45th European Congress of the Regional Science Association

Aug. 23 - 27, 2005, Amsterdam

WHAT DETERMINES PRODUCTIVITY LEVEL IN THE LONG RUN? EVIDENCE FROM ITALIAN REGIONS

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This version: June 2005

Abstract

In this paper we estimate the long-run relationships between total factor productivity and three types of capital stocks: R&D capital, human capital and public capital, between 1980 and 2001. We exploit recent developments of panel cointegration techniques to estimate cointegration vectors that control for endogeneity of regressors. In the empirical literature on economic growth a central issue is the direction of causality between economic growth and regressors. In order to deal with this question, we shall estimate the error-correction model, which allows long and short-run Granger causality tests to be performed. Empirical evidence shows firstly that there exists a long-run equilibrium between productivity level and the three kinds of capital; among them, human capital has the strongest impact on productivity level. Secondly, results of the Granger-causality tests support the hypothesis that human capital and public capital cause productivity growth in the long run while the opposite is not true. Only for R&D capital stock is the bi-directional causality found.

JEL classification: O4, O18, R11, C23.

Keywords: Total factor productivity, research and development, public capital, panel cointegration, Granger causality.

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1. Introduction[1]

It is widely known that the Italian economy is profoundly affected by strong territorial disparities. GDP per capita of the southern region is around 60 per cent of that in the Centre and North; labor productivity about 80 per cent. In the South, unemployment rate is three times higher than that in the Centre and North. Even though the economic gap between South and North originated a long time ago, and during the last decade has shown a slight reduction, differences in the standard of living amongst Italian regions remain profound. In face of this evidence, it is understandable why regional growth is still at the centre of the economic debate and the empirical research, and how to reduce regional disparities remains a central question in the Italian economic policy.

Several recipes have been proposed to lower the regional gap. Inspired by endogenous growth models, economists have pointed to different factors able to boost regional productivity, among others, research and development (R&D) effort and human capital are widely recognised as the most influential. In addition to these, various researchers have also stressed how the endowment of infrastructure can promote growth, since infrastructure can expand the productivity capacity of an area, both by raising the availability of resources and by enhancing productivity of existing resources.

The aim of this paper is to measure the effect of different types of "capitals" on regional productivity. In particular, we assess the contribution of technological knowledge, as measured by the stock of R&D capital, the human capital, and the stock of public capital in enhancing Total Factor Productivity (TFP) of Italian regions over the period 1980-2001. Measuring the impact of these factors on regional productivity can be helpful in designing an appropriate regional policy and also in understanding the origin of the territorial gap.

Unlike the majority of the empirical models on economic growth that investigate growth rates, we focus on the level of the variables. As Hall and Jones (1997) have argued, the investigation of the level may be a more natural research question since differences in the level of productivity, or income, reflect differences in the welfare, and growth rates are studied only for the their effect on the level of variables. Moreover, some scholars suggest

[1] The views expressed in the paper are personal and do not represent those of the Bank of Italy.

that these capital factors enter significantly in the levels in the multifactor production function (Benhabib and Spiegel 1994, Everaert and Heylen 2001). However, the estimation of a model in which the variables are in level poses the well known problem of spurious regression if the variables are I(1) and are not cointegrated. We handle this issue following the panel cointegration approach, therefore testing for unit roots and next carrying out panel cointegration analysis of the model.

But our empirical investigation might be altered by further drawbacks that affect empirical models on economic growth. As Temple (1999) has remarkably pointed out, endogeneity of the regressors and reverse causality can bias the results of econometric estimates of growth models. Since such models are usually implemented within the production function framework, and factor inputs are decision variables, the regressors could be correlated with the error term and the results of OLS estimates might be biased by the endogeneity of regressors due to simultaneity. Moreover, the direction of causality among productivity and the explanatory variables might also go from productivity to the regressors, as well as vice versa. In the period of productivity expansion, investment in R&D, human capital or infrastructure could increase as well, owing to the larger availability of economic resources, therefore usual econometric estimates might capture simply correlations instead of measuring causality effects. In order to deal with these issues, first we use an instrumental variables estimator, the Fully Modified OLS Pedroni's estimator (see Pedroni 1996, 2000, 2001) that controls for endogeneity of the regressors as well as for autocorrelation of the error term. Next, we examine the direction of causality by carrying out Granger causality tests in the error correction panel models, to detect possible reverse causality among the variables. In the cointegrating framework, Granger causality has the advantage of allowing us to verify both the long-run and the short-run causality.

The paper adds to the existing literature on regional productivity determinants in several respects. First of all, it is the first time that the effect of R&D capital stock, human capital and public capital on productivity have been assessed together, within the same model. The linkage between productivity and the stock of R&D has been investigated in several studies since the seminal paper by Coe and Helpman (1995) (see van Pottelsberghe de la Potterie and Lichtenberg 2001, Frantzen 2002, among others). Others have extended this basic framework including a human capital variable, in order to capture both the role of human capital in fostering economic growth and the complementarity between R&D and human capital investment (Coe et al. 1997, Xu and Wang 1999, Engelbrecht 1997 and 2002, Frantzen 2000). Finally, beginning with the influential work of Aschauer (1989), the positive impact of public capital on productivity and output has been studied by a number of empirical works (see Munnell 1990, 1992, Holtz-Eakin 1994, Garcia-Milà et al. 1996, Fernald 1999, Ligthart 2000, Everaert and Heylen 2001, Canning and Pedroni 2004, Bonaglia et al. 2000 and Picci 1999 on Italian regions, Cutanda et al. 1994 on Spanish regions). If all these factors affect productivity and interact with each other, their contribution can be properly measured only within a unified model. If one of the relevant inputs is omitted, estimations of elasticities of the other factors are bound to be biased (Frantzen 2000).

Secondly, differently from previous literature, our goal is to understand the long-run impact of human capital, R&D effort, and infrastructure on regional productivity level rather than explaining regional differences in productivity growth rates. Thus, our analysis explores the long-run relations through recent panel-cointegration techniques, that also allow us to control for omitted or unobservable factors through fixed effects.

Thirdly, we tackle the issue of reverse causality between productivity (output) and right-hand side variables of the model carrying out Granger causality tests; in order to check whether capital stocks determine productivity or whether productivity has a feedback on the stocks of capital.

With respect to the majority of similar works, based on panels of countries, we have the advantage of adopting a sub-national perspective that reduce the weaknesses of cross-country analysis, plagued by the scant cross-country comparability of data on education system, R&D expenditures and infrastructure.

The remainder of the paper is organised as follows. In section two we present the different specifications of the empirical model we are going to estimate. Next, we examine data together with cross-region and over-time characteristics of the variables. In section four, we describe the econometric strategy followed. The results of the econometric exercise together with the causality tests and robustness checks will be discussed in section five and six. The final section contains some summarising remarks.

