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Human capital, technology intensity and growth in a regional context

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Human Capital, Technology Intensity, and Growth in a Regional Context[♠]

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Abstract

This paper contributes to the vast literature on the regional application of endogenous growth theory. A well-known feature of capitalist growth and development is the vast and persistent divergence in per capita income growth between regions. These differences have been explained theoretically and empirically using neoclassical approaches emphasising increasing returns at a regional level, with reference, for example, to the development of industrial districts. The new economics of urban and regional growth look at the 'local' dimension focussing on the role of the so-called knowledge economy as an explanation for uneven development across regions. Within this heterogeneity, the operation of human capital and knowledge spillovers play roles in differentiating growth rates. The study of the concentration of a specific mix of economic activities and human capital, with a 'fine grain' focus at the local level, is a useful tool to understand growth and spatial differentials. In this study, we develop an empirical analysis of the pattern of growth in the Veneto region, focusing mainly on the role played by human capital employed in sectors with different technological intensities. To do so, we built up an original dataset by merging data available at a very local level (*Local Labour Systems*-LLS), which was produced by the National Institute of Statistics, with our elaborations on data from an employee-employer dataset made available by the Local Labour Agency (Veneto Lavoro). The latter dataset included all employment spells in the Veneto region. Our new dataset allows both definition of the human capital content of every worker and classification of firms according to their technological intensity. This dataset is used to estimate growth equations for the cross-section of the Venetian LLSs and to test the validity of different growth models. The results underline how growth in the Veneto region is positively affected by human capital employed not in high to medium-high technology industries, but in medium to medium-low ones.

JEL Classification: O1, O3, C21.

Keywords: regional growth, human capital, technological intensity, spatial analysis

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1. Introduction

The recent world financial and economic crisis and its deep effects on the structure of productive systems in the most developed countries are posing major challenges to long-term growth capacity for both national and local economies. In Europe, even the fastest growing regions are experiencing difficulties in maintaining the targets imposed by the Lisbon strategy in terms of the development of a knowledge-based economy (European Commission, 2010).

It is well known that Europe's average growth rate has been structurally lower than that of our competitors (OECD, 2003). Economic theory maintains that a major cause of difference in economic performance is explained by different levels of investment in R&D and innovation. Empirical studies at the levels of firm and industry have established the roles of innovation and diffusion of new technology as engines of growth (Ahn, 2002; Nadiri, 1993). However, in the EU regions, persistent economic performance gaps are widespread (Armstrong and Vickerman, 1995; Cappelen, 1999). This persistence and its causes have been studied in some detail (Cappelen, et al., 2003; Dunford and Smith, 2002).

The role of education in economic growth has been recognized (Barro, 1997; Stevens and Weal, 2004); a higher quality of education works as a driver for promoting innovation and knowledge transfer among sectors and regions (OECD, 2007; Antonelli, 2002). Education is a fundamental determinant of innovation. Romer (1990), in his endogenous growth model, considers human capital as the only input for the R&D sector, where new ideas, especially for intermediate goods, are developed. Therefore, human capital is important for economic sustained growth only if it is applied where ideas are produced and where innovation eventually takes place; moreover, human capital endowment as such, and not its variation, is the trigger for growth. Romer (1990) develops the idea of horizontal innovation, which is the creation of a larger variety of new products. On the other hand, Aghion and Howitt (1992) focus on 'vertical' innovation, which takes the form of improving the quality of existing products by creating new and different versions of goods, thus diversifying an existing innovation and transferring its benefits across the economy. International Institutions (OECD, 1996) have emphasized not only the challenges imposed by moving towards a knowledge-based economy but also the importance of providing vigorous stimulus to the accumulation of human capital, especially in those sectors which need R&D to maintain their position in a globalized and competitive market.

Among EU, the Veneto Region, the area under study in this paper, is characterized by relatively high levels of revenues per capita. However, a closer look shows a fragile economic structure, in which traditional sectors have experienced continuous economic decline and knowledge-based sectors have failed to become new drivers for growth (Regione Veneto, 2010). The resulting picture is that of a region exhibiting disparate patterns of growth in different subareas and districts and among different economic sectors. Understanding these differences is both a stimulus for our investigation and a necessity for appropriate policy-making.

The research questions we want to answer in this study point to the presence of persistent performance gaps in the economy of the Veneto Region. Specifically, our aims is to study in detail and at a sub-regional scale the origin of these gaps by looking at the role of human capital in promoting overall economic growth and by analysing its role in specific sectors, according to and in combination with differences in technological intensity.

By studying the underlying endowment of human capital and its utilization as a major determinant of the Veneto growth model, as evolved at the beginning of this century, we wish to contribute to the debate on the future of the regional economy and its position within the EU. Furthermore, we wish to provide evidence to support a vision for future growth by discussing those features of the regional growth model that may provide Veneto with the capacity to continue to maintain its potential for future growth, which is critical for its recovery from deep economic crisis.

A typical economic growth model such as that of Krugman (1995) would describe past growth patterns as the result of both industrial concentration and adaptive labour markets, and would advocate the exploitation of scale economies and the reduction of transport costs. However, the application of this model to the Veneto economy needs to be substituted. Instead, attention should be paid to those factors explaining long-term growth. The first factor is the endowment of human capital and its utilization in those sectors where growth could be maintained through time, spreading its positive effects to the overall economy. Given a certain amount of human capital and its distribution across the region – in our case the Veneto region – local and sectoral endowments are crucial for the production of new knowledge (Rodiguez-Pose and Crescenzi, 2006), which provides the foundation for differences in the capacity to grow.

For our purpose, the distinctions between modes of the diffusion of innovation benefits throughout the economy in terms of sustaining economic growth are particularly interesting and useful. Our hypothesis is that the persistence in growth-rate differences at the sub regional level is related not only to the way in which human capital endowments are present in the different sectors but more specifically are related to the way in which such capital is concentrated and applied in those sectors, which historically have proved to be the driver for economic growth and which constitute the 'core' of the Veneto Economy. These sectors happen to be those characterized by medium to medium-low levels of technological intensity (OECD, 2004), that is, not necessarily high tech or information sectors. As a matter of fact, these sectors, although investing less as a percentage of revenues than high-technology firms, do nevertheless generate new products, particularly, production processes that have considerable aggregate impact (Robertson and von Tunzelmann, 2009).

The article is structured as follows: in Section 2, we briefly summarize some economic aspects of the territory of study; in Section 3, we describe the dataset used for the empirical analysis; in Sections 4 and 5, we discuss the results of the empirical analysis; in Section 4, we examine the outcomes of an OLS model; in Section 5, we analyze the results of different spatial specifications.

2. The Veneto Region in the European and Italian Context: Human Capital Endowment and Technology Intensity

Veneto is one of the richest areas in Europe. In 2007, its GDP in 2007 exceeded 147 billion Euros, making a contribution of 1.2% to the EU-27 GDP. [1] In terms of GDP per capita, Veneto ranks in the top quartile among the richest regions in Europe. It ranks sixth among the Italian regions,[2] and with a GDP per capita equal to 123% of average EU-27, it holds the sixty-third position in the ranking of European regions[3]. Despite its annual GDP per capita in current prices increased from 25,900 Euro in 2001 to 30,600 Euro in 2007, Veneto lost ranking with respect to the beginning of the new millennium. If we consider the 2007 GDP per capita adjusted for purchasing power, the region of Veneto ranks forty-ninth in Europe; it was twenty-fifth in 2001 and forty-fourth in 2005 (out of 270 regions).

