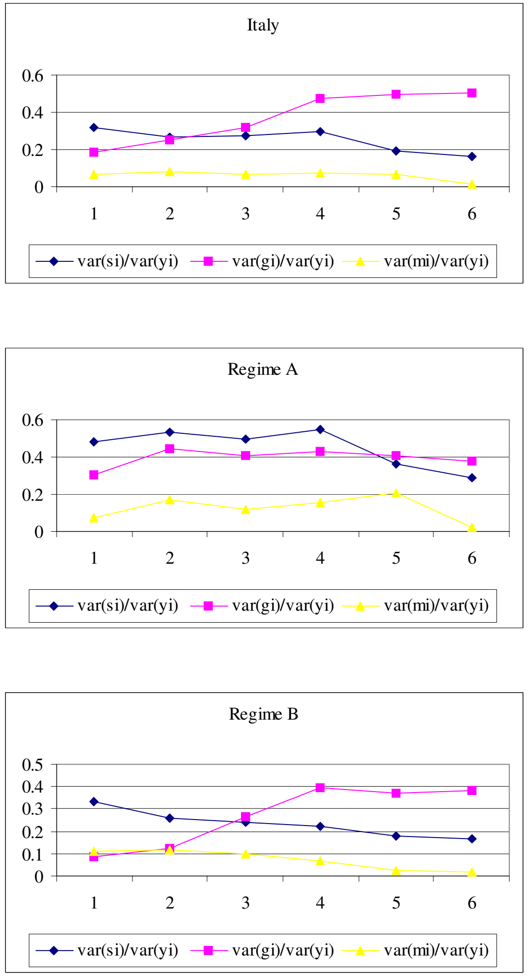
SHIFT SHARE ANALYSIS OF LABOR PRODUCTIVITY

	Labor productivity $\ln y_i - \ln y_{ITA}$	*Industry-mix component* s_i	*Productivity differential component* g_i	*Allocative component* m_i
		1975		
Regime A	-0.010	0.008	0.001	-0.019
Regime B	-0.307	-0.129	-0.154	-0.024
		1980		
Regime A	-0.002	0.013	0.010	-0.025
Regime B	-0.296	-0.110	-0.158	-0.024
		1985		
Regime A	-0.007	0.005	0.006	-0.017
Regime B	-0.204	-0.080	-0.111	-0.013
		1990		
Regime A	-0.012	0.008	0.008	-0.020
Regime B	-0.178	-0.067	-0.120	0.009
		1995		
Regime A	0.001	0.000	0.025	-0.024
Regime B	-0.167	-0.059	-0.112	0.007
		2000		
Regime A	0.012	-0.005	0.022	-0.005
Regime B	-0.139	-0.053	-0.099	0.013
		1970-2000		
Regime A	-0.003	0.005	0.012	-0.018
Regime B	-0.215	-0.083	-0.126	-0.005

Table 2: Share on total variance by components, 14 sectors (1970-2000)

	$var(s_i)/var(y_i)$	$var(g_i)/var(y_i)$	$var(m_i)/var(y_i)$	$2\Sigma cov/var(y_i)$
Italy	0.271	0.296	0.070	0.361
Regime A	0.479	0.390	0.126	0.018
Regime B	0.259	0.179	0.093	0.458

Figure 1: Analysis of variance for the shift-share components over time
(Italy, Regime A, Regime B)



Note: t = 1, 2, 3, 4, 5, 6 correspond to 1975, 1980, 1985, 1990, 1995, and 2000, respectively

Table 3: Parameter estimates for 14 sectors

		ai	bi	Adj-R2
Italy				
Model M1	s_i	-0.04	1.71	0.79
	(t value)	*-4.48*	*21.23*	
Model M2	g_i	-0.02	1.54	0.69
	(t value)	*-2.15*	*16.48*	
Model M3	m_i	-0.07	1.14	0.08
	(t value)	*-4.39*	*3.45*	
Regime A				
Model M1	s_i	-0.01	0.98	0.45
	(t value)	*-0.88*	*7.73*	
Model M2	g_i	-0.02	1.16	0.52
	(t value)	*-2.00*	*8.76*	
Model M3	m_i	0.01	0.62	0.03
	(t value)	*0.64*	*1.88*	
Regime B				
Model M1	s_i	-0.06	1.90	0.94
	(t value)	*-5.90*	*26.03*	
Model M2	g_i	0.01	1.83	0.59
	(t value)	*0.43*	*8.26*	
Model M3	m_i	-0.21	1.87	0.31
	(t value)	*-8.34*	*4.73*	