2. Specification of the model

In standard literature on economic growth it is assumed that output is driven by labour, capital and technical progress. Accordingly, we assume a standard Cobb-Douglas production function with Hicks-neutral technical change:

$$Y_{i,t} = TFP_{i,t} L_{i,t}^{\alpha} K_{i,t}^{\beta} \tag{1}$$

where i = 1, …19 is a regional index; t = 1980,…2001 is a time index; Y_i is the output in region i; L_i is the labour input; K_i is the private physical capital stock; TFP_i is the total factor productivity representing technical change. We assume that total factor productivity is driven by human capital, public capital and R&D activity:

$$TFP_{i,t} = A_{i,t} HC_{i,t}^{e1}\, G_{i,t}^{e2}\, R\&D_{i,t}^{e3} \tag{2}$$

where HC is the human capital stock, G is the public capital stock, R&D is the stock of research and development expenditure and A is the part of technical progress non-caused by the indicated factors. Substituting equation (2) into equation (1) we get:

$$Y_{i,t} = A_{i,t} HC_{i,t}^{e1}\, G_{i,t}^{e2}\, R\&D_{i,t}^{e3}\, L_{i,t}^{\alpha} K_{i,t}^{\beta} \tag{3}$$

We consider three different empirical specifications of model (3). First, we assume constant returns to private inputs (L and K) and perfect competition. This is the standard assumption that allows us to compute α as the labour income share and β=1-α as the capital income share calculated as residual. By knowing income shares, we are able to compute total factor productivity as $TFP_{i,t} = Y_{i,t}/L_{i,t}^{\alpha}K_{i,t}^{\beta}$. Moreover, we assume that the "unexplained" technical progress depends on regional and time fixed effects in the form: log $A_{i,t} = \theta_i + \theta_t$. Thus, taking log of equation (2) we get the following equation to be estimated:

$$tfp_{i,t} = \theta_i + \theta_t + e_1\, hc_{i,t} + e_2\, g_{i,t} + e_3\, rd_{i,t} + \varepsilon_{i,t} \tag{4}$$

where lower-case variables denote logarithms; θ_i and θ_t represent country-specific and time-specific intercepts, respectively, that allow us to take account of regional unobservable, or omitted factors, affecting productivity and control for common factors that simultaneously impact on all-region productivity, as common cyclical dynamics or common productivity shocks; $\varepsilon_{i,t}$ is a stochastic error term. In the equation (4) the parameters denote elasticity of productivity with respect to the explanatory variables. In other words the coefficient indicate the percentage change in productivity for a given percentage change in the corresponding variable. Equation (4) is our baseline specification of the empirical model.

In the second specification we divide equation (3) by labour input and use labour productivity as dependent variable. Thus taking logs we obtain:

$$y_{i,t} - l_{i,t} = \theta_i + \theta_t + e_1\, hc_{i,t} + e_2\, g_{i,t} + e_3\, rd_{i,t} + \beta\, (k_{i,t} - l_{i,t}) + \eta_{i,t} \qquad (5)$$

The advantage of this specification is that it does allow us to estimate private inputs elasticities, which in equation (4) are computed as income share. However, we are still assuming $\alpha+\beta=1$.

In the third specification, we make no assumption on the returns to scale and market structure and we let all the parameters free to vary. Hence the model to be estimated is equation (3) that rewritten in log takes the form:

$$y_{i,t} = \theta_i + \theta_t + e_1\, hc_{i,t} + e_2\, g_{i,t} + e_3\, rd_{i,t} + \alpha\, l_{i,t} + \beta\, k_{i,t} + \varphi_{i,t} \qquad (6)$$

The equations (4)-(6) represent our empirical setting on which the econometric analysis will be based. It is worth noticing that in all the models proposed we impose no constant returns to scale to all inputs. This because factors affecting output or productivity may generate positive externalities, which make their social marginal benefits exceed their private benefits as measured by the rewards they earn. This is particularly true for R&D efforts and public capital, but it is also valid for human capital (see among others Acemoglu and Angrist 2001). Therefore, we choose a framework that allows us to measure the contribute of each factor to productivity (output) increase.

Of course, the estimation of the above equations poses the well-known problems of simultaneous equation bias and reverse causation in the production function estimates (Griliches and Mairesse 1995). It is likely that input and output variables are jointly determined in a system in which all are endogenous, therefore bias due to simultaneity may occur. Moreover, observing that output or productivity move together with the right-hand side variables does not preclude the possibility that the direction of causality goes from the productivity to the regressors. For example, public capital can increase during the period of output, or productivity, expansion since more resources can be devoted to increase infrastructure (Hurst 1994). Therefore, in order to appropriately estimate these models, we require, first, an estimator that controls for endogeneity of the regressors and, next an empirical setting through which reverse causality can be tested for. This is the route that we are going to follow.

3. Data

In the specification of the baseline model, total factor productivity of the business sector[2] is estimated as the Solow residual $TFP_{i,t} = Y_{i,t}/L_{i,t}^{\alpha}K_{i,t}^{\beta}$. The output is measured by the value added at constant price; labour input by the standard units of labour; the private physical capital stock of each region by breaking down the national series, using regional investment to calculate the regional shares. Finally, α is measured by the national labour income share and β=1-α by the residual national capital income share. Output and labour data are provided by Istat (the National Institute of Statistics).

In order to compute regional R&D capital stock, we use the methodology designed by Coe et al. (1995), who apply the perpetual inventory method to R&D investment data[3]. Istat provides data on regional R&D expenditure made by firms, public research institutes and universities, separately. Data are available from 1980 except for university expenditure, which is available only since 1993. In order to carry out the analysis over a longer time span, we construct R&D capital stocks using only expenditure of firms and public research institutes[4].

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[2] The business sector excludes the following sectors: public administration, education, health and security services, other public, social and personal services. More details on data used can be found in the Appendix.

[3] This method has become standard in the literature. Among others see: Coe and Helpman 1995; Coe, Helpman and Hoffmaister 1997; van Pottelsberghe de la Potterie and Lichtenberg 2001, Xu and Wang 1999, Frantzen 2002, Crispolti and Marconi 2004. The description of the method is in Appendix.

[4] This choice does not seem too restrictive: according to Istat from 1997 to 2000 R&D expenditure carried out by firms and public research institutes altogether absorbs in Italy about 70 per cent of the total R&D expenditure - respectively, about 50 per cent the former and 20 per cent the latter - and the remaining 30 per cent is carried out by universities. Therefore, our data cover the majority of the total expenditure in R&D,

In the empirical literature several measures of human capital stock are used. In this work we stick to one of the most commonly used: education, that is approximated by the average years of schooling of employees (see for example Frantzen 2000, Engelbrecht 1997, Xu and Wang 1999, Benhabib and Spiegel 1994, among others).

In the empirical analysis, stock of public capital is quantified either by some physical measures of infrastructure, such as the kilometres of road (Canning and Pedroni 2004), or by using perpetual inventory method on public investment (Ligthart 2000, Everaert et al. 2001). Following this second route, we make use of regional public capital stocks estimation provided by Montanaro (2003). The author calculates the regional public capital by employing the perpetual inventory method, starting from the flows of regional public investment. The regional public investment is estimated by breaking down the official series of national public investment, provided by the national institute of statistics, and using the survey on public works accomplished by region to calculate the regional series. Five stocks are constructed by the author corresponding to five type of public infrastructure. We only make use of the capital stocks corresponding to economic infrastructure: road and highways, railways, water and electrical facilities. Of course, the estimation of public capital is a complex task that leaves room for measurement errors. Thus, within the robustness exercises we check the results by using also an alternative measure of public capital in physical term.

Our empirical analysis is performed on nineteen Italian regions for the period 1980-2001. One region, Val d'Aosta, has been excluded due to the lack of human capital data. Variables are all constructed as indices with 1990=1. Data used to calculate the variables are provided by the Italian Statistical Institute. More details on the construction of the variables can be found in appendix.

