Schooling, Production Structure and Growth: An Empirical Analysis on Italian Regions*

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Abstract:
This paper analyses the growth effects of high levels of human capital at the industry level. By favouring technology adoption, human-capital-intensive industries grow faster compared to less human-capital-intensive industries in economies that have higher levels of human capital. Using data for nine macro sectors of manufacturing industries in the twenty Italian regions, the results show positive and significant effects of human capital levels and accumulation on value added growth. This result is robust to a series of sensitivity checks such as measures of productivity growth and different indicators of human capital. This finding is particularly important for Italy, as it has always had a model of industrial specialization focused on the traditional sectors which have a low content of technology and human capital.

Keywords: Growth, Human Capital, Technology Adoption, Regions, Sectors, Italy.

JEL Classification: O47, R11

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1 Introduction

Over the last twenty years, there has been an increase in the number of papers devoted to studying the effect of human capital on growth. In particular, the empirical literature has focused on the importance of schooling levels and accumulation over time on the growth rate of countries.

Although the effect of human capital on growth is theoretically recognised, the empirical evidence is not clear cut, and interpretation of results is a matter of discussion.[1] There are many reasons behind these puzzling results. Firstly, the functional form specification can be problematic (Temple, 1999; Durlauf, Johnson and Temple, 2005); also, the bias in estimated parameters can result from measurement error of the schooling variable (Cohen and Soto, 2007; De la Fuente and Doménech, 2005). Classic cross-country growth regressions also have standard econometric problems such as endogeneity and multicollinearity: countries with faster growth rates also tend to accumulate human capital faster (Vandenbussche et al, 2006; Mankiw, 1995). Finally, parameter heterogeneity and the quality margin of schooling are rarely captured with available data, resulting in biased results (Krueger and Lindhal, 2001; Barro, 2001).

In this paper, we test if higher levels of human capital facilitate adoption of new technologies increasing productivity and generating long run growth in the spirit of Nelson and Phelps (1966). Since 1970, new technologies have become more skilled labour augmenting than those available in the past: the main effect is that skilled workers become relatively more productive than the unskilled. As a consequence, TFP growth should be higher in more human capital intensive industries. Countries with higher levels of human capital should be able to adopt these technologies faster and, as a result, experiment faster growth in more human capital intensive sectors.

We study the effect of human capital, both in levels and accumulation, on growth of output. Using data for 9 large manufacturing sectors in 20 Italian regions for the period 1995-2003, we analyse the relationship between level of schooling and value added growth. To overcome standard econometric problems encountered in aggregate macro regressions, we implement the Rajan and Zingales (1998) methodology which consists of using human capital intensity of each sector obtained from US data. The underlying hypothesis is that the US represents a benchmark, with high levels of human capital and a very flexible labour market. This specification allows us to test the empirical prediction of higher output growth in more human capital intensive sectors.

Our results indicate that the level of human capital, expressed as average years of schooling in the population, does not have a statistically significant positive effect on

[1] Results in the literature are mixed: Romer (1990), Barro (1991), Benhabib and Spiegel (1994) find a significant positive effect of levels of schooling on output growth, while Cohen and Soto (2007) find no such effect. Temple (1999), Cohen and Soto (2007) and De la Fuente and Doménech (2005) find a positive correlation between the growth rates of the two variables. Viceversa, Benhabib and Spiegel (1994) and Barro (1991) do not find a positive relationship. Finally, Krueger and Lindahl (2001) do find both a level and growth effect of schooling on growth.

output growth (measured as real value added). The same result is found for the accumulation of human capital, again with a positive but statistically insignificant effect. However, when using both levels and accumulation of schooling as independent variables, we obtain a positive effect of both variables, with high significance of coefficients. When using productivity (value added per worker) as our dependent variable, we obtain again a double positive effect of schooling levels and accumulation, but not when considering them separately. Finally, we also run regressions for employment growth, but we do not find any relevant effect of schooling and its accumulation on this variable.

We also experiment with different indicators for schooling levels (such as the average years of schooling of the workforce, the fraction of population or workforce with a high school diploma, and the fraction of the population and workforce with a PhD) obtaining positive and significant results. Results are confirmed for value added but not for productivity. Finally, as a robustness check, we also consider the level and accumulation effects of human capital on growth when including a measure of financial development as suggested for example by Guiso et al. (2004). Controlling for financial development as another potential determinant of industry growth, we still obtain positive and highly significant results for schooling and schooling accumulation on growth.

The structure of the paper is as follows. In section 2 we briefly discuss the literature and the theoretical framework; while in section 3 we present the empirical application and its results. Section 4 concludes. An Appendix contains the description and definition of the variables as well as figures and tables.

2 Literature and Framework

The role of human capital in economic development has been widely recognised in the theoretical literature. There are basically two approaches to modeling human capital. On the one hand, Lucas (1988) studies the role of accumulation of human capital as the engine of growth; on the other hand, Nelson and Phelps (1966) emphasise the role of human capital stock in developing new technologies and in the catching up process of backward economies towards more advanced ones.

In this framework, output growth depends on the rate of innovation, and consequently on the level of human capital; it is not accumulation of human capital that determines growth. Technological progress depends on the combination of two distinct activities: innovation and imitation. The former is baseline research and takes place in more advanced economies, shifting the technological frontier; the latter is a mechanism that transfers knowledge from more advanced to less advanced economies and is a source of catching up. Of course, innovation and imitation require different levels of human capital, the former being more demanding in terms of skills.

More formally, technology flows from inventors to followers by increasing their total factor productivity (TFP). However, the capacity of adoption of a follower economy crucially depends on the level of human capital. In particular, the positive effect of human capital on productivity is differentiated across sectors of the economy: more human capital intensive sectors will benefit more from this technological transfer. As a consequence, human capital levels should have a positive effect on the output growth of those sectors, with higher human capital requirements of the workforce acting as an accelerator for technology adoption. Higher capacity of adoption then implies higher efficiency (Ciccone and Papaioannou, 2009).

An important implication of this approach is that the human capital endowment of an economy has two separate effects on the production structure of industrial sectors. The first is related to the shift of the technological frontier reflecting the rate of growth of innovations; while the second is related to the growth of TFP, this depends on the implementation of innovations. The TFP growth depends positively on the distance of the current productivity level from the technological frontier.

This theoretical result has an appealing counterpart in the empirical literature as it represents a potential explanation of the catching up and technological diffusion processes across different economies (see Benhabib and Spiegel, 2005). In this context, the leader economy represents the technological frontier; while the human capital level is a major determinant of the speed of the catching up process; it is the main source of reduction of the gap in productivity.