Note: Estimated M1-M2-M3 equations are reported in footnote 4

Table 4: Parameter estimates of the augmented Solow model (Sample: 20 Italian regions - 1970-2000; FGLS estimates)

1970-2000	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**			**Model 6**		
	s	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**
ly	0,41*	0,33*	0,13*	0,39*	0,35*	0,13*	0,21*	0,56*	0,08	0,11**	0,58*	0,16*	0,21*	0,56*	0,08	0,13*	0,61*	0,11
lsk	-0,06**	0,06	-0,004	-0,09*	0,08**	0,006	-0,05	0,06	-0,030	-0,02	0,03	-0,019	-0,06**	0,07**	-0,027	-0,016	0,05	-0,04
lsh	0,02	-0,02	0,00	0,00	0,00	0,00	-0,04	0,02	0,02	-0,08*	0,04	0,03	-0,04	0,02	0,02	-0,08*	0,00	0,06
lndx	-0,11*	0,013	0,01	-0,09*	0,00	0,01	-0,09*	0,00	0,00	-0,10*	0,00	0,03	-0,08*	0,00	0,00	-0,10*	0,023	0,00
d_regimeA	-0,01	0,07*	-0,05*	0,00	0,06*	-0,05*	0,02	0,08*	-0,09*	0,01	0,07*	-0,06*	0,02	0,08*	-0,09*	0,01	0,07*	-0,07
district				-0,26*	0,17	0,11							-0,15	0,14	0,04			
lspec_ag										0,01	0,00	0,05				0,04	0,12*	-0,08**
lspec_inss										0,21*	-0,15*	0,06				0,35*	0,46*	-0,47*
lspec_c										0,06*	-0,06**	0,05**				0,11	0,36*	-0,25*
lspec_ms										0,28*	-0,24*	0,12				0,29**	-0,30	0,11
lspec_nms										0,26*	-0,14*	-0,03				0,31*	-0,13	-0,11
ldiv_ag							0,33*	-0,32**	-0,01				0,33*	-0,31**	-0,01	-0,08	-0,77**	0,42
ldiv_inss							0,07	0,03	-0,14*				0,04	0,06	-0,14**	0,10	0,09	-0,25
ldiv_c							-0,07	0,34	-0,35**				-0,10	0,36	-0,35**	0,25	3,20*	-2,04*
ldiv_ms							-0,01	0,16	-0,21*				0,00	0,16	-0,21**	-0,09	-0,92*	0,53**
ldiv_nms							-0,19**	-0,04	0,25*				-0,14	-0,08	0,23**	-0,05	-1,30*	0,81**
constant	0,02**	-0,05*	0,03*	0,02**	-0,05*	0,03*	-0,02	-0,03**	0,05*	-0,03*	-0,03**	0,04*	-0,01	-0,04**	0,05*	-0,02**	-0,02	0,04*

Rate of convergence	0,028*	0,028*	0,033**	0,033**	0,033**	0,030**

* 1% significant level; **5% significant level

Explanatory variables: *ly, lsk, lsh, lndx, d_regimeA, district, lspec_j* and *ldiv_j* ,with *j = ag, inss, c, ms, nms* are lagged per capita GDP level, lagged investment rates in physical and human capital, lagged sum of population growth rate and 0.05, a dummy with value 1 if the region is comprised in regime A, regional district intensity, lagged sector specialization indexes and lagged sector diversity indexes, respectively.

Table 5: Parameter estimates of the augmented Solow model (Sample: 20 Italian regions – '70s; FGLS estimates)