In table 1, we tabulate regional stocks in percentage of GDP as well as TFP by region. Data on TFP confirm the well-known productivity gap between the Centre-North and South; in 2001 TFP of southern regions was on average about 85 per cent of the national average, while in the central and northern regions it was 115 per cent the Italian mean. However, over

coming out as a reasonable approximation of the total regional stock. Since R&D outlay is relatively larger in the South, in order to rule out the possibility of potential bias, we have also checked that in the years for which data are available R&D expenditure of universities grows basically at the same rate in the Centre-North and in the South.

the two decades, the gap has shown a slight reduction: in 1980 TFP in the South was 80 per cent of the mean, while in the Centre-North about 111 per cent. The R&D capital stocks shows that research efforts are concentrated in a few regions, namely Piedmont, Lombardy and Lazio. This because of territorial concentration of the biggest firms and public research institute in these areas. Furthermore a sizeable, and expected, gap between centre-northern and southern regions is revealed: in Centre-North R&D capital stock in 2001 was about 120 per cent the national average against about 38 per cent of the South[5]. As productivity, the human capital is lower in the southern regions, even though the gap is relatively smaller than productivity gap. Finally, public capital in percentage of GDP turns out to be larger in the southern regions that in the Centre North. This may be surprising since we consider the South of Italy as the area that needs more economic help, thus also more infrastructure, to raise its productivity. But, the above-the-average public capital registered in the South might not mean that southern regions are more endowed with infrastructure. First because, as is pointed out, public administration in the South is relatively less efficient and a larger amount of expenditure does not necessarily convert into larger physical infrastructure (see for example Picci 1995). Second, and maybe more importantly, GDP might not be the best scale variable to compare infrastructure across different territorial areas. The large majority of our public capital stock consists of transport and water facilities that should be commensurate with size of the supplied area more than with GDP. If we use the size of the area as scale variable we obtain a different picture: endowment of public capital in Centre North is above the Italian mean (in 2001 equal to 106 per cent of Italian mean) and that of South is below (91 per cent).

4. The econometric strategy

In order to estimate model (4)-(6) where variables are in levels, we need to first establish whether the variables are stationary and, in this case, if they are cointegrated. If variables are non-stationary and non-cointegrated, ordinary panel techniques of estimation by least squares are conducive to biased estimates and standard inference on significance of

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[5] In interpreting these results we should take into account that total R&D stock of the South is under-estimated relative to the Centre-North, since the R&D expenditure of universities (excluded by the

the coefficients cannot be carried out. As stock variables and productivity usually exhibit time trend we should estimate equations that are cointegrated.

Some authors tend to overcome the problem of estimating non-stationary data (or a mixture of stationary and non-stationary) by differencing out the series and using conventional panel techniques (Coe, Helpman and Hoffmaister 1997, Engelbrecht 1997, 2002). However, only in the absence of cointegration can one differentiate the data and estimate the model in growth rates, otherwise, if variables are cointegrated, a model in differences is misspecified as it ignores the long-run information. Additionally in doing so, higher frequency relationships are actually estimated and long-term relationships are relegated to fixed effects (Bottazzi and Peri 2004).

Panel cointegration techniques have been used in the analysis of TFP determinants since the Coe and Helpman's (1995) seminal work. In the last few years several papers have been published in this field and further econometric techniques have been developed (e.g. de la Potterie and Licthenberg 2001; Xu and Wang 1999; Frantzen 2000 and 2002; Park 2004; Canning and Pedroni 2004). Following this stream of research, we use recently developed unit root and cointegration tests for panel data to analyse the long-run relationship between the variables. Next, once the cointegrating relationships have been tested, we use the Fully Modified OLS (FMOLS) estimator developed by Pedroni (1996, 2000, 2001), that controls for endogeneity of regressors and serial correlation of the errors, to estimate the long-run elasticities of the empirical models[6]. Finally, to detect the direction of causality among the variables we estimate the Error Correction Model and we run Granger-causality tests.

4.1 Unit roots tests

Actual implementation of the cointegration estimation is based on the hypothesis that data are indeed non-stationary. Therefore we start applying three unit root tests for panel data to our series. Tests are introduced by Levin, Lin and Chu (2002), Im, Pesaran and Shin

computation) is relatively higher in the South.

[6] This estimator is the panel version of the Phillips and Hansen's (1990) estimator, suggested to correct for possible simultaneity equation bias in a time series regression. Everaert and Heylen (2001) use this estimator to tackle simultaneity of public capital in estimating a production function.

(2003) and Maddala and Wu (1999), henceforth LLC, IPS and MW, respectively. All are based on an ADF specification and include individual constants and individual trends[7].

Table 2 shows the unit root tests for all the variables involved in our models. For all the series at least two of three tests accept the hypothesis of non-stationarity at the standard conventional significance. The findings of the unit roots tests make results of standard panel estimation procedure, of production function models analogous to ours, suspicious due to possible spurious correlation. This belief is reinforced by taking account of the high power of these unit roots tests, that tend to reject the hypothesis even if only a small fraction of the series in the panel are stationary (Karlsson and Lothgren 2000). We also test for unit roots in the differences of our variables. As expected, there is large evidence that series are difference-stationary[8].

4.2 Panel cointegration test and estimation method

The next step is to run cointegration tests. We test the hypothesis of cointegration in the long-run equations by carrying out Pedroni's (1999, 2004) cointegration tests, which allow coefficients (cointegration vectors) to vary across units and the inclusion of individual fixed effects and time trends. Pedroni introduces seven statistics asymptotically normally distributed[9].

If tests reject the null of no cointegration, it is well known that OLS estimates of panel cointegration relationship are "superconsistent" and also possess a normal limit distribution (Kao and Chang 2000). Accordingly, in the case of cointegrated variables many authors

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[7] LLC assume a common unit root, while IPS allow for individual unit root process so that the autoregressive coefficient can vary across units. Finally, MW derive a statistic that combines the p-value from the individual ADF unit root tests (ADF-Fisher type test). Under the null hypothesis of non-stationarity (presence of unit root) the first two tests are normally distributed, while the third is a χ^2 with 2N degrees of freedom. These are three of the most common unit root tests in non-stationary panel econometrics. Presenting more than one unit root test is common practice, due to the different hypothesis underlying each test and their diverse power in small samples. See for a discussion Maddala and Wu (1999), Karlsson and Lothgren (2000).

[8] At least according to one of three tests, only $\Delta(K/L)$ turns to be still non-stationary after differencing. However, ΔK and ΔL present some evidence of stationarity, so we assume that their difference is still stationary. In light of these results, we proceed on the assumption that all series are difference-stationary. Should this assumption be incorrect, we expect that the cointegration tests and the estimated ECM do not support the hypothesis of a long-run stable relationships between the variables of interest (Kremers et al 1992).

[9] We refer the reader to Pedroni (1999) for further details on these tests.

perform standard OLS estimates[10]. However, in finite samples OLS estimates generally have non-standard distribution and suffer from strong finite sample bias caused by endogeneity of regressors and serial correlation of residuals (Phillips and Moon 1999, Kao and Chang 2000). Therefore, we follow a different approach and we use the Fully-Modified OLS estimator (FMOLS) developed by Pedroni (1996, 2000, 2001) to correct for endogeneity and serial correlation. In particular, we use the between-dimension (group-mean) FMOLS, which has a relatively lower distortion in small samples than the other FMOLS estimators and allows cointegration vectors to be heterogeneous across units[11].

In our analysis, the advantages of this estimator appear remarkable. Temple (1999) has pointed out that many of the explanatory variables used in growth equations are likely to be endogenous, and that generally there is a shortage of good instruments, as discussed in Hall and Jones (1999)[12]. Thus, endogeneity can seriously undermine the quality and the consistency of standard estimates based on other estimators.

5. Results

In column (1) of Table 3 we report the results of econometric estimates together with these results of cointegration tests of our baseline model (4), in which total factor productivity is regressed on R&D, human and public capital stocks[13]. All the estimates include regional and time fixed effects. Cointegration tests are run without heterogeneous trends[14].

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[10] Coe and Helpman 1995, Frantzen 2000, Xu and Wang 1999, de La Potterie and Licthenber 2001.

[11] More details can be found in appendix.

[12] Hall and Jones (1999) emphasise the reverse linkage between R&D and TFP growth, when growth opportunities can cause an increase in R&D spending and boost human and capital accumulation.