Benhabib and Spiegel (1994) empirically implement the Nelson and Phelps (1966) model to distinguish between the two hypotheses regarding the effect of human capital on growth. In particular, they interact the human capital stock with a measure of backwardness, i.e., the distance from the technological leader. If the technological diffusion hypothesis is correct, human capital levels should have an effect on TFP growth and technological diffusion generating output growth. An important implication of this model is the long run effect of human capital level on output growth: since human capital affects TFP during transition, in the long run, for the same level of human capital, we should observe convergence both in levels and growth rates. What is more, the economy with the highest level of human capital is the leader and remaining economies grow at the same rate with no catching up as predicted by Nelson and Phelps (1966). Benhabib and Spiegel (1994) run cross-country regressions to test this hypothesis and conclude that technology flows from leaders to followers where higher levels of human capital have a positive effect on the speed of this technological diffusion.

In the same spirit, Vandenbussche et al (2006) argue that imitation and innovation are equally important activities that do require different types of human capital; the former requires unskilled human capital, while the latter requires what is called skilled human capital. In this framework, composition of human capital, its level, and the distance from the technological frontier are relevant for growth. The paper has basically the same specification used in Benhabib and Spiegel (1994) with the important difference that the effect of human capital on growth is divided into a level and composition effect. Holding human capital composition constant, higher levels of human capital have positive effects on growth; viceversa, with constant levels of human capital, growth enhancing effects of human capital depend on composition and distance from the technological frontier. In particular, the positive effect of skilled labour increases as economies get closer to the technological frontier, where proximity is measured by the ratio between TFP and the corresponding value for the US, the leader economy. The complementarity arises because reallocation of labour, generated by the increase in the supply of educated workers, is higher when productivity is higher and its contribution to growth is higher. On the other hand, the contribution of unskilled labour decreases as the technological frontier approaches.

Along these lines is also the contribution by Ciccone and Papaioannou (2009). They argue that skilled labour-augmenting technologies have become available since the 70s, increasing the productivity of more skilled workers; as a consequence, TFP growth should be higher in industries with more intensive use of human capital. This is due to the technology adoption mechanism stressed above, so that growth is related to higher levels of human capital. Following Rajan and Zingales (1998), who develop a similar model to study the effects of financial development on growth, they use sectorial data to investigate the relationship between human capital and growth. They study the effect of human capital levels on growth rates in more human capital intensive industries during the 80s and 90s; moreover, they study the effect of accumulation of human capital on growth in more schooling intensive industries.

They use data on 37 manufacturing industries in 42 countries, where US data are used to calculate human capital intensity requirements in each sector. They find that there is a positive and significant effect of human capital on growth, both in levels and in growth rates. To quantify this effect, they calculate the annual differential in growth rates of output between an industry at the 75th percentile of the human capital intensity distribution (chemicals) and one at the 25th percentile (pottery). Using different measures for human capital, their estimates indicate a growth differential respectively equal to 1.3% and to 2.1% for a country at the 75th percentile of the schooling distribution and one at the 25th percentile. The accumulation effect is about 1.2% for countries at the same percentiles of the schooling distribution and that have increased their schooling level.

Although the international evidence is not clear cut and no consensus has been reached regarding the relationship between human capital and growth, to the best of our knowledge, studies dealing with the above relationship are even more rare when considering the national context. A relevant exception is the recent study carried out by Di Liberto (2008) in which the role of human capital as a source of growth is explicitly considered for the post-war period 1961-1991. Introducing lagged human capital endowments in a seemingly unrelated regression she considers the catching-up process across Italian regions. Her results clearly indicate only statistically weak effects of human capital on growth. The interpretation is in terms of distorted structural composition of the labour force and inefficient allocation of human capital across sectors, with great importance of the public sector size. In addition, regional differences are detected in the role of human capital on growth: while tertiary education does not have a positive effect on growth, primary education seems to contribute to growth particularly in the southern regions.

In what follows we analyse the relationship between human capital and growth putting particular emphasis on the role of technology adoption and cross sectorial differences in growth dynamics.

3 Empirical Analysis

In this section, we discuss the empirical strategy used by Ciccone and Papaioannou (2009) to test the theoretical framework used by Nelson and Phelps (1966) and adopted for our purposes. In this setup, technology adoption depends on human capital; the latter has a positive effect on productivity in those sectors that make more intense use of it. The level of human capital has two effects on steady state production: the factor supply effect and the technology adoption effect. As discussed above, higher relative supply of human capital in factor markets increases production in human capital intensive sectors; additionally, higher levels of human capital can induce the adoption of skilled labor augmenting technologies and increase efficiency.

3.1 Methodology

In previous sections, we discussed why aggregate cross section studies can deliver unsatisfactory results when studying empirical implications of theoretical models discussed in this paper; in this subsection, we briefly discuss the advantage of using sectorial data, as first proposed by Rajan and Zingales (1998), and applied by Ciccone and Papaioannou (2009) to study the relationship between human capital and growth at the country level.

Sectorial data allows to exploit within country (or region) variation in variables at industry level by interacting a country level characteristic with industry level one. This allows to control for industry and country fixed effects and is less subject to standard econometric problems as omitted variable bias and misspecification of the model.

The specification also includes industry and country dummies. The former group of dummies captures the effect of variations in prices and technological progress at the industry level, while the latter controls for the effect of omitted variables affecting the accumulation of human capital that could create an upward bias in the result.

Our main goal in this paper is that of identifying a causal link between human capital and growth, for this purpose, we exploit both within-region and across-sectors variation in those variables. Our investigative hypothesis is that less human capital intensive sectors should exhibit a weak correlation between human capital and growth, whereas the relation between these variables should be stronger and robust for more human capital intensive industries. To formally test this hypothesis, we interact initial level of human capital at the regional level and a measure of human capital intensity at sector level. The interaction coefficient in our regression measures the marginal effect of human capital on value added growth of more human capital intensive sectors.

We use human capital intensity in each sector, as it represents the instrument through which human capital affects growth. If we used human capital intensity data of each region, we would have a hard time solving standard endogeneity problems, as regional human capital intensity in each industry depends both on demand and supply of skilled workers, the latter being a major determinant of human capital level at the regional level. To overcome this problem, we use the measure of human capital intensity derived from US data. Higher education levels and less regulated markets help in determining the real technological characteristics of industries. Observed differences in human capital across industries should better reflect differences in technological adoption choices. Using US data for human capital intensity allows us to propose an exogenous measure of labour demand for skilled labour in manufacturing sectors in Italian regions.