Italy '70s	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**			**Model 6**		
	s	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**
ly	0,48*	0,27*	0,20*	0,46*	0,30*	0,20*	-0,06	0,83*	0,12	-0,01	0,59*	0,34*	-0,07	0,87*	0,12	-0,023	0,94*	0,02
lsk	-0,03	0,03	0,03	-0,07	0,08	0,03	0,01	0,09**	-0,05	0,01	0,04	0,00	-0,01	0,14*	-0,06	-0,035	0,12*	-0,039
lsh	0,02	-0,02	-0,01	0,00	0,01	-0,01	-0,14*	0,08	0,04	-0,15*	0,08	0,05	-0,14*	0,08	0,04	-0,11**	0,04	0,08
lndx	-0,18*	0,09	0,08	-0,14**	0,04	0,08	-0,19*	0,19*	-0,01	-0,18*	0,12**	0,07	-0,17*	0,11**	0,00	-0,15*	0,16*	-0,02
d_regimeA	-0,01	0,09*	-0,05**	0,02	0,06**	-0,05**	0,05**	0,11*	-0,12*	0,04*	0,06**	-0,07*	0,05**	0,11*	-0,12*	0,03	0,10*	-0,08*
district				-0,49*	0,58*	0,03							-0,23	0,66*	-0,09			
lspec_ag										0,13	0,16	-0,01				0,16	0,22	-0,10
lspec_inss										0,45	0,08	-0,09				0,11	1,23*	-0,85**
lspec_c										0,09	-0,11	0,09				0,47	0,46	-1,05**
lspec_ms										0,51**	-0,16	0,03				-0,52	1,84*	0,41
lspec_nms										0,47*	0,06	-0,20				1,16*	0,06	-1,02**
ldiv_ag							0,53*	-0,57*	-0,09				0,54*	-0,60*	-0,08	-0,86	-1,94	2,64**
ldiv_inss							0,02	0,04	-0,19				-0,02	0,15	-0,20***	-1,42	0,42	1,07
ldiv_c							0,68*	0,59**	-0,68**				0,63*	0,73*	-0,70**	3,02	1,09	-6,23
ldiv_ms							-0,17	0,42*	-0,31*				-0,15	0,34*	-0,30**	-2,61	1,98	2,91
ldiv_nms							-0,80*	-0,15	0,57*				-0,76*	-0,27	0,59*	1,59	-1,88	-0,23
constant	0,02	-0,08**	0,04	0,03	-0,08*	0,03	-0,08*	-0,01	0,07*	-0,07*	-0,02	0,06*	-0,07*	-0,04**	0,07*	-0,06*	0,00	0,03

Rate of convergence	0,009	0,008	0,021	0,014	0,016	0,014

* 1% significant level; **5% significant level

Explanatory variables: *ly, lsk, lsh, lndx, d_regimeA, district, lspec_j* and *ldiv_j* ,with *j = ag, inss, c, ms, nms* are lagged per capita GDP level, lagged investment rates in physical and human capital, lagged sum of population growth rate and 0.05, a dummy with value 1 if the region is comprised in regime A, regional district intensity, lagged sector specialization indexes and lagged sector diversity indexes, respectively.

Table 6: Parameter estimates of the augmented Solow model (Sample: 20 Italian regions – '80s; FGLS estimates)

Italy '80s	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**			**Model 6**		
	s	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**
ly	0,34*	0,31*	0,04	0,33*	0,31*	0,04	0,06	0,61*	0,04	0,03	0,55*	0,07	0,06	0,61*	0,04	0,082	0,63*	-0,01
lsk	-0,08	0,00	-0,03	-0,12**	0,00	-0,02	-0,01	-0,01	-0,06	-0,02	-0,01	-0,04	-0,02	-0,02	-0,05	-0,023	-0,04	-0,03
lsh	-0,02	-0,10	-0,02	-0,05	-0,10	-0,01	0,00	-0,12	0,00	-0,01	-0,10	0,01	0,00	-0,12	0,00	-0,01	-0,02	0,00
lndx	-0,08**	-0,04	0,04	-0,07**	-0,04	0,03	-0,06**	-0,04	0,03	-0,08*	-0,04	0,04	-0,04	-0,03	0,02	-0,06**	-0,02	0,00
d_regimeA	-0,01	0,06**	-0,04**	0,01	0,06**	-0,05*	0,01	0,07**	-0,06**	0,00	0,06	-0,05**	0,00	0,06	-0,06**	-0,02	0,06	-0,02
district				-0,35*	-0,02	0,15							-0,33**	-0,14	0,11			
lspec_ag										-0,07	0,04	0,05				0,03	0,18	-0,24**
lspec_inss										0,10	-0,17	0,11				0,76	0,97	-1,49*
lspec_c										0,08	-0,15	0,06				1,04**	2,02*	-2,29*
lspec_ms										0,24	-0,21	0,11				0,65	2,23*	-0,99
lspec_nms										0,10	-0,10	0,02				0,65	0,75	-0,66
ldiv_ag							0,67*	-0,89*	0,12				0,64*	-0,90*	0,13	-3,18**	-8,05*	7,18*
ldiv_inss							0,19**	-0,10	-0,04				0,11	-0,13	-0,01	-1,66	-4,44*	3,79*
ldiv_c							-0,36	1,20**	-0,56				-0,39	1,19**	-0,55	7,73**	17,78*	-19,53*
ldiv_ms							0,01	-0,05	-0,03				0,02	-0,05	-0,03	-1,99**	-2,76	4,54*
ldiv_nms							0,02	-0,22	0,23				0,13	-0,18	0,19	-1,55	-4,80**	5,46*
constant	0,02	-0,05**	0,01	0,02	-0,05**	0,01	-0,03	-0,02	0,03	-0,02	-0,02	0,03	-0,01	-0,01	0,02	-0,01	-0,01	0,00