[13] Since the estimation of initial level of R&D stock might likely be imprecise, we run the regression starting from 1985 given that the impact of errors in estimate of initial stock should have a relatively small impact on 1985. The empirical literature is aware of the possibility of imprecise estimates of initial technological knowledge stock and to post-pone the initial year is common practice to overcome such a problem (see for example Bottazzi and Peri 2004).

[14] We should bear in mind that the probability of rejecting the null of no cointegration will be higher in models with trends than those without, in that heterogeneous trends may have a high explanatory power of productivity dynamics. For that reason, we prefer running the cointegration tests in models without trends, where only regressors explain productivity.

Results of cointegration test strongly support the hypothesis of cointegration relationship among our variables. In column (1) of the Table the null of no cointegration is rejected by five, out of seven, tests at 10% probability level: this evidence displays that there exists a long-run relationship among productivity and the regressors. Moving to the elasticities estimated by FMOLS, we find stronger elasticities for human capital and public capital while research and development stock shows a small coefficient. However, all have the expected sign and are statistically significant. According to our findings a 1% increase in the human capital stock would raise total factor productivity by 0.38%. The same percentage increase in the public capital stock, or in R&D stock, would boost regional TFP by 0.11 and 0.03, respectively.

Compared to previous studies, human capital elasticities appear relatively larger. For example, in panel data models based on a large sample of countries, Frantzen (2000), Xu and Wang (1999) and Engelbrecht (1997) found human capital elasticities that vary from 0.10 to 0.16. Such a discrepancy can be due to several factors, such as data characteristics, model specification or estimation method. However, it is worth noting that the cited studies are based on cross-country data in which heterogeneity of education system or quality of schooling across countries could be substantial. Thus, in such studies, human capital variables might be affected by stronger measurement error than our human capital variable, which is computed across regions within the same country. As it is well known measurement error biases downward the relative coefficient, and human capital elasticities could result in lower coefficients in the cross-country model.

The estimated elasticities of TFP with respect to R&D capital stock and public capital are quite consistent with the elasticities previously found by the empirical literature[15], even though we find R&D elasticities relatively smaller. Griliches (1988) for example reports elasticities found in the studies for industrial countries in the range of 0.06 to 0.1[16]. The smaller R&D elasticity, that comes out in our regional model, may be due to the occurrence

[15] The coefficient on the public capital turns out to be very similar in magnitude to the elasticities estimated by the empirical literature: reviewing several papers on the subject, Munnell (1992) points out that the elasticity of public capital with respect to output is, on average, about 0.15.

[16] In the cross-countries model of Frantzen (2000) elasticities are about 0.1; in the estimates of Xu and Wang (1999) it varies from 0.035 to 0.15, while in Engelbrecht (1997) from 0.055 to 0.079.

of technological spillovers. Especially within the same country, inter-regional technical spillovers may exist; as a consequence the correlation between R&D efforts made in a region and productivity of the same region can be relatively small[17].

It is also of interest to split public capital into different categories, in order to explore the contribution of different types of infrastructure to productivity growth, and also to check the robustness of the link between public capital and productivity. We consider three main categories: road and highways, railways, and water and electric facilities, then we run three regressions, one for each type of public capital as regressor. In columns (2)-(4) of table 3 we report the results. The findings tend to confirm our expectation: the infrastructure more connected to economic activity also has the larger impact on productivity growth. We see that road and highways have the strongest positive relationship with productivity, while the correlation slightly decreases for railways and substantially drops for water and electric facilities. It is worth noting, however, that in all the models, Pedroni's tests accept cointegration and that the elasticities of the variables are all positive and significant. In addition, the new estimates do not change substantially the magnitude of the coefficients related of human capital and R&D variables previously obtained.

We proceed with the econometric exercise by relaxing some assumption of the baseline model, in particular in table 4 we present the estimates of equations (5) and (6). In the first column labor productivity is our dependent variable and the coefficient of private capital/labor ratio, used as regressor, represents the elasticity of output with respect to private capital. The results indicate again a long-run relationship among the variables, since four cointegration tests accept cointegration. The coefficient of R&D, human capital and public capital remain similar in magnitude to the previous estimates. The coefficient of private capital/labour ratio, corresponding to the parameter β of our model, is equal to 0.4, very close to the value used to calculate TFP[18].

The second column of the table contains the estimates of equation (6), where regional output is the dependent variable and there are no restrictions on the coefficients of the

[17] Costa and Iezzi (2004) estimate a spillover-augmented convergence model, where the contribution of local R&D to convergence of Italian regions is smaller than technological spillovers from the other regions.

explanatory variables. In the unrestricted model the cointegration tests confirm long-run relationships previously detected. As regards the coefficients, we note a slight increase in R&D and human capital elasticities, while the coefficient of private capital is relatively low, showing a size consistent with previous empirical findings (Picci 1999).

On the whole, when we assume constant returns to scale with reference to private inputs (labor and capital) as in equation (1)-(5), in accordance with other empirical works on Italian data (Lodde 2000, Maroccu, Paci e Pala 2001) we find increasing returns with respect to all inputs; since the other variables taken into account, such as human or public capital, produce positive externalities on output. This result holds in specification (6) as well, when we do not impose constant returns to scale to labour and capital.

At this stage we are able to compute the rates of return on investment in R&D and in public infrastructures[19]. Based on our data for the year 2001, we obtain an overall rate of return to R&D equal to 0.43, which means that in Italy a 1 million euro increase in the R&D capital stock increases output by 0.43 million of euro. This is reasonable rate of return, which falls in the range reported by Wang and Tsai (2003)[20]. The rate of return of public capital turns out to be smaller than R&D capital, about an average of 0.23.

6. Granger-causality tests and robustness analysis

In this paper we tackle a central issue of the empirical literature on economic growth, which is the problem of reverse causation. According to the theory, public capital, research and development expenditure, and human capital are usually assumed to cause productivity growth, but the direction of causality might well run the other way around. As income and

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[18] According to our data labour income share used to calculate TFP was equal to 0.65 and capital income share 0.35.

[19] Assuming a the simple Cobb-Douglas production function of equation (3), the returns to R&D investment will be: $\partial Y/\partial SR\&D = e_3 Y/SR\&D$. Therefore the rate of return are calculated as: $e_3 Y_{g,t}$/ *Stock* $R\&D_{g,t}$, where Y stands for the output, *g* denotes the geographic area.

[20] They report values of returns on R&D capital estimated by the literature from 0.1 to 0.5. By geographic area we find that the unequal territorial distribution of R&D stock across areas produces strong territorial heterogeneity of returns: in the North and in the Center the rate of return is 0.37 and 0.33, respectively, in the South it rises to about 1. Of course, this calculation can be largely sensitive to the method of calculation of R&D capital stock and measurement errors, therefore we do not pay excessive attention to precise estimates;

productivity increase, more resources can be devoted to investment in R&D or to improve infrastructure; moreover, during expansion periods people are also able to increase investment in education. Therefore, the detected relationships amongst the variables might capture just correlation instead of causality links. In the light of this concern, we are interested not only to estimate the signs and significance of the relationships between productivity and its regressors, but also to test for the direction of causality of these relationships.

After having found cointegration amongst the variables, we can re-parameterise the model in a error correction form. In a cointegrating framework, the estimation of the error correction model and Granger causality tests allow us to verify the direction of causality in both the long and the short-run. It is worth noticing that if series are cointegrated the Granger-causality test can be run only in the error-correction model (Granger 1988).