Still, using US data as a proxy for differences in human capital intensity across industries can generate additional problems: since these data can have problems in representing differences in human capital intensity in other countries, we could reject the hypothesis that human capital accumulation is related to growth of human capital intensive industries. However, this doesn't seem to be a relevant problem in our case, as it is not necessary that Italian industries have the same human capital intensity as their US counterparts; what is really needed is that differences in human capital intensity in the US mirror differences in human capital intensity in Italy. To us, this seems an appropriate restriction for two countries with similar levels of development as Italy and the US.

3.2 Data

Data on growth rate of real value added and employment from 1995 to 2003 come from ISTAT (Italian Statistics Institute), they are aggregated at the regional-sectorial level and relate to 9 macro industrial manufacturing sectors in the 20 Italian regions.

We decided to use sectorial value added, we measure, therefore, the annual average growth rate of sector *s* in region *r* during the period of analysis, 1995-2003. As in Ciccone and Papaioannou (2009), we consider solely the industrial manufacturing sectors as these are less dependent on country-specific factors. We apply the same framework at the regional level. For descriptive statistics, detailed variable definitions and their respective sources, see Table 1 in the Appendix.

The indicator of human capital intensity in the industrial sectors is calculated using data from the US; characterized by a high level of detail and quality of information capturing the differences in the intensity of human capital, which very likely reflect the specific technological characteristics of the industrial sectors.

We extract information on human capital intensity from Ciccone and Papaioannou (2009).[2] Their source is the *Integrated Public Use Microdata Series* (1980) which contains sectorial data regarding the number of working hours and the average years of schooling at the 4 digit classification level, so that they can calculate the average years of schooling per worker in each sector. We had to group the 28 original manufacturing industries into 9 macro-sectors and we calculated the average of each aggregate. Italian data at a 4 digit level of disaggregation are not available, in fact, we use a 2 digit industrial classification (for sector aggregations see Table 2). The most human capital intensive industry is Coke with 12.61 average years of education, while Leather and footwear is the industry with lowest human capital intensity, with 10.13 years of education.

In the paper, we use different measures of human capital levels. The first indicator we use is the average years of schooling of the resident population over six years of age, the second measure is the average years of schooling of the work force. We then carry out the analysis using the fraction of the population and the work force with a high school degree

[2] Table I of their paper.

as our measure of human capital stock. Finally, we calculate the fraction of the population and the work force holding a university degree[3] or a PhD.

We begin our empirical analysis by looking at cross sectional correlations for main variables of interest. In the first part of these descriptive statistics, we show scatter plots and histograms for value added and human capital, in the form of schooling.

In Figure 1, we just report the dynamics of value added for all regions in the period 1995-2003. During this period, value added grows in all parts of the Country, however, important differences emerge across regions. Apart from known differences in starting levels at the beginning of the period, interesting differences in growth of value of added show up. For example, while Northern regions have very similar patterns, Southern ones are differentiated among them. Puglia, Sicilia and Sardegna have substantially flat profiles, while Basilicata, Calabria and Molise show a stable increase in their level of income.

In Figures 2 to 4, we consider differences in human capital endowment in different regions of Italy by using three different indicators for the year 1995. First, in Figure 2, we consider average years of schooling both in the population and in the workforce. A visual inspection of the graph indicates some differences in schooling levels between the North and the South. The region of Lazio, together with Lombardy, Liguria and Friuli had the more educated population and workforce, with more than 8 and 10 years of average education respectively. On the other hand, Southern regions were the less rich regions in terms of human capital levels, with about 7 and 9 years of schooling in the population and in the workforce respectively. The human capital endowment showed important differences across the two areas of Italy.

Things change slightly when we consider the share of population with tertiary or higher education (laurea degree or PhD) in Figure 3. The national figure was equal to 4%, with just four regions (Liguria, Lombardia, Umbria and Lazio) well above the average, with a percentage equal to 7%. In this case, the share of population with higher degree in the workforce was twice as much as the one in the population. Again, regions mentioned above had very high levels for this variable. Finally, note that Calabria and Sicilia had quite highly educated workforce.

Finally, in Figure 4, we consider the share of the population and of the workforce with secondary education (high school diploma). In this case, the average value for Italy was equal to 17% with Northern regions having higher human capital endowments than Southern ones. As expected, differences between the population and the workforce were smaller than for higher levels of education.

In Figure 5, we analyse the cross sectional correlation between level of schooling in 1995 and average growth of schooling during the period 1995-2003. As expected, regions with lower levels of human capital endowment at the beginning of the period (measured as average years of schooling in the population) are those that increase more the education level. The fitted regression line has a clear negative slope.

[3] We would like to specify that by "university degree" we intend at least a four year degree course, and not the short cycle, three year degrees.

On the other hand, levels of schooling, measured as average years of education in the population, do not seem to be positively correlated to value added growth during the period. Evidence from Figure 6 indicate a negative relation between the two variables. A clear and strong positive association emerges from Figure 7, where we plot the accumulation of value added against accumulation of schooling. In what follows, we directly analyse these correlations by using sectorial data with a robust econometric methodology.

3.3 Econometric Analysis

We begin our econometric analysis by comparing the main first order predictions of theoretical framework presented in previous section. In particular, we test if regions with higher levels of human capital at the beginning of the period grow faster in more human capital intensive sectors. Then, we also consider the role of accumulation of human capital for growth in these manufacturing sectors; finally, we model both the effect of levels and human capital accumulation on growth. Formally, we first estimate the following regression:

$$\Delta \ln y_{s,r,1995\text{-}2003} = \lambda_r + \mu_s + \delta\left(hk_{r,1995} * HCINT_s\right) + \lambda \ln y_{s,r,1995} + \varepsilon_{s,c}$$

where the dependent variable is the average annual growth rate of value added in sector *s* in region *r*; $lny_{s,r,1995}$ is the natural logarithm of initial level of value added in sector *s* in region *r*, λ_r is a region fixed effect, (capturing infrastructural level, geographical characteristics and social policies); μ_s is and industry fixed effect that represents variations in prices and industry specific technological progress; $hk_{r,1995}$ is the initial level of schooling in each region; finally, $HCINT_s$ is human capital intensity in each sector. By interacting the latter two variables we should be able to overcome econometric problems discussed above.

We expect a positive impact of human capital on output growth if δ is positive.[4] Results in Table 3, column 1, indicate the latter effect is positive but not statistically significant. On the other hand, there is some evidence of convergence in income levels, with a negative and statistically significant effect of initial level of value added.