In Veneto, as in the most advanced economies, the share of value-added produced by industry (35% in 2007) is declining (Regione Veneto, 2010); the region is, in fact, relocating part of the activities to the service sector. Between 2000 and 2007, the share of wealth produced by this sector rose to the level of 62.6%[4].

Within the manufacturing sector, a significant proportion of the added value (30.3%) is created by machinery and mechanical; electrical and optical appliances; and means of

[1] Eurostat, Regional Statistics, http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/themes.

[2] There are 20 regions in Italy. The region with the highest level of GDP per capita is Lombardy, which reached 136.1% of the EU average and finished 37th at the European level.

[3] We refer to the NUTS 2 division.

[4] The Italian average is 70.5%.

transport. Significant contributions are also made by metals and manufacturing of metal products (18% of VA); wood, rubber and other manufacturing products (15%); and textiles and clothing (9.3%). Regarding the services sector, the most substantial contribution to added value is made by the various services to enterprises and households (31%); trade and reparations (20%); and transport, storage, and communications (11.6%) (Bank of Italy, 2009).

Although Veneto is following a sector relocation path from industry to services, a switch that highlights its dynamicity alongside the most advanced economies, at the same time it shows some aspects of weakness in long-term growth, particularly in strategic sectors such as high-tech industries and those engaged in R&D. In the period 2002-2006, R&D spending was lower than the Italian average, which is modest compared to European standards, both as a percentage of GDP and in terms of the number of people employed in research (Regione Veneto, 2010). Veneto is the seventh Italian region in absolute terms of spending in R&D – with over 776 million Euros in 2005. In terms of R&D expenditure to GDP ratio, the region falls to fifteenth place among all Italian regions. Considering that the region of Braunschweig in Germany spends 5.76% of GDP in R&D and Lombardy in Italy spends 1.8%, the 0.57% of Veneto shows the region's weakness. This weakness is confirmed by data on the employment in R&D sectors. In 2005, with only 2.2 employees per thousand inhabitants, against a national average of 3, Veneto ranks only eleventh among the Italian regions. To illustrate the gap that separates Veneto from others at the top of the list, we cite the datum of Lazio, the first region in Italy, which has more than 5.8 persons per thousand inhabitants employed in R&D positions.

Another indicator of the ability to create knowledge and innovation is the number of patents in a given time period.[5] Between 2001 and 2007, Veneto registered a discrete increase

[5] The region is divided into seven provinces: Belluno, Padua, Rovigo, Treviso, Venice, Verona, Vicenza. In terms of the number of patents, there are strong differences between the provinces of Veneto. The more virtuous province is Padua (1.900 in 2007, 29% of regional total). Three other provinces, Vicenza, Verona and Treviso, contribute with similar shares between them (around 18%) while in the province of Venice were registered about

of the number of patents per capita, from 1.144 patents per one million inhabitants in 2001 to 1.353 in 2007,[6] ranking fifth among the most successful Italian regions[7].

The ability of a territory to position itself strategically can be measured by its productive composition in terms of technological content. In terms of active high technology manufacturing firms (Regione Veneto, 2009)[8], in 2007, Veneto, at 9.4%, was the second region in Italy after Lombardy at 22%. Although the data would indicate Veneto as a centre of excellence for high technology, in fact, in 2007 more than half of the manufacturing industry in Veneto was low tech. Only 5.6% of companies were located in the high-tech sector[9] (Regione Veneto, 2009). On the other hand, an analysis of data referring to the period 2000-2008 could indicate that the number of firms in both low-tech and high-tech sectors is gradually decreasing. These companies might find it more profitable to locate in other areas of the world for different reasons such as cutting costs, or taking advantage of a higher number of skills in the most technologically developed sectors. It is therefore clear that the Veneto manufacturing industry is developed on mid-market products, which are characterized by high specialization and very high technical skills rather than technological ones (Regione Veneto, 2010).

Similarly, the Veneto region highlights the predominance of the traditional sectors, even in the aggregate of services. The tertiary sector, reclassified according to the varying degrees of knowledge, consists of mostly traditional services (61.5% of the entire sector in 2008). However, in recent years, services have shown a greater dynamism compared with the

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13% of patents. The remaining two provinces, Belluno and Rovigo, have insignificant shares. The differences persist also considering the number of European patents submitted to the European Patent Office – EPO. In this case, the leading province is Vicenza that in 2006 submitted 35% of patents in Veneto. Follow Padua and Treviso (21% and 22%). More detached Venice (14%) and very low values for Belluno and Rovigo (2% each) (Chamber of Commerce of Padua, 2008).

[6] Regione Veneto, Regional Statistics System Management, on-line data. Download at: http://statistica.regione.veneto.it/dati_settoriali_economia.jsp.

[7] Once more, the first Italian region is Lombardy with 2,066 patents per million inhabitants while the Italian average is 1,164.

[8] There follow Piemonte (8.8%), Lazio (8.7%) and Emilia-Romagna (8.4%).

[9] 52.8% in Low Tech, 26.9% in Medium-low Tech, and 14.7 in Medium-high Tech sectors.

industrial sector. From 2000 to 2008, firms that dealt with market services, namely business consulting firms, transportation, and real estate grew by 65.8%, constituting 22.5% of the whole sector, while those engaged in technology services, that is telecommunications firms, IT, and R&D reached 3.5% (Regione Veneto, 2010).

The theoretical literature and empirical evidence point to the strong link between the ability to innovate, the productivity of labour, the dissemination of new technological knowledge, of products and processes, and the human capital of a territory. We therefore look at the educational level of the population of Veneto in 2001[10] (which is the year of the last census and the reference year for the econometric analysis), in order to determine whether there is a link between the reduced propensity to innovate and the availability of human capital. The percentage of Veneto inhabitants who have a tertiary education qualification[11] (only 6.5%) is lower than the Italian average by one percentage point. In the Veneto population, one in four holds a secondary school diploma (in line with the national average). The rest of the population, approximately 59%, has a lower secondary school diploma (*scuola media inferiore*), professional training (*avviamento professionale*), or an elementary school diploma (*licenza elementare*). About 9% of the population ages 6 years and over does not hold a diploma (analphabetic or without study title) (ISTAT, 2001).

A comparison of regional data helps us to better understand the situation in Veneto, which has one of the lowest percentages of graduates in relation to the population aged 6 and over out of twenty Italian regions, placing it in the lowest quartile. The regions with the highest number of graduates are Lazio (10.6%), Liguria (8.6%), Umbria and Emilia Romagna (8.1%) and Lombardy (7.8%). The placement improves noticeably for the percentage of the population holding a high school diploma. This finding raises Veneto to the middle position on the list of regions. The combined data show that of the percentage of the population that

[10] Resident Population aged 6 or older.
[11] University degree or non-university tertiary diploma.

holds a secondary school diploma or a university degree (approximately 32.4%), among the Centre-North regions of Italy only Piedmont and Valle d'Aosta are positioned lower than Veneto. Moreover, some Southern regions, such as Abruzzo (35%) and Basilicata (32.6%), surpass Veneto.