Rate of convergence	0,074*	0,077*	0,070**	0,089*	0,070**	0,069**

* 1% significant level; **5% significant level

Explanatory variables: *ly, lsk, lsh, lndx, d_regimeA, district, lspec_j* and *ldiv_j* ,with *j = ag, inss, c, ms, nms* are lagged per capita GDP level, lagged investment rates in physical and human capital, lagged sum of population growth rate and 0.05, a dummy with value 1 if the region is comprised in regime A, regional district intensity, lagged sector specialization indexes and lagged sector diversity indexes, respectively.

Table 7: Parameter estimates of the augmented Solow model (Sample: 20 Italian regions – '90s; FGLS estimates)

Italy '90s	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**			**Model 6**		
	s	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**	**s**	**g**	**m**
ly	0,34*	0,50*	0,03	0,35*	0,49*	0,04	0,22*	0,52*	0,09	0,22*	0,56*	0,10	0,15*	0,52*	0,15	0,21*	0,46*	0,16**
lsk	-0,08*	0,14*	-0,01	-0,07*	0,13*	0,00	-0,05	0,04	0,01	-0,04	0,05	0,00	-0,04	0,04	0,00	-0,046	0,09**	-0,017
lsh	0,06	0,09	-0,04	0,07**	0,09	-0,02	0,04	0,06	-0,05	0,06	0,10	-0,04	0,02	0,06	-0,04	0,04	-0,06	0,00
lndx	-0,07*	0,04	-0,01	-0,07*	0,05	-0,02	-0,05*	0,06**	-0,03	-0,05*	0,06**	-0,03	-0,03	0,07**	-0,04	-0,05*	0,06**	-0,01
d_regimeA	-0,01	0,06*	-0,03*	-0,01	0,06*	-0,04*	-0,03	0,06	0,00	-0,04*	0,05**	-0,02	-0,04**	0,06	0,01	-0,02	0,09*	-0,01
district				0,06	-0,08	0,12							-0,35*	-0,04	0,27			
lspec_ag										0,06	0,14	-0,08				0,07	0,11	-0,13
lspec_inss										0,30*	0,32	-0,26				0,48	0,46	-1,25*
lspec_c										0,10*	0,17*	-0,11				0,14	-0,69	-1,07
lspec_ms										0,48*	0,51	-0,46				0,71	-1,31	-1,00
lspec_nms										0,24**	0,28	-0,23				0,17	-1,31**	0,55
ldiv_ag							0,43*	0,23	-0,22				0,58*	0,25	-0,34	-0,26	4,83	3,58
ldiv_inss							-0,02	0,29**	0,07				-0,08	0,28	0,11	0,37	4,34*	0,57
ldiv_c							-0,33**	-0,94*	0,38				-0,34**	-0,94*	0,39	0,22	-8,17	-10,44
ldiv_ms							0,05	0,23	0,22				0,18	0,24	0,11	0,28	1,34	1,65
ldiv_nms							0,10	0,32*	-0,06				0,28*	0,34	-0,20	-0,29	-0,04	4,73**
constant	0,01	-0,03**	0,01	0,01	-0,02**	0,01	0,01	-0,02	0,00	0,02**	-0,02	0,01	0,03**	-0,02	-0,01	0,01	-0,05*	0,01

Rate of convergence	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	0,028**	0,025**	0,036	0,027	0,041	0,037***

* 1% significant level; **5% significant level

Explanatory variables: *ly, lsk, lsh, lndx, d_regimeA, district, lspec_j* and *ldiv_j* ,with *j = ag, inss, c, ms, nms* are lagged per capita GDP level, lagged investment rates in physical and human capital, lagged sum of population growth rate and 0.05, a dummy with value 1 if the region is comprised in regime A, regional district intensity, lagged sector specialization indexes and lagged sector diversity indexes, respectively.

Table 8: Estimates of the rate of convergence
(dependent variable: $Z_{it} = \ln y_{it} - \ln y_{ITA,t}$)

	1970-99	**70s**	**80s**	**90s**
Model 1	0,030*	0,008	0,086*	0,028**
Model 2	0,029*	0,006	0,088*	0,026
Model 3	0,036**	0,017	0,085**	0,041
Model 4	0,034**	0,010	0,099**	0,031
Model 5	0,036**	0,015	0,081**	0,046
Model 6	0,033**	0,011	0,089**	0,041

* 1% significant level; **5% significant level