We now consider if growth of schooling at the regional level has any effect on growth of value added. We then interact growth in *hk* with HCINT. Equation below analyses this relation:

$$\Delta \ln y_{s,r,1995-2003} = \lambda_r + \mu_s + \theta\left(\Delta hk_{r,1995-2003} * HCINT_s\right) + \\ + \lambda \ln y_{s,r,1995} + \varepsilon_{s,c}$$

Results reported in Table 3, column 2, indicate again a positive but not statically significant effect of human capital accumulation on value added. Again the initial level of

[4] Initial schooling is endogenous, as far schooling decisions depend on expected output growth. We don't instrument initial levels here.

value added as a statistically significant negative effect on growth. Note also the R-squared of the regression increases substantially.

Finally, following Ciccone and Papaioannou (2009) in column 3 of the same Table, we jointly consider level and accumulation effects by estimating the following regression equation:

$$\Delta \ln y_{s,r,1995-2003} = \lambda_r + \mu_s + \delta\left(hk_{r,1995} * HCINT_s\right) + \\ + \theta\left(\Delta hk_{r,1995-2003} * HCINT_s\right) + \lambda \ln y_{s,r,1995} + \varepsilon_{s,c}$$

Interestingly, when considering both human capital level and its accumulation, both coefficients turn out to be positive and statistically significant. These specification, including both measures of schooling, indicates human capital is an important determinant of growth facilitating technology adoption in more advanced sectors of the economy. This is true when considering general equilibrium effects of schooling, as we do in the latter specification.

To have an idea of the size of these effects, we rank regions according to our variables of interest and we calculate percentiles of distributions for human capital levels and human capital intensity. Our calculations indicate that the growth rate differential between a sector at the 75^{th} percentile (Non metal-minerals) and a sector at the 25^{th} percentile (Food, Beverages and Tobacco) of the human capital intensity distribution is equal to about 2.5. Our estimates implicate a human capital level differential between a region at the 75^{th} percentile (Umbria) and a region at the 25^{th} percentile (Molise) of the human capital level distribution equal to about 0.3. Multiplying these figures with our coefficient for human capital level, we obtain a value of 2%. The latter represents the growth rate differential between the two sectors above in the region at the 75^{th} percentile against the region at the 25^{th} percentile. Analogous calculations for human capital accumulation provide a growth rate differential equal to 3.5%.

Previous results indicate there is no significative effect of human capital level on value added growth. However, as discussed in the literature, this result can be related to which human capital variable is considered. In descriptive part above we also verified there are some differences when using different variables for human capital endowment. In Table 4, we provide some robustness checks for our previous results by considering the following stock variables for human capital: average years of schooling in the workforce (hk_f), the share of population and of the workforce with a laurea degree or a PhD ($dott_p$ and $dott_f$ respectively), and the share of population and workforce with diploma or high school degree (dip_p and dip_f).[5] All variables are interacted with human capital intensity.

The general results is that human capital levels have a positive and significant effect on value added growth. With the relevant exception of results in column 1, remaining regressions indicate strong positive effects: the most important effects are that of the share of the population or workforce with a laurea degree or a PhD. The share of population or

[5] Unfortunately, for these variables we are not able to obtain measures of accumulation of human capital.

workforce with a high school diploma as a lower quantitative effect on growth. Again, initial level of value added in 1995 has a negative statistically significant effect on growth, indicating some convergence across regions. Interestingly, these results are in line with those found by Ciccone and Papaioannou (2009) who focus on both level and accumulation effects at the country level.

In what follows, we extend our analysis by using different dependent variables as measures of growth. In Tables 5 and 6 we experiment by using growth of productivity (measured as value added per worker) and growth of employment. As far as productivity is concerned, there is no statistically significant effect of human capital levels on growth; however, when using accumulation of human capital as independent variable, the effect is positive and statistically significant. When considering both level and accumulation effect in column 8 of Table 5, both variables turn out to be positive and significant.[6] Finally, in Table 6, we consider the effect of human capital on employment growth as a measure of shift of production structure. Results clearly indicate there is no effect of these variables on occupation. Probably, labour market effects of human capital accumulation are not very important for employment, while they could be for wages.

Our empirical analysis suggests there are positive effects of human capital on growth of value added and productivity but no effect on employment. However, some other elements are missing from this analysis. Financial development plays an important role in this context, as more human capital intensive industries are more likely to depend on external finance. In what follows we include this measure in our econometric specification. Guiso et al. (2004) study the effect of credit rationing for families on various growth and industry indicators at the regional level in Italy. They find that well developed financial markets are important for creation of new enterprises, entry of new firms, and growth; they also find that regional economic outcomes are influenced by financial development. We use their measure of credit market functioning. As long as financial development is an omitted variable from our previous regressions, we should expect some relevant effects in our baseline specification.

Formally, we add an interaction term between our financial indicator (fin_r) and human capital intensity at industry level ($HCINT_s$) to our first regression equation. We report our results in Table 7. First thing to note is that financial development doesn't have any statistically significant effect on growth; however, when including this variable, both human capital level and accumulation turn out to be significant (columns 1 and 2). This result is even stronger when in column 3, we jointly model level and accumulation effects: again both variables are strongly statistically significant, with stronger effects than those found in previous specifications.

To conclude, our results are in line with those obtained by Ciccone and Papaioannou (2005) which represents the main reference point for our study. They also find a joint positive and significant effect of schooling levels and improvements on output growth in

[6] Note the magnitude of coefficients is very similar to that obtained in Table 3 using value added.

schooling intensive industries. Their results are also robust to inclusion of financial development indicators and property rights protection.[7]

We believe this evidence is quite reassuring for the technology adoption model on which we base our working hypothesis. Still, more empirical research is needed to better disentangle the sources of growth across Italian regions.

4 Concluding Remarks

We study the effect of human capital on growth. Facilitating technology adoption, human capital should have a higher positive effect on growth in more human capital intensive sectors. We test this hypothesis by using Italian regional data for nine macro sectors in the manufacturing industry for the period 1995-2003 and data for human capital intensity from US manufacturing sectors. By interacting these variables with our different measures of human capital we are also able to solve standard econometric problems encountered in this type of analysis.

Our results indicate there is a joint effect of human capital levels and accumulation on growth of value added and on productivity, while there is no effect of both variables when separately considered. We also find no effect on employment, while the inclusion of financial development indicators is important to strengthen the relation object of study.

We conclude that human capital endowments and accumulation are important determinants for growth and that the latter are of primary importance for Italy; however, we leave for further research the questioning of some relevant issues; as the role of human capital quality in the development process; the role of wages and skill composition of the workforce on technology adoption. We believe these to be important questions to answer to understand the paths of development.

[7] We don't include these variables in our work as we assume institutions and property rights protection are the same at the national level.

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Appendix

The Italian Regions

Piemonte, Valle d'Aosta, Lombardia, Trentino- Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna, Toscana, Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna.