Let us define the disequilibrium term of long-run estimates of the baseline model (4) as $\hat{u}_{i,t} = tfp_{i,t} - \theta_i - \theta_t - \hat{e}_1\, hc_{i,t} - \hat{e}_2\, g_{i,t} - \hat{e}_3\, rd_{i,t}$, where coefficients are the long-run elasticities previously estimated. $\hat{u}_{i,}$ represents how far our variables are from the equilibrium. Hence, we can write the following error correction models:

$$\Delta tfp_{i,t} = \theta_{1i} + \theta_{1t} + \lambda_1\, \hat{u}_{i,t-1} + \gamma_{11}\, \Delta rd_{i,t-1} + \gamma_{12}\, \Delta hc_{i,t-1} + \gamma_{13}\, \Delta g_{i,t-1} + \chi_{1i,t} \tag{7}$$

$$\Delta rd_{i,t} = \theta_{2i} + \theta_{2t} + \lambda_2\, \hat{u}_{i,t-1} + \gamma_{21}\, \Delta rd_{i,t-1} + \gamma_{22}\, \Delta hc_{i,t-1} + \gamma_{23}\, \Delta g_{i,t-1} + \chi_{2i,t} \tag{8}$$

$$\Delta hc_{i,t} = \theta_{3i} + \theta_{3t} + \lambda_3\, \hat{u}_{i,t-1} + \gamma_{31}\, \Delta rd_{i,t-1} + \gamma_{32}\, \Delta hc_{i,t-1} + \gamma_{33}\, \Delta g_{i,t-1} + \chi_{3i,t} \tag{9}$$

$$\Delta g_{i,t} = \theta_{4i} + \theta_{4t} + \lambda_4\, \hat{u}_{i,t-1} + \gamma_{41}\, \Delta rd_{i,t-1} + \gamma_{42}\, \Delta hc_{i,t-1} + \gamma_{43}\, \Delta g_{i,t-1} + \chi_{4i,t} \tag{10}$$

where Δ is the first difference operator; and the coefficient λ measures how fast the variables adjust to the disequilibrium, in other words indicates the speed of adjustment. The equations (7)-(10) are error correction representations of the model (4) (see Canning and Pedroni 2004;

yet, we believe they are indicative of the relative importance of investment in R&D and of a stronger effect of the investment in the Southern regions.

Strauss and Wohart 2004)[21]. Long-run causality is tested by the significance of the error correction term λ. For example, if λ_2 turns out to be different from zero, the other variables included into the model, comprised productivity, cause *rd* in the long-run, that is they have long-run effect on research and development stock. Short-run causality is tested by the joint significance of the lagged differentiated variables, i.e when the parameters γ are jointly different from zero. If only long-run test is accepted, that is if only λ is non-significantly different from zero, then the corresponding dependent variable is weakly exogenous. If the both tests are accepted, i.e. long-run and short-run causality is found (λ and γ jointly found non-different from zero) the corresponding dependent variable turns out to be strongly exogenous (Hendry 1995).

Since cointegration relationships are found, the right hand side variables of equations (7)-(10) are all stationary, then the system can be estimated by OLS method. Moreover, no assumptions on the exogeneity of the variable with respect to the system are made, thus we have inserted the lag of explanatory variables and we have estimated the system equation by equation.

Table 5 contains the results of the error correction model estimates. The first column shows that in the equation with TFP as dependent variable, the error correction term is strongly significant with the correct sign: hence the evidence supports the hypothesis of long-run Granger causality between productivity and the explanatory variables and confirms the results obtained through the cointegration analysis. The quite large coefficient in absolute value, about 0.2, means that we do not move far away from the long-run equilibrium and that approximately in five years we return to equilibrium after a deviation from it[22]. Note that, only the model with time fixed effects is reported, since likelihood-ratio test accepts the hypothesis of no heterogeneous regional intercepts, which suggests homogeneity of TFP

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[21] By inserting the lagged variables we are able to carry out the Granger-causality test; on the other side if we use contemporaneous regressors we implicitly assume weak exogeneity of explanatory variables.

[22] The magnitude of the error correction coefficient is consistent with those previously found by the literature. Frantzen (2000) in a cross-country model in which TFP is a function of human capital and R&D stock, estimates an error correction term by about -0.12.

trends among regions when error correction term is taken into account[23]. On the other hand, there is no evidence of short-run impact of the regressors on productivity dynamics.

In the second column, the results for R&D show that regional fixed effects are significant, therefore there should exist heterogeneous trends. Accordingly, the ECM is estimated with regional fixed effects. Moreover, that error term is significant together with the short-run dynamics of some of explanatory variables. On the whole R&D turns out to be endogenous in the long and short-run, and the significance of regional effects would suggest the model might not be appropriate for describing R&D dynamics.

On the other hand, results for human capital equation (third column) denote a strong exogeneity of education with respect to the model. The jointly F test of no long and short-run causality is strongly accepted and the unique significant regressor is the lagged change of the dependent variable. Finally, for public capital we obtain a mixed result. Public capital turns out to be only weakly exogenous, in that the long-run causality test is rejected, but the short-run causality is not: education apart, the other variables seem to cause short-run dynamics of public capital.

Summarising, it is interesting to note that with the exception of R&D, both human and public capital are exogenous in the long-run with respect to the model, that is they determine the level of productivity, while the opposite is not true. The fact that R&D capital accumulation depends on productivity of the business sector might be an expected result: about half of the regional research is carried out within private enterprises and higher productivity could boost R&D investment in private sector. The exogeneity of public infrastructure and education tell us instead that they could become useful policy instruments to reduce regional economic disparities.

6.1 Robustness analysis

We check the robustness of our results in several ways. A first group of checks concerns causality tests. First of all, we have estimated the error correction model also for

[23] This is consistent with the cointegration tests carried out without heterogeneous trends. Results are qualitatively similar even including regional effects, though.

equation (5) and (6) and we have obtained qualitatively similar results. Second, we have checked the results of error correction model including also regional fixed effect in the equations, without substantial changes of the outcomes[24].

A second group of controls are concerned with how we have calculated our baseline TFP. In particular, in the benchmark model (4) we have measured productivity of the entire private sector. However, it is likely that in real estate sector productivity can be only imperfectly calculated, since the rise in housing prices and in rents can increase output without an actual improvement in productivity. For these reasons, we have excluded this industry from our baseline model. The result of this check is shown in the first column of Table 6. We see there are no substantial modification of the outcome previously obtained. In a second check, we assume regional heterogeneity of labour share and we compute α by each region, while in the baseline model we have used a (national) parameter equal across regions. The second columns of table 6 shows that there are no significant changes in the outcomes.

A third group of checks deal with how we have chosen some regressors. First, instead of using a measure of public capital variable in value, we use a physical measure of infrastructure: the Km of highways and road by region, provided by the National Institute of Statistics (see Canning 1999, Canning and Pedroni 2004, Fernald 1999). Second, we have recalculated the R&D stock using a depreciation rate of 10%, instead of 15%. Columns (3) and (4) of Table 6 contains the results of these checks: our basic results are not affected by these changes and it is worth highlighting that the physical measure of infrastructure have coefficient close in magnitude to that obtained in the model with the corresponding public capital stock in value.

7. Conclusions

In this paper we have assessed the impact of R&D, human and public capital stocks on the level of TFP of Italian regions between 1980-2001. Our results summarize consistently the evidence in favour of the positive effect of these three kinds of capital factors on

[24] Results are not reported but available under request.

productivity. Long-run relationships have been detected and the elasticities, estimated by Pedroni method robust to endogeneity and serial correlation, show that all are statistically significant. Moreover, we have examined the question of reverse causality running Granger causality tests, and showing that two variables, human capital and public capital, are exogenous in the long-tun, and only R&D comes out endogenous.