If the data of 2001 depict a region with a low human capital stock, the latest data show a region that does not keep pace with the rest of the country. Indeed, if we look at the ratios of students enrolled in the university in the age group 19-26 years in two moments in time, that is, the academic years 2001/2002 and 2007/2008, we can make two observations. Firstly, the percentage of enrolled students increases over time both in Veneto (from 26.6% to 29.4%) and in Italy in general (from 30% to 34.6); secondly, the increase is smaller in Veneto than in the rest of Italy. Therefore, the gap that separates the Veneto region from the rest of the country widens during this period. Further confirmation comes from data on new graduates in the year 2007. The Italian average reaches the level of 5.0 new graduates per thousand inhabitants, while Veneto averages 4.5 new graduates per thousand inhabitants. On the other hand, many Southern regions rank among the highest. The better performance of the regions of Southern Italy, however, must be interpreted in light of the local labour market. In the South, the choice between work and higher education is very often conditioned by the lack of job opportunities.

3. The Dataset and a First Descriptive Analysis

The study required the construction of an original dataset, both for the territorial level of reference and the variables that were created. In fact, by merging data from different sources and using a matched employee-employer database that contained detailed information on working spells in the Veneto region, we were able to recover information on human capital and technology contents of the Local Labour Systems (LLSs) of Veneto.

Regarding the definition of the territorial unit of analysis, it is necessary to remember that the Veneto region is characterized by strong territorial and productive differences. However, it has a highly developed and articulated infrastructural network and a workforce that presents a high degree of inter-communal mobility. The mobility of the workforce makes the definition of the territorial unit of reference very important. In fact, very often the sub-regional administrative divisions (municipalities and provinces) do not coincide with the territorial areas where the supply and the demand of labour are satisfied. Therefore, in order to have a better knowledge of the effective labour supply and of the workforce's human capital, it is essential to take into consideration the territorial unit that best satisfies this necessity. For this reason, our analysis has been carried out at the level of LLSs, which are aggregations of municipalities that identify homogeneous labour markets. The LLSs were built on routes of commuting between home and work identified during the population census of 2001. As a result, our dataset consists of 34 LLSs.

Some of the variables we used in the study were obtained or constructed using the information provided by ISTAT. We refer in particular to data on value added expressed in industrial prices[12] (2001-2005), the resident population, and the number of employees in the industry and service sectors. Using ISTAT data we were able to calculate the per capita value added produced by industry and service sectors separately, as well as the growth rates of value added per capita and what we call the Production Concentration Index, which will be explained in Section 4. Unfortunately, although the information available from ISTAT allowed a sector disaggregation of the workforce, it did not allow qualitative analysis of the workforce (at the local level), that is, in terms of human capital and professional content. Therefore, in order to overcome this lack of information and to carry out the study of the relationship between growth, human capital availability, and technological intensity, we

[12] To adjust for changes in the price level we use an industrial price index.

merged ISTAT data with information retrieved from the database *Giove*,[13] which was provided by the Labour Agency of the Veneto Region, *Veneto Lavoro*.[14]

This original database contains matched employee-employer data, including all employment spells in the Veneto region in the period 1995-2007. The distinctive feature of *Giove* is its uniqueness in the Italian scene. Indeed, this database contains information on educational attainment and professional levels that allow definition of the workforce's human capital content. Moreover, considering that all the registered firms are classified according to their production sector at a very high level of disaggregation (5 digits), *Giove* allows classification of firms according to their technological intensity. To the best of our knowledge, this paper is the first to make use of this database in order to build human capital and technology intensity indicators at such a disaggregated level.

Giove consists of three main archives that include original information on employment relationships, workers and companies, and several tables of support and decoding. The employment relationships archive includes information, on the type of contract – permanent, fixed-term, apprenticeship, part time or full time – the start and the expected end of the employment spell, and the employees' qualifications. The information on workers includes their tax code[15], place and date of birth, sex, citizenship, place of residence, and educational level[16]. The information on the firm includes its tax number/code[17], the municipality where its

[13] The Database *Giove* is the result of a corrective and integrative work on micro-data extracted from the databases managed by the Regional Employment Centres –REC (in Italian *Centri per l'Impiego - CPI*) in the Veneto region. The first version of *Giove* was released in 2004. The version used in the present paper contains information updated to the end of December 2007. Giove stands for Jupiter. For a lengthy discussion on *Giove* and its precursors please refer to Maurizio, 2006)

[14] Veneto Lavoro, established in 1998, is a technical agency of *Regione Veneto*, with organizational, accounting, administrative and financial autonomy.

[15] In Italian *Codice Fiscale.*

[16] Data on attainment level of circa 20% of the workers are missing. To remedy this lack of information we performed standard imputation techniques on missing data. However, estimations presented in Section 4 were performed on the complete case data.

[17] It is the Value-Added Tax number called "Partita IVA" which is the acronym of"Imposta sul Valore Aggiunto" in Italian.

units are located, and the sector classification adopted by the Italian Institute of Statistics, ATECO.[18]

To have an idea of the size of *Giove*, one must remember that the December 2007 release registers more than 8 million working relationships between nearly 2.7 million workers and approximately 570 thousand local units of Veneto companies or companies that have employee workers that reside in the Veneto region.

Although *Giove* is very rich in information, it must be used with caution because its database has some limitations. Indeed, the registered employment spells are those derived from the obligatory recruitment communications that firms are supposed to deliver to the Regional Employment Centres. Therefore, *Giove* does not include information on those spells for which communication to the Regional Employment Centres is not compulsory, such as in the case of public servants and the self-employed. In addition, employees hired prior to the computerization of obligatory communications – which became systematic in the second half of the 1990s – and still working in the same company on the date of observation are not included in the dataset[19]. The first limitation of *Giove* was not a problem in our study since our analysis was conducted on the private sector alone. Regarding the second limitation, we performed some controls by comparing the consistency of *Giove* with official ISTAT data and the results indicated that the weakness is insignificant to this study.

With regard to the measure of human capital that we created, the starting point is taken from the information on the highest education level attained by each worker. The education levels we consider are the following: no education[20], elementary school, professional training, upper-secondary diploma, and university degree (Bachelor, Master, Doctoral Programme). Given this classification, which is supported by the structure of the Italian schooling system

[18] ATECO is the Italian classification of the economic activities. Its class level corresponds to the NACE classification (at 4 digits level) while its division level corresponds to the ISIC classification (at 2 digits level).

[19] There are absences also among the firms. It is the case of firms without employees or firms that have not changed their structure since the beginning of the computerization era.

[20] Probably it would be more appropriate to say no diploma.

and the actual use of different qualifications in the labour market, we have obtained for each LLS the percentages of workers with a given level of education. Next, we constructed a measure of human capital for every LLS, given the number of workers with a diploma of secondary school or university. Subsequently, the measures were refined by intersecting the information on the human capital with the sector where it is used.[21]

Using the strengths of the *Giove* database, we created a second measure of the potential human capital embedded in the experience gained in the workplace, based on information relating to the professional qualification of the workers. To do this we reclassified the categories contained in *Giove* according to the ILO classification, which divides the occupations into nine main categories[22]. However, we have not used that classification at this stage of the empirical analysis although we intend to use it to complete the study.

One of the limitations in using the number of workers to measure employment is the fact that many employment relationships last less than a year. As a result, if such short contractual arrangements are more frequent among workers with higher levels of education, then our measure of human capital would overestimate this productive factor. To overcome this limitation, a different measure of human capital was adopted by recalculating all the variables described above in worker-months[23] weighting each contract for its actual length in months.