Variable definitions and descriptions

Region-sector specific

$\Delta va_{s,r}$ — average annual real growth rate of value added (industrial production) of sector *s* in region *r* during the period of analysis 1995-2003. Source: *ISTAT.*

$\Delta empl_{s,r}$ — average annual real growth rate of employment at the regional-sectorial level during the period of analysis 1995-2003. Source: *ISTAT.*

$\Delta prod_{s,r}$ — average annual real growth rate of productivity at the regional-sectorial level during the period 1995-2003. The variable is calculated dividing value added by the total number of people employed. Source: *ISTAT.*

Industry specific

$\mathbf{HCINT}_s$ — average years of schooling at the sectorial level. This is constructed taking the total number of hours worked in each sector, the number of people employed and the respective years of schooling. The calculation is based on 8 different levels of schooling: 0, 1-4, 5-8, 9-11, 12, 13-15, 16, >16. The average years of schooling in each sector are obtained by multiplying the fraction of the population belonging to each group by 0, 1, 6, 10, 12, 14, 16, 18 respectively. Source: *Ciccone and Papaioannou (2009).*

Region specific

$\mathbf{hk}_p$ — average years of schooling of the resident population of 6 years and over. Souce: *National Census 1991*

$\mathbf{hk}_f$ — average years of schooling of the workforce, i.e. the part of the population that is employed or actively in search of employment. Source: *National Census 1991*

$\mathbf{dott}_p$ — fraction of the resident population with a university degree or PhD. Source: *National Census 1991*

$\mathbf{dott}_f$ — fraction of the workforce with a university degree or PhD. Source: *National Census 1991*

dip_p fraction of the population of 6 years of age and over with a high school diploma. Source: *National Census 1991*

dip_f fraction of the work foce with a high school diploma. Source: *National Census 1991*

fin_r indicator of financial development which measures the ease with which one can obtain a loan at the regional level. Source: Guiso, Sapienza and Zingales, 2004.