Larger stock of R&D is associated with productivity expansions. However, the contribution is very low and smaller than that of the other capital factors. This might be due to inter-regional knowledge spillovers, which attenuate the effect of local R&D activity on the local TFP; given that thanks to knowledge spillovers, each region might benefit from knowledge produced elsewhere. According to our Granger causality tests, R&D efforts also turns out to be endogenous to productivity model; in other words is detected a bi-directional causality that also goes from the other variables in the model to R&D stock. Event though R&D efforts have been found by empirical researches important to boost country economic growth, these results suggest how they can be considered a weak instrument for reducing productivity regional disparities and that the location of the R&D activity have a relatively weak impact on the regional productivity.

On the other hand, human capital and infrastructure seem to play an important role in explaining productivity differences. Both affect positively regional productivity and the impact seems quite remarkable. In our baseline model an increase of 1 per cent in human capital or public capital, increases productivity by approximately 0.39 and 0.11 per cent, respectively. Moreover, both the factors are found exogenous in the long-run by our causality tests: this means that (at least in the Granger sense) a causality direction from human and public capital to productivity is verified but not vice versa. In our opinion, these two factors can be considered as suitable instruments to design a regional policy aimed at lowering the regional gap.

Appendix

A1. Physical capital stock

In order to calculate regional physical capital stock we have used the method introduced by Piselli (2001), who proposes a methodology that breaks down national capital stock by region, sector and type of capital good. As live services and depreciation of capital goods differ significantly between types and sectors, a disaggregated approach will be more accurate than an aggregated one[25]; moreover, this method approximates quite well the estimates based on the standard perpetual inventory method[26].

Piselli's procedures can be divided in four steps, all described in more detail below: 1) we disaggregate regional gross investment by sector and type of capital good; 2) then, the national capital stocks, by sector and type of capital good, are split by regions in a benchmark year (2000); 3) next, we calculate regional stocks over the entire period with the capital stock in the benchmark year, the annual investment and depreciation of capital; 4) finally, total regional capital stocks have been calculated by adding up sectoral and by-type regional stocks.

Step 1 is based on an iterative procedure, which splits regional investment by sector and type of capital good. The procedure estimates I_{RST} , the investment in region R, sector S and type of capital good T, when only I_{RT} and I_{RS} are available, by exploiting the national series by sector and type of capital good I_{ST} . Our starting estimate is based on the assumption that for each region, the following equality holds

$$I^*_{RST} = I_{RS} \bullet I_{ST} / I_S.$$

where I_{ST} / I_S is the national composition of investment by type of capital good and the star denotes the estimated values.

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[25] Disaggregation should be ideally as fine as possible. In practice, data constraints have limited disaggregation to 14 sectors and two main types of capital goods (building and plant, machinery and vehicles).

[26] However, unlike our method, the perpetual inventory method would require regional series of gross investment that extend back for many years. Such long series are often not available at regional level.

For each region, across sectors, we have that $\sum_S I^*_{RST} = I^*_{RT} \neq I_{RT}$; we can correct this difference, multiplying our estimation by the ratio $\beta_{RT} = I^*_{RT} / I_{RT}$. After this correction, however, aggregating by type or region, we have again $\sum_T \beta_{RT} I^*_{RST} \neq I_{RS}$ and $\sum_R \beta_{RT} I^*_{RST} \neq I_{ST}$. Hence, we introduce two other correction coefficients $\gamma_{RS} = I^*_{RS} / I_{RS}$ and $\delta_{RS} = I^*_{RS} / I_{RS}$. The iterative procedure finds the coefficients β_{RT}, γ_{RS} δ_{ST} and I^*_{RST} , which solve the system:

$$\beta_{RT} \sum_S \gamma_{RS} \delta_{ST} \bullet I^*_{RST} - I_{RT} = 0$$

$$\gamma_{RS} \sum_T \beta_{RT} \delta_{ST} \bullet I^*_{RST} - I_{RS} = 0$$

$$\delta_{ST} \sum_R \beta_{RT} \gamma_{RS} I^*_{RST} - I_{ST} = 0$$

$$\beta_{RT,} \gamma_{RS,} \delta_{ST} > 0.$$

The availability of regional investment series by sector and type of capital good allows us to account for the differences in depreciation patterns in (de)cumulating regional stocks.

Step 2 can be expressed in the following formula

$$K_F(R,S,T) = \frac{\sum_{t=1}^{F} I_t(R,S,T)}{\sum_{t=1}^{F} I_t(S,T)} K_F(S,T)$$

where I and K are investment and capital stock, respectively, t=1…F indicates the period over which investment series are available and F is the benchmark year. The regional capital stock in sector S and type T $K_F(R,S,T)$ is then equals to the share of regional investment over the F years to the national investment, times the national capital stock $K_F(S,T)$. If one assumes that depreciation and service lives of capital goods depend only on S and T, but not on R and if investment series are not too short, the estimation of regional capital stocks are very close to those based on the perpetual inventory method.

In step 3 we decumulate regional capital stock (by sector and type of capital good) from the benchmark year backward to the initial year. Assuming that regional depreciation rate is the same as the national one, the stock in year F-i is simply:

$$K_{F-i}(R,S,T)= [1+\delta(S,T)]\ K_{F-i+1}(R,S,T) - I_{F-i}(R,S,T)$$

where δ(S,T) is the national depreciation rate by sector and type of capital good.

In Step 4 we calculate regional capital stock: $K_R=\sum_S\sum_T K(R,S,T)$.

A2. Human capital stock.

The years of schooling in each region is obtained by the number of years required to reach a certain level of qualification (see below), weighted by the share of workers with that qualification to the total employees:

$$\textit{Average years of schooling}_R=\frac{1}{N_R}\sum_q \mathrm{w(R,Q)}\cdot \mathrm{Y}S\mathrm{(R,Q); w(R,Q)}=\frac{\mathrm{N(R,Q)}}{\mathrm{n(R,Q)}}$$

where n(R,Q) is the number of individuals of the sample in region R with qualification Q, and N(R,Q) is the total number of employees in the region with qualification Q; YS is the years of schooling per employee with qualification Q in region R; the weight w is provided in the survey. Data are from Istat (Indagine sulle forze lavoro). Before 1993, data are not homogeneous with the present survey and we use data on age and qualification of employees reconstructed by Baffigi (1996). From 1993 to 2001, we attribute 0 to a person with no qualification, 5 for completing primary school, 8 for lower secondary school, 10.5 for a professional diploma, 12.5 for people completing secondary education, 15.5 for a "short" degree (laurea breve), 17.5 for a standard degree and finally 21.5 years of schooling to those with a doctoral qualification or specialisation. Before 1993, we have only three kinds of qualification: up to primary school, lower secondary school, secondary school diploma or more. We assign 5 and 8 years of schooling to the first two qualifications. In the third class, in order to estimate the share of graduated people in the third class in each region i (G*i*), we use the average shares from 1981 and 1991 Census regarding regional population. Hence, we calculate the average years of schooling in region *i* as 13*(1-G*i*)+17*G*i*. Finally, to detect possible breaks in the series over the entire range 1980-2001, we compare the estimates obtained in the two samples in the overlapping year 1993. Differences turn to be very small, about 1 per cent or less in all regions, regardless of the variable you take into account. This means that, at this level of aggregation, the two data-sets, despite different detail of information contained, are largely comparable. However, we calculate a correction coefficient based on the ratio of the data in 1993. This coefficient, different by region and variable, is applied to the series before 1993.

A3. R&D capital stock.

In order to calculate R&D capital stock, first of all we have to deflate R&D nominal expenditure to obtain the real R&D expenditure series. The price index (*prd*) used to deflate R&D is set equal to: $prd = 0.5*p + 0.5*w$; where p is a price index obtained as implicit deflator of the value added and w is a wage index. Next, R&D capital stock is calculated from the real R&D expenditure (R) following the perpetual inventory method: $SR\&D_t=(1-\delta)SR\&D_{t-1} + R_t$; where δ is the depreciation rate (set equal to 15 per cent). Finally, as commonly found in the literature, the benchmark capital stock for the beginning year is given by: $SR\&D_0=R_0/(g+\delta)$; where R_0 is the average of the initial five years for which data on R&D are available and g is the average growth rate of R&D expenditure over the whole period. It should be noted that in the literature R_0 is usually set equal to the first year R&D expenditure for which data are available. We preferred averaging over the first five years in order to obtain a more robust estimate.