We consider now more concrete aspects of the study. However, before discussing the empirical model, we propose a brief descriptive analysis of the region's growth in relation to factors of human capital and technological innovation based on the data we have constructed and discussed in the previous section. This exercise, conducted at the LLS level, allows us to

[21] Firstly considering the two macro-sectors of Industry and Services sectors and subsequently disaggregating into subsectors according to varying degrees of technology.

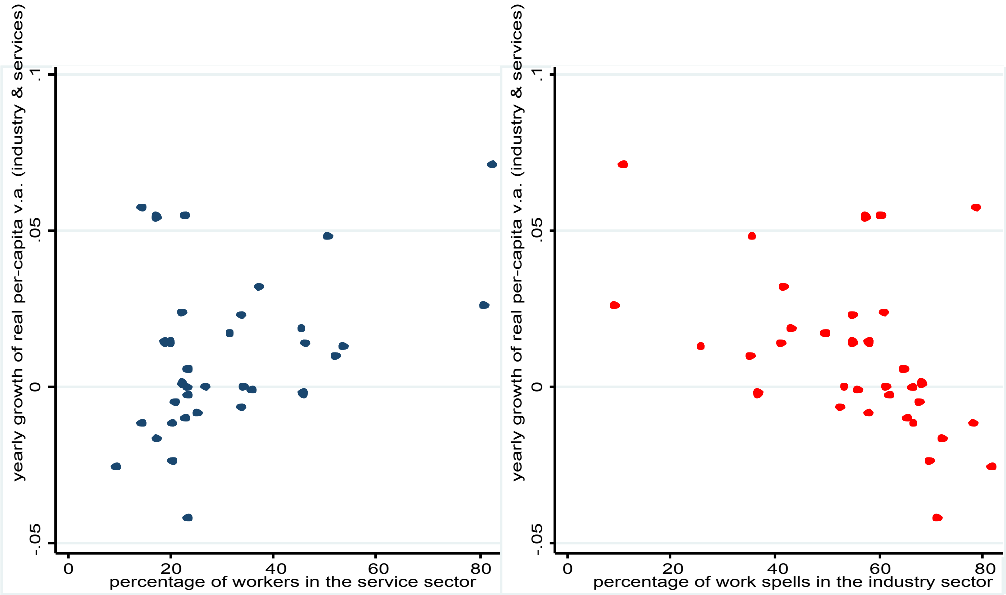
[22] The nine categories are: legislators, senior officials and managers; professionals; technicians and associate professionals; clerks; service workers and shop and market sales workers; skilled agricultural and fishery workers; craft and related trades workers; plant and machine operators and assemblers; elementary occupations.

[23] The rule that we adopted in contract duration calculation in year 2001 consisted in assigning a full month if the employment spell lasted at least 15 days and zero otherwise.

highlight the variety and diversity entrenched in Veneto's territorial composition and its endowment of human capital and innovation.

Evidence of this heterogeneity is presented in Table A1 in the Appendix. Consider, for example, the percentage of workers with a an upper-secondary school or university diploma in 2007 among the LLSs. There is a wide gap between the minimum of *San Giovanni Ilarione* (20.6%) and the maximum of *Padua* (nearly 42%). Consider now the percentage of workers in each of the four divisions of economic activity according to the technological intensity in 2007. While the figures are uniformly low as far as the high technology sector is concerned (the highest level is reached in *Belluno*, at 2.1%), the differences are striking if we consider the other three sectors: we begin from minimum levels very near to zero and arrive at figures near 34% in medium-high tech (*Agordo*), 32% in medium-low tech (*Pieve Di Soligo*) and 36% in low tech (*San Giovanni Ilarione*).

The relationship between growth and sector distribution (in terms of macro-sectors and subsectors) of the workers will be the topic of the following paragraph. We begin the analysis considering the industry and service sectors. Figure 1 represents the relationship between the growth in the Veneto LLSs in the period 2001-2005 and the percentage of workers employed in the industry and service sectors. It clearly depicts a strong and positive correlation between the growth of Veneto and the relative importance of the service sector in terms of employment. In contrast, it shows a strong and negative relationship between the weight of the industrial sector and growth.



Note: Whole Industry and Services

Figure 1. Growth rate of per capita value added (2001-2005) and percentage of workers employed in Industry (left-hand side) and Services

Figure 2 shows the industrial sector as unbundled or disaggregated according to the OECD classification on technological intensity. The graphical analysis suggests that the high-tech industries have a positive impact on the growth of the area, even though several LLSs do not have industrial activities in their territory, and therefore, there are many null values. Instead, the relationship between economic growth and the relative territorial importance of the medium-high and low technology sectors is not clear. Finally, with regard to the correlation between growth and the medium-low technology intensity sectors, the data seem to follow a positive trend.

The figures below represent the relationship between growth and human capital employed in various sectors, including a technological content disaggregation. We want to verify that human capital plays a role in stimulating growth, conditional to the sector where it is employed. Human capital is measured in terms of the percentage of workers holding a high-school diploma or university degree, that is, post-compulsory education.