Figures

Figure 1
Value added in Italian regions, 1995-2003

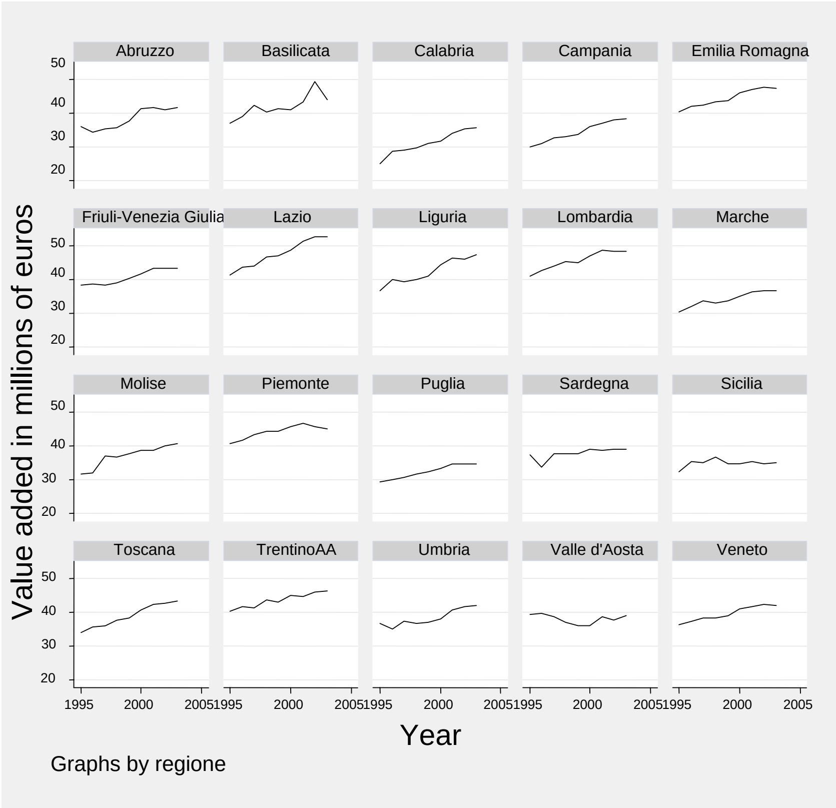


Figure 2

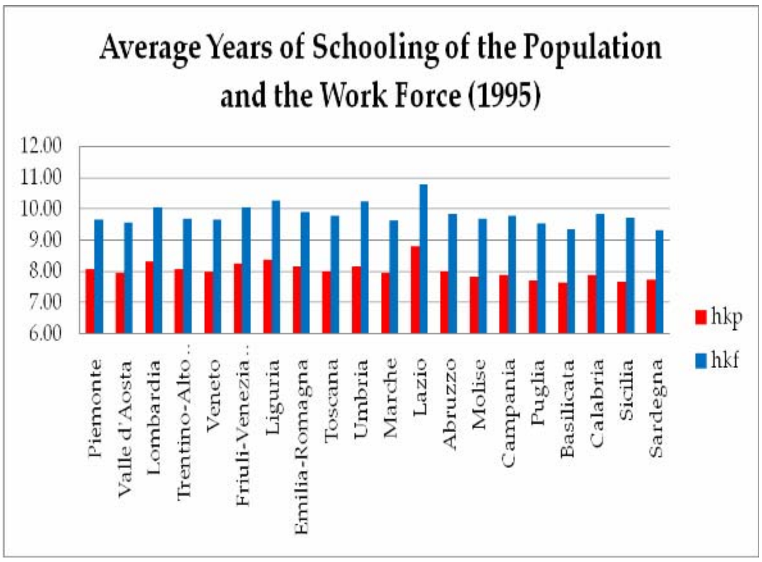


Figure 3

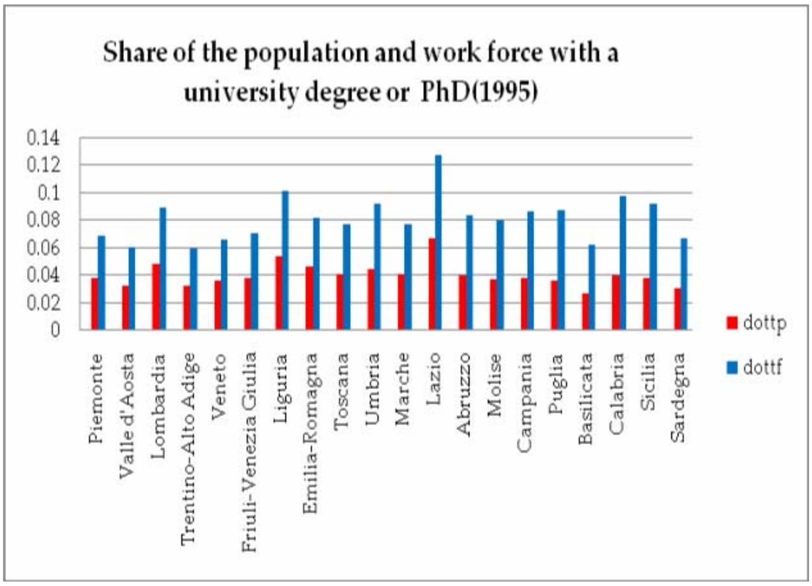


Figure 4

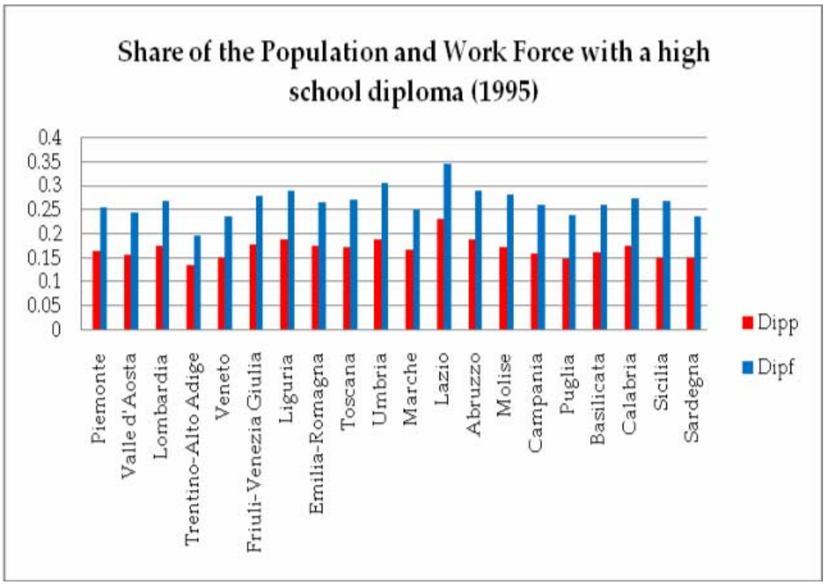


Figure 5

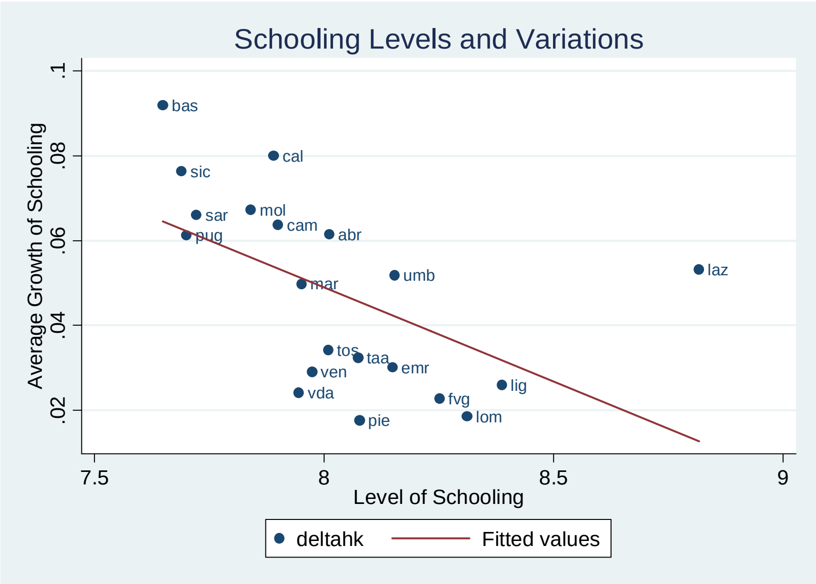


Figure 6

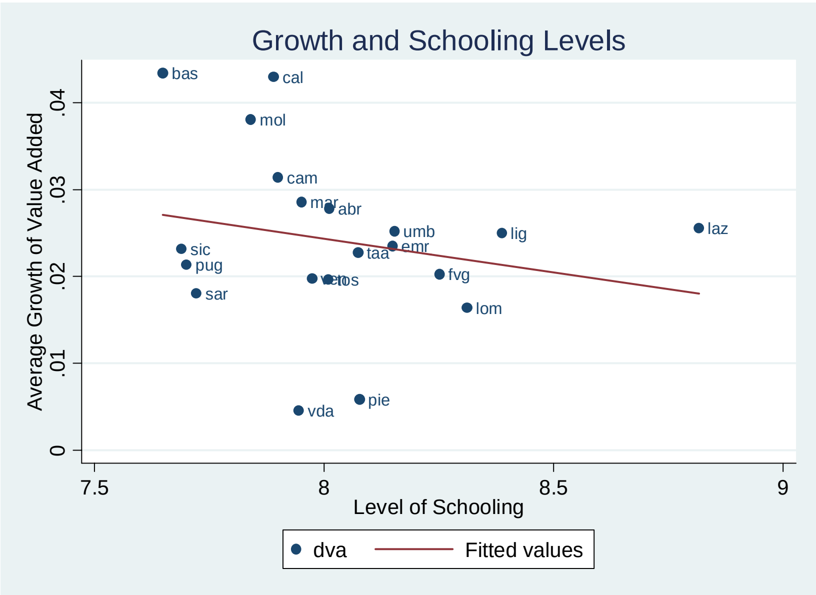
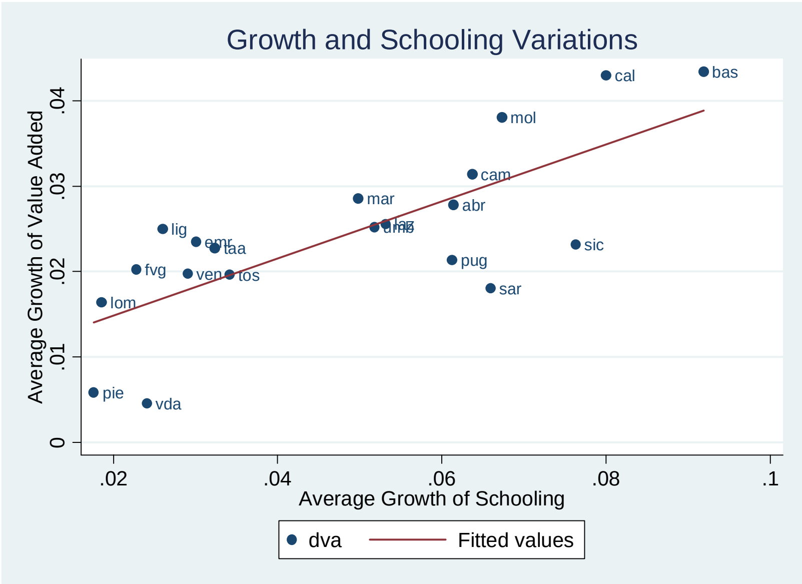