A4. Pedroni's FMOLS estimator.

In the following, we briefly describe the estimator, referring the reader to the original papers for details. Let us consider a simple panel regression between y_i and x_i for individual i:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}$$

where y_i and x_i are I(1) for all i and $x_{it} = x_{it-1} + \varepsilon_{it}$. Under the assumption of cointegration, $(u_{it},\varepsilon_{it})'$ is a stationary vector with long-run covariance matrix $\Omega_i=\begin{pmatrix}\Omega_{ui} & \Omega_{u\varepsilon i}\\ \Omega_{\varepsilon ui} & \Omega_{\varepsilon i}\end{pmatrix}$. This latter can be decomposed as $\Omega_i = \Omega^0_i + \Gamma_i + \Gamma'_i$, where the first term is the contemporaneous covariances and Γ_i is a weighted sum of autocovariances.

Pedroni's estimator modifies the standard OLS estimator

$$\hat{\beta}_{OLS} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(x_{it} - \overline{x}_i\right)\left(x_{it} - \overline{x}_i\right)' \right]^{-1} \cdot \left[\sum_{i=1}^{N} \sum_{t=1}^{T} \left(x_{it} - \overline{x}_i\right)\left(y_{it} - \overline{y}_i\right)' \right]$$

as

$$\hat{\beta}_{FM} = \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{t=1}^{T} \left(x_{it} - \overline{x}_i\right)\left(x_{it} - \overline{x}_i\right)' \right]^{-1} \cdot \left[\sum_{t=1}^{T} \left(x_{it} - \overline{x}_i\right)' \hat{y}^{+}{}_{it} - T\hat{\gamma}_i \right] \tag{5}$$

where

$$y^{+}{}_{it} = \left(y_{it} - \overline{y}_i\right) - \frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}} \Delta x_{it}$$

acts as an instrument for the endogeneity of the regressor and

$$\hat{\gamma}_i = \hat{\Gamma}_{21i} + \hat{\Omega}^0{}_{21i} - \frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}} (\hat{\Gamma}_{22i} - \hat{\Omega}^0{}_{21i})$$

is the serial correlation correction term.

It is worth noting that the expression in square brackets in equation (5) is the conventional FMOLS estimator, introduced by Phillips and Hansen (1990) in a time series context. The Pedroni’s between-dimension group-mean FMOLS estimator is constructed as the mean of N conventional FM estimates that allows for heterogeneity of cointegration relationships across individuals.

Table 1

SUMMARY STATISTICS: ITALIAN MEAN=100

Region	TFP of business sector (1)		Education		R&D stock in percentage of GDP		Public capital stock in percentage of GDP	
	1980	2001	1980	2001	1980	2001	1980	2001
Piedmont	113.9	108.5	99.4	99.5	215.6	218.0	59,5	83,6
Lombardy	121.3	119.9	102.6	102.1	128.8	134.8	47,8	49,8
Trentino Alto-Adige	110.1	104.5	97.0	98.3	8.3	38.5	120,4	125,1
Veneto	103.3	106.7	97.4	99.0	26.9	41.6	73,4	64,1
Friuli Venezia-Giulia	105.4	107.9	104.2	102.7	103.5	93.6	97,5	119,6
Liguria	142.8	125.7	108.0	103.5	175.8	111.8	160,9	157,6
Emilia-Romagna	116.8	111.6	99.8	100.9	120.1	82.1	83,6	74,9
Tuscany	117.7	112.0	100.2	99.2	50.6	64.8	113,3	108,5
Umbria	103.3	101.7	99.1	104.4	22.3	28.4	174,5	147,4
Marche	96.3	100.9	94.6	99.0	29.3	23.6	133,2	104,7
Lazio	130.6	124.8	114.4	107.5	137.0	215.2	84,8	100,6
Abruzzo	88.9	91.9	99.4	99.8	15.2	67.1	220,8	185,4
Molise	74.7	85.2	94.8	98.7	0.7	8.9	140,8	158,4
Campania	79.1	86.5	98.7	99.5	65.5	59.3	103,5	113,5
Puglia	84.3	84.6	95.8	96.0	76.2	29.5	83,4	93,3
Basilicata	66.1	78.7	93.1	93.9	85.2	48.3	357,8	322,1
Calabria	64.6	77.9	101.0	99.3	17.8	8.0	313,2	262,3
Sicily	86.8	84.9	100.0	99.6	31.7	28.3	170,8	175,1
Sardinia	94.1	86.1	100.5	97.2	177.5	30.1	152,5	168,9
Centre-North	114.7	111.3	101.5	101.5	113.6	120.2	81,5	82,6
South	79.8	84.5	97.9	98.0	60.7	38.3	155,6	155,6
Italy (2)	100.0	100.0	100.0	100.0	100	100	100,0	100,0

Source: based on Istat data. (1) The business sector is computed excluding from the total: public administration, education, health and security services, other public, social and personal services. (2) For TFP and human capital, Italy refers to the regional means.

Table 2

UNIT ROOTS TESTS

Variable	Levin, Lin & Chu	Im, Pesaran and Shin	ADF-Fisher	Variable	Levin, Lin & Chu	Im, Pesaran and Shin	ADF-Fisher
tfp	1.49	-1.39*	48.54	Δtfp	3.21***	6.41***	110.82***
	(0.93)	(0.08)	(0.11)		(0.00)	(0.00)	(0.00)
rd	-4.22***	-0.53	49.93	Δrd	3.56***	-2.11**	51.81*
	(0.00)	(0.29)	(0.26)		(0.00)	(0.02)	(0.07)
hc	1.85	0.12	31.15	Δhc	3.22***	6.83***	118.82***
	(0.97)	(0.55)	(0.77)		(0.00)	(0.00)	(0.00)
g	-4.86***	-0.61	40.81	Δg	-0.89	-1.49*	39.59
	(0.00)	(0.26)	(0.34)		(0.19)	(0.07)	(0.39)
y-l	4.46	2.20	22.83	Δ(y-l)	-2.39***	-3.92***	72.18***
	(1.00)	(0.98)	(0.97)		(0.00)	(0.00)	(0.00)
y	1.00	-1.15	39.49	Δy	-1.64***	-5.47***	94.95***
	(0.84)	(0.12)	(0.40)		(0.05)	(0.00)	(0.00)
k-l	6.10	5.51	9.64	Δ(k-l)	1.15	-0.27	28.57
	(1.00)	(1.00)	(1.00)		(0.87)	(0.40)	(0.87)
k	-2.42	-0.70	33.88	Δk	-1.37*	-1.02	37.77
	(0.99)	(0.24)	(0.66)		(0.08)	(0.15)	(0.48)
l	5.42	2.67	14.15	Δl	0.88	-1.99**	45.15
	(1.00)	(1.00)	(1.00)		(0.81)	(0.02)	(0.20)

Note: (***) denotes parameters significant at, or below, 1%; (**) denotes parameters significant at, or below, 5%; (*) indicates the parameters that are significant at, or below the 10% probability level. TFP refers to business sector; Val d'Aosta is excluded for lack of data on human capital. All the tests are carried out with individual fixed effects and individual linear trends. The specified lags of the models are 2. The null hypothesis is Ho: Unit Roots. P-values in parenthesis.