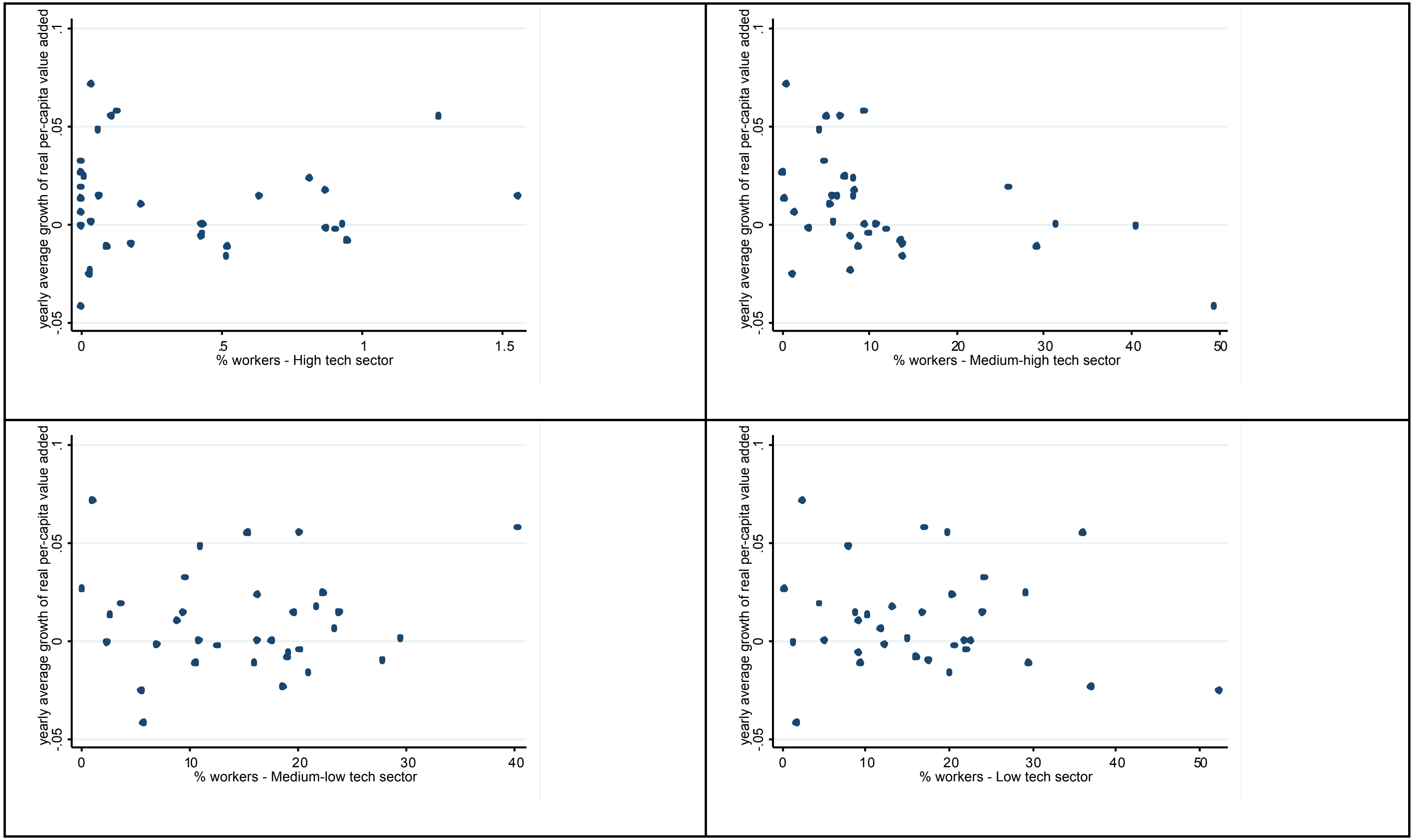


Figure 2. Growth rate of per capita value added (2001-2005) and percentage of workers in industrial sectors by technology intensity

Note: Whole Industry and Services

Figure 3 partly confirms what we described in Figure 1, albeit in terms of use of the labour force with high levels of human capital. The service sector is clearly positively influenced by the large number of workers with high human capital employed therein.

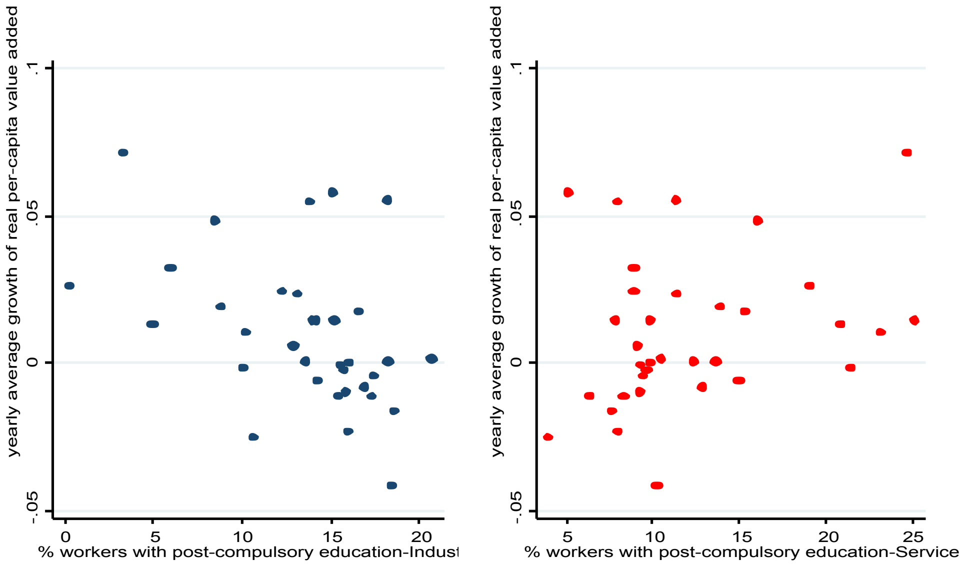


Figure 3. Growth rate of per capita value added (2001-2005) and human capital in Industry (left-hand side) and Services

Finally, Figures 4 and 5 show the relationship between growth and human capital intensity in the industrial sectors with high/medium-high/medium-low and low technology intensity. The growth data represented in this case are net of the convergence component. This exercise aims to highlight the relationship, net of the convergence factor, which might explain much of the pattern of growth. Figure 4 shows a certain positive relation between growth and human capital employed in high-technology intensive sectors (top left) and in medium-low technology (lower left). The relationship seems to have a negative trend in the medium-high technology sectors but is non-existent for the low-tech ones. In the next Section, we will see that these intuitions are confirmed by regression analysis in which we verify these relations simultaneously and including other variables.