Figure 7



Growth and Schooling Variations
Average Growth of Value Added
0
.01
.02
.03
.04
.02
.04
.06
.08
.1
Average Growth of Schooling
cal
bas
mol
cam
mar
abr
lig
emr
taa
laz
umb
sic
fvg
ven
tos
pug
sar
lom
pie
vda
dva
Fitted values

Tables

Table 1: Descriptive Statistics

(A) Levels, 1995

	Ln(va)	Ln(prod)	Ln(empl)	hk_p	hk_{fl}	$dott_p$	$dott_{fl}$	dip_p	dip_{fl}	fin	ln(HCINT)
Mean	6.1235	3.5425	2.5793	8.0254	9.8170	0.0405	0.0817	0.1701	0.2670	0.3509	2.4283
Median	6.2198	3.5315	2.6496	7.9915	9.7551	0.0384	0.0815	0.1697	0.2680	0.3860	2.4330
Standard Deviation	1.9030	0.3995	1.7152	0.2775	0.3361	0.0088	0.0165	0.0209	0.0306	0.1769	0.0724
Variance	3.6215	0.1596	2.9420	0.0770	0.1129	0.0001	0.0003	0.0004	0.0009	0.0313	0.0052
Obs	200	198	188	20	20	20	20	20	20	20	9

(B) Growth rates

	Δva	Δprod	Δempl	Δhk_p
Mean	0.0218	0.0165	0.0065	0.0479
Median	0.0237	0.0179	0.0059	0.0508
Standard Deviation	0.0279	0.0219	0.0183	0.0226
Variance	0.0007	0.0004	0.0003	0.0005
No. Observations	200	198	188	20

Table 2: Human capital intensity measure calculated for each sector

Industrial Sector	ISIC	Composition	HCINT
I1	311+313+314	Food, Beverages, Tobacco	11.24
I2	321+322	Textiles and Apparel	10.21
I3	323+324	Leather and Footwear	10.13
I4	342+3411+341	Paper products	11.91
I5	3522+353+3511+351+352+354	Coke	12.61
I6	369	Non-metal minerals	11.48
I7	381+371+372	Metals	11.39
I8	382+3841+3843+384+383+3832	Mechanics	12.10
I9	331+355+356	Wood, Rubber, Plastics	11.23

Table 3: Level and accumulation of human capital on value added growth

Dependent variable: $\Delta va_{s,r\ 1995-2003}$	1	2	3
hk_{p1995} ***HCINT**	0.0063		0.0307***
	(0.0067)		*(0.0020)*
$\Delta hk_{p1995-2003}$ ***HCINT**		0.1631	0.3751***
		(0.1053)	*(0.1233)*
$va_{s,r1995}$	-0.0046**	-0.0098***	-0.0118***
	(0.0023)	*(0.0028)*	*(0.0028)*
Constant	-0.4955	-0.0449*	-3.3689***
	(0.57071)	*(0.0269)*	*(1.0625)*
R^2 **adjusted**	0.5524	0.8442	0.8528
No. observations	176	176	176
Sector and Region Fixed Effects	Yes	Yes	Yes
F- Test (p-value)	0.0000	0.0000	0.0000

*The dependent variable in all the columns is the annual average growth rate of value added during the period 1995-2003. The interaction variables are composed of the average years of schooling of the population in 1995 and the measure of human capital intensity calculated for each sector (column 1), the growth rate of human capital and the measure of human capital intensity calculated for each sector (column 2), and in column 3 we show the combined effect; both the interaction between the average years of schooling of the population and the measure of human capital intensity calculated for each sector as well as the interaction between the growth rate of human capital and the measure of human capital intensity calculated for each sector. We use * to denote a 10% significance level, ** to denote a 5% significance level and *** to denote 1% significance level. The number in parenthesis under the coefficient is the standard error*

Table 4: Human capital levels and value added growth, different measures

Dependent variable: $\Delta va_{s,r\ 1995\text{-}2003}$	1	2	3	4	5
hk_{f1995}*HCINT	0.0069				
	(0.0056)				
$dott_{p1995}$*HCINT		0.5422**			
		(0.2647)			
$dott_{f1995}$*HCINT			0.2962**		
			(0.1426)		
dip_{p1995}*HCINT				0.2682***	
				(0.1114)	
dip_{f1995}*HCINT					0.1633**
					(0.0776)
$va_{s,r1995}$	-0.0048**	-0.0104***	-0.0106***	-0.0106***	-0.0106***
	(0.0023)	*(0.0028)*	*(0.0028)*	*(0.0028)*	*(0.0028)*
constant	-0.8435	-0.0030	-0.0392	-0.4684***	-0.4167**
	(0.7092)	*(0.1213)*	*(0.1399)*	*(0.1884)*	*(0.1910)*
R^2 adjusted	0.5543	0.8461	0.8462	0.8477	0.8463
No. observations	176	176	176	176	175
Sector and Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-Test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000

The dependent variable in all four columns is the annual average growth rate of value added during the period 1995-2003. The interaction variables are composed of the average years of schooling of the population in 1995 and the measure of human capital intensity calculated for each sector (column 1), the fraction of the population with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 2), the fraction of the work force with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 3), the fraction of the population with a high school diploma and the measure of human capital intensity calculated for each sector (column 4), and the fraction of the work force with a high school diploma and the measure of human capital intensity calculated for each sector(column 5).

*The last line shows the real growth differential effect of human capital level on the growth of value added. The real growth differential indicates how quickly the value added of an industrial sector located at the 75th percentile of the distribution human capital intensity grows compared to an industrial sector at the 25th when comparing a region with a human capital level at the 75th percentile and another at the 25th percentile. We use * to denote a 10% significance level, ** to denote a 5% significance level and *** to denote 1% significance level. The number in parenthesis under the coefficient is the standard error*