Table 3

TOTAL FACTOR PRODUCTIVITY ESTIMATION RESULTS

Dependent variable: log (Total Factor Productivity); FMOLS estimates
Time period: 1985-2001; 19 regions.

Variable	*(1)*	*(2)*	*(3)*	*(4)*
log R&D Capital	0.026***	0.015***	0.054***	0.036***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
log Human capital	0.379***	0.530***	0.486***	0.537***
	(0.061)	*(0.097)*	*(0.082)*	*(0.106)*
log Public Capital	0.109***			
	(0.004)	–	–	–
log Public capital: roads		0.149***		
	–	*(0.007)*	–	–
log Public capital: railways			0.090***	
	–	–	*(0.002)*	–
log Public capital: water and electric facilities	–	–	–	0.020***
				(0.000)
Time fixed effects	yes	yes	yes	yes
Regional fixed effects	yes	yes	yes	yes
Pedroni's (1999) coint. tests (1)				
Panel ν-Statistic	1.761**	1.805**	1.763**	1.579*
Panel ρ-Statistic	0.359	0.404	0.252	0.451
Panel t-Statistic (non- parametric)	-2.721***	-2.567***	-2.892***	-2.585***
Panel t-Statistic (parametric)	-3.572***	-2.391***	-3.812***	-3.825***
Group ρ-Statistic	2.013**	2.214**	1.888**	2.193**
Group t-Statistic (non- parametric)	-2.572***	-2.199**	-2.787***	-3.66***
Group t-Statistic (parametric)	-5.187***	-3.510***	-5.841***	-4.608***

Note: (***) denotes parameters significant at, or below, 1%; (**) denotes parameters significant at, or below, 5%; (*) indicates the parameters that are significant at, or below the 10% Unreported time and region-specific fixed effects. TFP refers to business sector. Standard error in parenthesis.

(1) The distribution of Pedroni's cointegration tests is normal; the left tail of the normal distribution is used to reject the null hypothesis, except for the first test, which rejects with large positive values. The null is no cointegration. The cointregration tests do not include heterogeneous trends.

Table 4

LABOUR PRODUCTIVITY AND OUTPUT ESTIMATION RESULTS

Estimation results of equations (5) and (6)

Time period: 1985-2001; 19 regions.

Variable	*Dependent variable: Labour productivity*	*Dependent variable: Regional value added*
log R&D Capital	0.043***	0.076***
	(0.000)	(0.001)
log Human capital	0.393***	0.476***
	(0.045)	(0.070)
log Public Capital	0.192***	0.190***
	(0.007)	(0.011)
log (Private capital/Labour)	0.427***	–
	(0.031)	
log Private capital	–	0.146***
		(0.019)
log Labour	–	0.557***
		(0.033)
Time fixed effects	Yes	Yes
Regional fixed effects	Yes	Yes
Pedroni's (1999) coint. tests (1)		
Panel ν-Statistic	0.537	-0.002
Panel ρ-Statistic	1.666	2.276
Panel t-Statistic (non- parametric)	-4.403***	-4.304***
Panel t-Statistic (parametric)	-3.221***	-3.301***
Group ρ-Statistic	2.951	3.760
Group t-Statistic (non- parametric)	-4.604***	-5.558***
Group t-Statistic (parametric)	-5.205***	-4.981***

Note: (***) denotes parameters significant at, or below, 1%; (**) denotes parameters significant at, or below, 5%; (*) indicates the parameters that are significant at, or below the 10% Unreported time and region-specific fixed effects. Labour productivity and value added refer to business sector. Standard error in parenthesis.

(1) The distribution of Pedroni's cointegration tests is normal; the left tail of the normal distribution is used to reject the null hypothesis, except for the first test, which rejects with large positive values. The null is no cointegration. The cointregration tests do not include heterogeneous trends.

Table 5

GRANGER CAUSALITY TESTS:
ERROR CORRECTION MODEL RESULTS

Time period: 1985-2001; 19 regions. OLS estimates.

	Dependent variable			
Variable	Δlog TFP$_t$	Δlog R&D Capital$_t$	Δlog Human capital $_t$	Δlog Public capital $_t$
Intercept	0.013***	0.035***	0.018***	0.004***
	(0.003)	(0.011)	(0.001)	(0.001)
Δlog TFP$_{t-1}$	-0.046	-0.217	0.018	0.039*
	(0.058)	(0.197)	(0.026)	(0.023)
Δlog R&D capital $_{t-1}$	0.021	0.237***	0.001	0.015***
	(0.015)	(0.056)	(0.006)	(0.006)
Δlog Human capital $_{t-1}$	0.070	1.099**	-0.134**	0.005
	(0.131)	(0.429)	(0.060)	(0.052)
Δlog Public capital $_{t-1}$	-0.090	-1.517***	-0.062	0.664***
	(0.098)	(0.412)	(0.045)	(0.039)
ECM $_{t-1}$	-0.183***	0.254**	-0.001	-0.007
	(0.036)	(0.117)	(0.016)	(0.014)
Time effects	Yes	Yes	Yes	Yes
Regional effects	No	Yes	No	No
LR-Test $\chi(18)$ on the significance of regional dummies	28.72*	61.98***	11.66	27.53*
F-test of short-run causality: Ho: $\gamma1=\gamma2=\gamma3=0$	1.115	7.457***	0.786	3.209**
F-test of long-and short-run causality: Ho: $\lambda=\gamma1=\gamma2=\gamma3=0$	7.204***	6.301***	0.668	2.409**
Number of Observation	285	285	285	285
R-squared	0. 38	0.46	0.41	0.64

Note: (***) denotes parameters significant at, or below, 1%; (**) denotes parameters significant at, or below, 5%; (*) indicates the parameters that are significant at, or below the 10% . Δ log y=logy$_t$-log y$_{t-1}$ for variable y.

Table 6

ROBUSTNESS

Time period: 1985-2001; 19 regions. FMOLS estimation.

	Dependent variable: TFP without real estate and business services	*Dependent variable: TFP with α heterogeneous by region*	*Dependent variable: TFP*	*Dependent variable: TFP*
log R&D Capital	0.018***	0.006***	0.077***	—
	(0.000)	(0.000)	(0.001)	
log R&D Capital 10%	—	—	—	0.019***
				(0.000)
log Education	0.329***	0.528***	0.429***	0.447***
	(0.059)	(0.096)	(0.054)	(0.082)
log Public Capital	0.108***	0.013***	—	0.139
	(0.005)	(0.001)		(0.005)
log Km of Highways and streets	—	—	0.183***	—
			(0.011)	
Time fixed effects	Yes	Yes	yes	Yes
Regional fixed effects	Yes	Yes	yes	Yes
Pedroni's (1999) coint. tests (1)				
Panel ν-Statistic	1.353*	1.918**	1.115	1.853**
Panel ρ-Statistic	0.080	0.385	0.816	0.189
Panel t-Statistic (non-parametric)	-4.300***	-2.321***	-2.037**	-2.914***
Panel t-Statistic (parametric)	-2.028**	-2.681***	-1.656**	-3.412***
Group ρ-Statistic	1.674**	2.112**	2.539***	1.837**
Group t-Statistic (non-parametric)	-5.006***	-2.014**	-1.612*	-2.851***
Group t-Statistic (parametric)	-4.481***	-4.699***	-2.471***	-4.974***

Note: (***) denotes parameters significant at, or below, 1%; (**) denotes parameters significant at, or below, 5%; (*) indicates the parameters that are significant at, or below the 10% Unreported time and region-specific fixed effects. TFP refers to business sector. Standard error in parenthesis.

(1) The distribution of Pedroni's cointegration tests is normal; the left tail of the normal distribution is used to reject the null hypothesis, except for the first test, which rejects with large positive values. The null is no cointegration. The cointregration tests do not include heterogeneous trends.

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