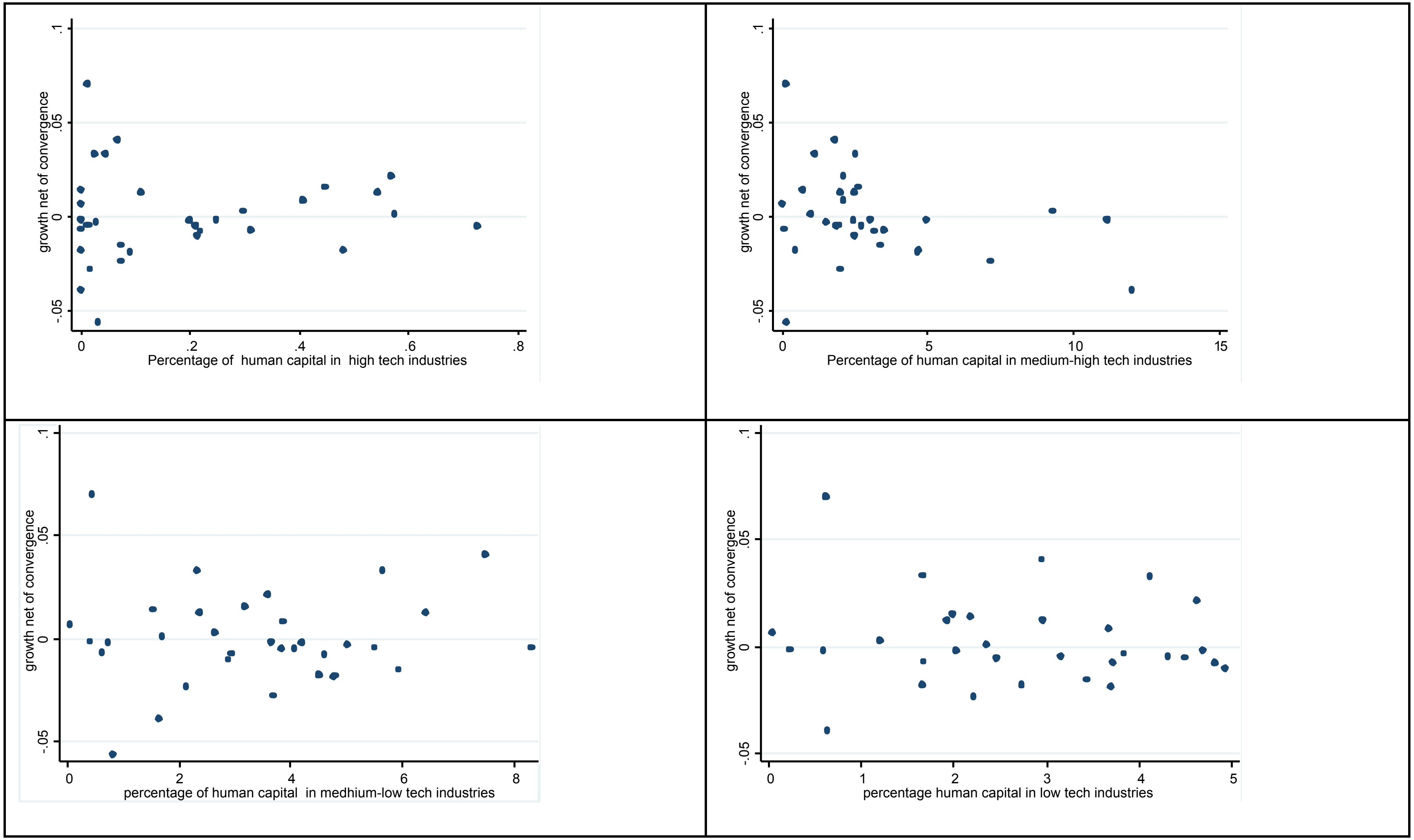


Figure 4. Growth and human capital in sectors by different technology intensity

4. Theoretical model and empirical specification

The theoretical model on which we base our empirical analysis is the model of endogenous growth driven by sectors engaged in innovation and, to this end, using human capital. The main model of reference goes back to Romer (1990), which describes an economy with several sectors, one of which carries out innovation activities whose output in terms of new ideas is sold to the intermediate goods production sector. The innovative contribution of the Romer model, with respect to the relationship between human capital and growth, consists primarily in the formalization of the dependence of innovation on the amount of human capital employed in this sector – the only factor of production – and thus on the availability of human capital in the economy, and secondly, in the specification of the correlation between human capital employed in R&D and growth of per capita income. Therefore, growth is highly dependent on the size of the R&D sector and, consequently, on the amount of human capital employed in it.

Our purpose is to verify the validity of this model at a sub-regional level by going through the breakdown of sectors according to their intensity of research and development, in a productive context, the Veneto region, which appears to be characterized by not particularly high rates of schooling and limited diffusion of high-tech sectors. The literature on empirical testing of the hypotheses of the Romer model, developed also at a regional level, does not deal with human capital employment across sectors. Due to limited availability of data and lack of information on the content of human capital of the workforce among the sectors of economy, the Romer hypothesis has been only partially verified. These models include, among the explanatory variables, the dimension of human capital and the activity of R&D – usually measured by the number of patents – carried out in the territory of reference. Therefore, these models fail to test the hypothesis that human capital is crucial for growth when used in sectors that are engaged in R&D.

The model we propose attempts to fill this gap. By using matched employer-employee data on employment spells occurring in Veneto starting from the year 2000, we are able to determine, for each territory of analysis, the number of workers with a certain level of education working in a certain sector. This allows us to work at a higher disaggregation level with respect to that proposed by the literature. Moreover, it makes feasible a deeper investigation of the relationship between human capital, intensity of research and development activity, and development of different sectors. As described in the previous section, we can calculate not only the share of workers employed in different sectors (we have a 5-digit breakdown) and percentages by level of education but also the measure of worker-months – that is, the number of workers weighted by the proportion of the year in which they have actually worked.

The classification we take into account is the one developed by the OECD (2004), which classifies industry in sectors characterized by high, medium-high, and medium-low and low technology[24]. This classification is based primarily on the intensity of R&D, that is, the expenditure on R&D[25], and therefore, it indicates the diverse propensity to spend on R&D; this allows a growth analysis by means of a theoretical model with several sectors that differ in the intensity of R&D they perform. Moreover, the OECD classification incorporates an index of the technological content in terms of the usage of the technology. That index weighs the intensity of technology embodied in intermediate goods and capital goods purchased by the sector itself.

[24] High-technology industries: Aeronautics and Aerospace, Pharmaceuticals, Office machinery and computers, radios and television and communications, medical, surgical and orthopaedic instruments and machines of precision and control, optical instruments and photographic equipment . Areas to medium-high technology: machinery and apparatus n. e. c (not elsewhere classified), motor vehicles, trailers and other transport equipment n. e. c, chemicals and synthetic fibbers (not pharmaceuticals), machinery and equipment n. e. c. Areas to medium-low technology: shipbuilding, rubber and plastics, coke, refineries, nuclear fuel processing, products non-metallic mineral processing, metal products and processing and other alloys. Low-tech sector: manufacturing n.e.c., recycling and recovery, wood pulp, paper, publishing and printing, food, beverages and tobacco manufacture of textiles, leather products, leather and footwear.

[25] The data used by the OECD are built considering the expenditure on R & D for the period 1973-1995, disaggregated by industrial sectors for 15 OECD countries (*Analytical Business Enterprise Research and Development* –ANBERD data).

Therefore, the final rating in sectors of high, medium-high, medium-low and low technology derives from direct indices (based on the intensity of spending on R&D) and indirect indices (use of technology) that are both in the same category; industrial sectors that are placed in a higher level have higher technological indices, both direct and indirect, with respect to the categories below.[26]

The OECD classification may well represent, in our opinion, the differing propensities to perform R&D. In fact, as can be seen from a survey on patents held in Italy (Trigilia and Ramella, 2008), innovative activity is particularly common in sectors that incorporate a medium-high technology. More than a half of patent applications registered at the European Patent Office in 2008 (50.4%) fall in this OECD category. The remaining half is shared by high-tech industries (23.87%), medium-low-tech (18.13%), and low-tech firms (7.57%).[27] As for the sectors in which technology applied to production is generally at lower levels (the *Made in Italy* sectors), patenting activity is distributed mainly among furniture, musical and sporting equipment, jewellery, tools in the textile industry, footwear, and leather tanning.

Without doubting the validity of the OECD classification and the importance of sectors with greater technological intensity, it is important to note that the industrial activity of medium-low technology industries, which is particularly relevant in the context of Veneto, supplies more than ninety percent of the EU output. In addition, many firms in this sector survive and grow through technological upgrading, skills in design, and intensive use of knowledge for innovation. These

[26] This is not surprising, given that the companies that channel greater percentage of value added to the R&D are also the most intensive users of advanced intermediate goods and machinery.

[27] Among high-technology industries, those with the highest concentration of patents are pharmaceuticals, medical apparatus and orthopaedic surgery, radio, television and communications and, finally, manufacture of machinery and precision instruments and control. In the category of medium to high technology companies stand out for their patenting firms in the sector of machinery and mechanical appliances (with 31.1% of total patents), followed, with much lower performance, but not less negligible, the chemical and automotive industries (both around 7% of national patents). These percentages are also registered among the best sectors in terms of patenting, companies to medium-low technology: the fields of rubber and plastic processing and metal and other alloys.

sectors often have unique forms of industrial organization and knowledge creation, complex linkages with the infrastructure of scientific and technological knowledge, and important regional dimensions (Kreinsen-Hirsch, et al., 2003). For this reason, such macro group production contributes substantially to aggregate growth. The medium-low technological intensity sectors, in the same way as high-tech industries, generate new products and, in particular, production processes that have a significant impact. Moreover, high and medium-low technology sectors are not independent from each other. Growth of high technology sectors derives, at least in part, from growth in other production contexts that are less R&D intensive (Hauknes and Knell, 2009).