Table 5: Human capital and productivity

Dep var: $\Delta prod_{s,r\ 1995-2003}$	1	2	3	4	5	6	7	8
hk_{p1995}*HCINT	-0.0018							0.0115*
	(0.0054)							*(0.0061)*
hk_{f1995}*HCINT		0.0014						
		(0.0044)						
$dott_{p1995}$*HCINT			0.0810					
			(0.1687)					
$dott_{f1995}$*HCINT				0.1370				
				(0.0898)				
dip_{p1995}*HCINT					0.1139*			
					(0.0699)			
dip_{f1995}*HCINT						0.0746		
						(0.0479)		
$\Delta hk_{p1995-2003}$*HCINT							0.2360***	0.3139***
							(0.0655)	*(0.0769)*
$prod_{s,r1995}$	-0.0425***	-0.0419***	-0.0419***	0.0428****	-0.0417***	-0.0423**	-0.0479***	-0.0473***
	(0.0070)	*(0.0070)*	*(0.0069)*	*(0.0069)*	*(0.0069)*	*(0.0069)*	*(0.0068)*	*(0.0068)*
constant	0.3042	-0.0129	0.1405*	0.0699	-0.1365	-0.1270	-0.0970	-1.0585**
	(0.4908)	*(0.4909)*	*(0.0782)*	*(0.0750)*	*(0.1728)*	*(0.1744)*	*(0.0632)*	*(0.5121)*
R^2 adjusted	0.4899	0.4898	0.4903	0.4976	0.4987	0.4979	0.5317	0.5399
No. observations	174	174	174	174	174	174	174	174
Sector and Region F. E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*The dependent variable in all the columns is the annual average growth rate of productivity during the period 1995-2003. The interaction variables are composed of the average years of schooling of the population in 1995 and the measure of human capital intensity calculated for each sector (column 1), the average years of schooling of the work force in 1995 and the measure of human capital intensity calculated for each sector (column 2), the fraction of the population with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 3), the fraction of the work force with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 4), the fraction of the population with a high school diploma and the measure of human capital intensity calculated for each sector (column 5), the fraction of the work force with a high school diploma and the measure of human capital intensity calculated for each sector (column 6). Then, in column 7 we show the interaction between the average growth rate of human capital and the measure of human capital intensity calculated for each sector, while in column 8 we show the combined effect both the interaction between the average years of schooling of the population and the measure of human capital intensity calculated for each sector as well as the interaction between the growth rate of human capital and the measure of human capital intensity calculated for each sector. We use * to denote a 10% significance level, ** to denote a 5% significance level and *** to denote 1% significance level. The number in parenthesis under the coefficient is the standard error*

Table 6: Human capital levels and employment growth

Dept Var: $\Delta empl_{s,r\ 1995\text{-}2003}$	1	2	3	4	5	6	7	8
hk_{p1995}*HCINT	0.0053							0.0052
	(0.0035)							*(0.0043)*
hk_{f1995}*HCINT		0.0041						
		(0.0029)						
$dott_{p1995}$*HCINT			0.1538					
			(0.1115)					
$dott_{f1995}$*HCINT				0.0256				
				(0.0608)				
dip_{p1995}*HCINT					0.0595			
					(0.0464)			
dip_{f1995}*HCINT						0.0347		
						(0.0322)		
$\Delta hk_{p1995\text{-}2003}$*HCINT							-0.0422	-0.0023
							(0.0457)	*(0.0564)*
$empl_{s,r1995}$	-0.0045***	-0.0045***	-0.0044***	-0.0041***	-0.0043***	-0.0043***	-0.0040***	-0.0045***
	(0.0013)	*(0.0013)*	*(0.0013)*	*(0.0013)*	*(0.0013)*	*(0.0013)*	*(0.0013)*	*(0.0013)*
constant	-0.4623	-1.4264	-0.0845	-0.0312	-0.1209*	-0.0806	-0.0023	-0.4540
	(0.2990)	*(0.3045)*	*(0.0556)*	*(0.0550)*	*(0.0732)*	*(0.0622)*	*(0.0087)*	*(0.3754)*
Adjusted R^2	0.6445	0.6434	0.6434	0.6389	0.6427	0.6415	0.6407	0.6418
No. observations	165	165	165	165	165	165	165	165
Sector-Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*The dependent variable in all the columns is the annual average growth rate of employment during the period 1995-2003. The interaction variables are composed of the average years of schooling of the population in 1995 and the measure of human capital intensity calculated for each sector (column 1), the average years of schooling of the work force in 1995 and the measure of human capital intensity calculated for each sector (column 2), the fraction of the population with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 3), the fraction of the work force with a university degree or PhD and the measure of human capital intensity calculated for each sector (column 4), the fraction of the population with a high school diploma and the measure of human capital intensity calculated for each sector (column 5), the fraction of the work force with a high school diploma and the measure of human capital intensity calculated for each sector (column 6). Then, in column 7 we show the interaction between the average growth rate of human capital and the measure of human capital intensity calculated for each sector, while in column 8 we show the combined effect both the interaction between the average years of schooling of the population and the measure of human capital intensity calculated for each sector as well as the interaction between the growth rate of human capital and the measure of human capital intensity calculated for each sector. We use * to denote a 10% significance level, ** to denote a 5% significance level and *** to denote 1% significance level. The number in parenthesis under the coefficient is the standard error*

Table 7: Level and accumulation of human capital on value added growth, with financial development

Dependent variable: $\Delta va_{s,r\ 1995-2003}$	1	2	3
hk_{p1995}*HCINT	0.0144^{*}		0.0399^{***}
	(0.0089)		*(0.0104)*
$\Delta hk_{p1995-2003}$*HCINT		0.2159^{**}	0.5397^{***}
		(0.1114)	*(0.1355)*
fin_r	0.0027	0.0044	0.0084^{***}
	(0.0029)	*(0.0031)*	*(0.0031)*
$va_{s,r1995}$	-0.0102^{***}	-0.0095^{***}	-0.0119^{***}
	(0.0029)	*(0.0028)*	*(0.0027)*
constant	-1.4902^{*}	-0.2140	-4.5590^{***}
	(0.8514)	*(0.1057)*	*(1.1186)*
R^2 adjusted	0.8443	0.8453	0.8588
N. observations	176	176	176
Sector and Industry Fixed Effects	Yes	Yes	Yes
F test (p-value)	0.0000	0.0000	0.0000

The dependent variable in all four columns is the annual average growth rate of value added during the period 1995-2003. The interaction variables are composed of the average years of schooling in the population in 1995 and the measure of human capital intensity calculated for each sector and the indicator of regional financial development and the measure of human capital intensity calculated for each sector (column 1), the growth rate of human capital and the measure of human capital intensity calculated for each sector and the indicator of regional financial development and of human capital intensity calculated for each sector (column 2). In column 3 we have the combined effect and thus the interaction between the average years of schooling in the population and the measure of human capital intensity calculated for each sector as well as well as the interaction between the growth rate of human capital and the measure of human capital intensity calculated for each sector and the interaction between the indicator of regional financial development and the measure of human capital intensity calculated for each sector

*We use * to denote a 10% significance level, ** to denote a 5% significance level and *** to denote 1% significance level. The number in parenthesis under the coefficient is the standard error*