In light of these considerations, the analysis of growth and its relationship to technology intensity in Veneto appears particularly interesting. As we shall see, the results of our study seem to emphasize the peculiarities of the Veneto system in terms of the important role played by medium-low technology sectors and the role played by human capital employed in them.

Before discussing the specifications of the empirical model, we would like to clarify what we mean by 'human capital'. Our concept of human capital refers uniquely to the education endowment of workers and not to the incremental component of the same stock that is normally generated during the working life of the individual or by means of continuous vocational training.[28] Furthermore, we refer to workers with a medium-high education, that is, an upper-secondary school diploma or a university degree –such as a university graduate or postgraduate diplomas –, which corresponds to levels 3 to 7 of the International Standard Classification of Education (ISCED).[29] Actually, in the first empirical model we controlled also for lower levels of education, corresponding to vocational training[30]. As expected, these levels proved not significant

[28] Data do not allow identifying other components of human capital.
[29] In international terms, this corresponds to ISCED 3-7 educational levels.
[30] In Italy, at the end of compulsory schooling (when they are between 13 and 14 years old), individuals can choose between different educational paths: professional, technical or scientific-humanistic. Whatever the case may

and we subsequently excluded them from the analysis. Therefore, the analysis focuses mainly on human capital constituted by workers who completed at least the upper-secondary school cycle.

The territorial unit of reference is the Local Labour System (LLS), which is an area not defined by administrative criteria. Rather it is defined by individuated grouping of the areas where the labour demand and supply match[31]. The LLSs, in fact, as defined on the basis of individual mobility of the labour force by place of residence to workplace, delineate areas where local labour demand meets supply. Such areas are substantially different from administrative municipalities and permit assessment of the actual availability of labour and human capital.

The empirical analysis was conducted using both the simple regression method, which we discuss in this section, and spatial regressions, which will be discussed in the following section. In both cases, the model specifications are several: from the simplest, where the territorial dimension of human capital is kept distinguished from the sector dimension, to more complex ones, where the human capital content of employment is defined for every single sector.

In all the specifications, the dependent variable is defined as the growth rate of per capita value added for the period 2001-2005. The focus of the analysis is on industry and services (I&S); the agriculture and public sectors were excluded. In accordance with the traditional scheme used in empirical growth analysis, we included among the explanatory variables of every specification the logarithm of value added in 2001. Since production and growth capacity of a local context depend also on externalities – positive and negative – linked to the concentration of activities, we include an index, referred to as the "I&S concentration index" from here onwards,

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be, if they complete the whole cycle of studies, they are allowed to enter university. On the other hand, if the professional path is chosen, individuals have the chance to attend the first three years only and obtain a "vocational diploma" that does not allow to take the path of higher education.

[31] The LLS are groups of municipalities identified from the information on commuting (movement of individuals between municipalities for working) in the questionnaire of the census.

calculated as the ratio between the number of employees in the I&S sectors and resident population, by each LLS[32].

The results that we are about to discuss are shown in Table 1 below. The table also includes the estimates of the simplest models, from which we began our empirical analysis and helped in defining the more detailed specifications. Only Models 4 and 5 have been estimated also using variables defined on employment corrected for actual months of work (Models 4'and 5') and for spatial correlation (the discussion of which will be addressed in the next section[33]). The models do not show correlation problems between the explanatory variables; therefore, the significance level is reliable[34].

The starting model (Model 1) is a simple specification to check how growth is affected by human capital availability and proportion of employment in the service sector. The result of all variables was significant, and the model explains 47% of growth rate variability. Veneto LLSs follow a path of convergence, the concentration of production creates positive growth externalities, and a greater specialization in services boosts growth. Finally, and most importantly, the use of human capital determines significantly the growth capacity of the area. In Models 2 and 3, we added interactions between macro-sector intensity (Industry kept distinct from Services) and variables of human capital use. In Model 3, we also added a variable measuring the proportion of workers with vocational training education in order to determine whether this kind of education can be strategic for growth.

[32] The data used to calculate the index are from ISTAT, Census of Population and Industry 2001.

[33] Respecting the numbers assigned to the models estimated using the heads of workers and worker-months (numbers with apostrophe), spatial models were numbered following the same principle, adding subscripts to distinguish models with spatial errors (subscript e) from models with spatial correction on the dependent variable (subscript a).

[34] The models, whose results are discussed here, are the ones that have a correlation between the regressors lower than 0.5 (in absolute value). Upon request, we can provide the correlation matrices.

Estimation results show a greater explanatory power of these models than the basic one. On the one hand, they confirm the presence of a convergence path of per capita value added and the presence of positive externalities of production increasing local capacity to grow. On the other hand, growth does not seem to be influenced in any way (neither positively nor negatively) by the use of the workers endowed with vocational education, regardless of the macro-sector of employment. Instead, human capital shows its ability to stimulate growth when used in services rather than in industry. The last result suggested proceeding towards a further sector breakdown, following the theoretical idea (discussed above) that human capital employed in sectors at least partially innovative may be a key driver of growth.

Following the OECD sector classification mentioned above, we enriched the model specification by including the percentage of workers in high, medium-high, medium-low and low technological intensity (Model 4) and successively by specifying the intensity of human capital employed in each of these sectors and in services (Model 5). The results clearly show how, in the Veneto region, the sector that significantly explains the growth path is the medium-low technological intensity one. On the other hand, the productive "specialization" which has potentially the greatest impact on LLSs growth is the one in high-technology sectors, with an estimated coefficient (in Model 4) equal to 0.54, against 0.06 in the medium-low technology industries. However, although the high technology-intensive sector is significant as a whole, the human capital employed in it does not explain growth significantly (Model 5), unlike what happens with the intensity of human capital employed in the firms in medium-low sector. This result seems to be indicative of an insufficient use of highly educated workers in this sector. Moreover, observing the results of Models 4' and 5', in which variables are built considering worker-months rather than simply the number of workers, this sector seems to lose in terms of the ability to explain growth. This result indicates that high technology industries are strongly

Table 1. Growth, human capital and sector intensity. OLS regressions

	Estimates with heads of workers					Estimates with man-months	
Dependent variable: growth rate of per capita Value Added in Industry and Services (I&S) - 2001-2005	Model 1	Model 2	Model 3	Model 4	Model 5	Model 4'	Model 5'
Log per capita Value Added. Industry and Services 2001	-.442 (-5.40)	-.442 (-5.39)	-.436 (-4.38)	-.315 (-5.13)	-.369 (-3.53)	-.352 (-5.77)	-.445 (-5.60)
I&S concentration index	.004 (3.71)	.004 (5.02)	.005 (3.23)	.003 (3.93)	.005 (5.83)	.004 (4.14)	.005 (6.66)
%workers in Services	.003 (3.08)			.004 (2.12)		.004 (1.91)	
% workers with at least upper-secondary education	.006 (2.25)						
Sectors' technology intensity							
%of workers in *high tech* sectors				.054 (1.73)		.046 (1.52)	
%of workers in *medium-high tech* sectors				.000 (0.16)		.001 (0.36)	
%of workers in *medium-low tech* sectors				.006 (2.74)		.006 (2.56)	
%of workers in *low tech* sectors				-.000 (-0.16)		-.001 (-0.35)	
Interaction between workers' educational level and macro-sectors of work							
% workers in Industry with a professional diploma			-.012 (-0.76)				
% workers in Services with a professional diploma			-.004 (-0.18)				
% workers in Industry with at least upper-secondary education		.006 (1.30)	.008 (1.28)				
% workers in Services with at least upper-secondary education		.012 (3.09)	.012 (2.25)		.008 (1.83)		.010 (2.39)
Interaction between workers' human capital and sectors' technology intensity							
%of workers in *high tech* sectors with at least upper-secondary education					.089 (1.33)		.077 (1.49)
%of workers in *medium-high tech* sectors with at least upper-secondary education					.002 (0.15)		.002 (0.29)
%of workers in *medium-low tech* sectors with at least upper-secondary education					.027 (1.91)		.024 (2.35)
%of workers in *low tech* sectors with at least upper-secondary education					-.005 (-0.47)		-.010 (-1.16)
Observations	34	34	34	34	34	34	34
R^2	0.47	0.56	0.54	0.69	0.69	0.67	0.69

Note: t-statistics in parenthesis. All models include constants. Robust estimates.

characterized by the use of temporary labour. This can have dual effects on productivity: firstly, temporary employment can cause the employee to commit less to achieve good results; and secondly, firms using mainly temporary employment may have no incentive to invest in specific training, which negatively affects system productivity.

5. Spatial models

The context in this study consists of an urbanized area spread along the flat part of the region where, despite the presence of large urban centres, we observed the phenomenon of urban sprawl, that is, an area with highly interconnected relationships and high mobility. In light of these facts, we were motivated to develop further an empirical analysis by means of regression models that account for a possible spatial correlation between the observations, albeit the territorial unit we use (the LLS) already embodies part of that spatial dependence. Indeed, spatial dependence is mostly a phenomenon that occurs when using data defined according to administrative criteria. It arises, essentially, for two reasons: firstly, if the administrative boundaries do not accurately reflect the nature of the underlying process that generates the data, the data collected may reflect measurement errors; secondly, in view of the fact that workers are mobile and can cross county or state lines to find employment, labour force or unemployment rates measured on the basis of where people live could exhibit spatial dependence (LeSage and Kelley Pace, 2004). In the present case, the territorial unit of reference we used was constructed taking into account the mobility of workers (as explained in the previous section) and data were mostly obtained from the aggregation of elementary information, according to the definition of these functional areas. Therefore, we should be free of both problems. On the other hand, if spatial dependence arises due to error correlation because of correlated omitted variables, our OLS estimates would no longer be reliable.

In light of these considerations, we estimate two different spatial models later in this section. Both specifications require the ex-ante definition of the matrix of spatial relations that best captures spatial dependence (Anselin, 1988), whether it is observed in the dependent variable or in the error term. The preliminary empirical results we are going to discuss have been obtained on the basis of a spatial dependence matrix defined on the criterion of contiguity between LLSs. Each *i-th* row of the matrix records a set of contiguity relations associated with one of the 34 LLSs. For example, the matrix element in row 1, column 2 would record the presence (represented by a 1) or absence (denoted by 0) of a contiguity relationship between LLSs 1 and 2. There are alternative ways to define the presence of contiguity (LeSage and Kelley Pace, 2004); the criterion we adopted consists in defining each matrix element equal to 1 if LLSs share a common side or a common vertex with the LLS of interest.

The first model we tested is the classical mixed regressive-spatial autoregressive model, in which some part of the total variation in the dependent variable across the spatial sample would be explained by each observation's dependence on its neighbours, according to a parameter that will capture that dependence, measuring the average influence of neighbouring or contiguous observations on observations in the vector y. Explanatory variables included in the regression discussed in the previous section have been added to the model. Using the traditional matrix notation, the model can be summarized in the following equations:

$$\begin{aligned} y &= \rho W y + X\beta + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I_n\right) \end{aligned} \qquad (1)$$

where y contains the 34x1 vector of cross-LLS dependent variables – the growth rates of per capita values added between 2001 and 2005 – and X represents the 34xk matrix of explanatory variables. As to W, this is the 34x34 spatial weight matrix we defined above, with zeros on the main diagonal, zeros in positions associated with non-contiguous observational units and ones in positions reflecting neighbouring units that are (first-order) contiguous. Parameter ρ captures the average influence in the dependent variable of neighbouring or contiguous observations. The error terms are normally distributed with unitary variance and null correlation.

As for the explicative variables included in the model, we tested the specifications of Models 4 and 5 discussed in Section 4; as previously, models have been estimated using variables defined both on the number of workers and on the number of worker-months. Results are reported in Table 2 in columns Model 4a and Model 5a – for estimates with head of workers – and columns Model 4a' and Model 5a' – for estimates using worker-months.

As previously argued, a likely source of spatial dependence in our model could arise because of the exclusion of explicative variables spatially correlated, which may affect the independence of the error terms. For that reason, we proceeded to estimate a spatial model with autoregressive disturbances. Spatial error correlation is modelled as follows:

$$\begin{aligned} y &= X\beta + u \\ u &= \lambda W u + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I_n\right) \end{aligned} \tag{2}$$

where u is the vector of spatially autoregressive error terms and parameter λ is a coefficient on the spatially correlated errors analogous to the serial correlation in time series. As previously, we proceed in estimating Equations 2 by using both regressors defined on head of workers and on worker-months. Results are reported in Table 2 – in columns Model 4e and Model 5e – for estimates with explicative variables defined on head of workers – and in columns Model 4e' and Model 5e' – when applying variables defined on worker-months.

Our aim is to determine which model – either spatial autoregressive or spatial error or OLS – best fits the data; essentially, whether $\rho = 0$ and/or $\lambda = 0$ or both differ from zero. If this is the case, then OLS is not applicable, and the larger of the two statistics probably indicates the correct model (Anselin and Rey, 1991).

Our results show that any source of spatial correlation we model, whether in the dependent variable or in the error term, is particularly high when Models 4 are estimated, that means when the explicative variables include sector disaggregation of employment but exclude sector breakdown of the use of human capital. When we introduce this in greater detail (in Models 5), spatial dependence is less important; this happens both in the autoregressive model and in the specification with spatially correlated errors. This result may suggest that the more detailed models are able to capture most of the spatial correlation. The only spatial specification that preserves a certain degree of significance is that performed on variables defined in terms of heads of workers; on the contrary, models that use worker-month measures lose significance completely. Those results suggest that, in our regional context, spatial dependence does not appear to be caused by unobservable variables not included in the model.

Table 2. Growth, human capital and sector intensity. Spatial models (*a*: autoregressive; *e*: correlated errors)

	Estimates with heads of workers				Estimates with worker-months			
Dependent variable: growth rate of per capita Value Added in Industry and Services (I&S) - 2001-2005	Spatial Autoregressive models		Spatial Errors Models		Spatial Autoregressive Models		Spatial errors models	
	Model 4a	Model 5a	Model 4e	Model 5e	Model 4a´	Model 5a´	Model 4e´	Model 4e´
Log per capita Value Added Industry and Services 2001	-.347 (-6.86)	-.404 (-5.55)	-.371 (-6.04)	-.404 (-5.55)	-.376 (-7.20)	-.398 (-4.75)	-.393 (-6.07)	-.454 (-5.87)
I&S concentration index	.005 (4.55)	.005 (4.69)	.003 (3.39)	.005 (4.69)	.006 (4.73)	.006 (5.12)	.004 (3.69)	.005 (4.94)
% workers in Services	.001 (0.62)		.004 (2.50)		.001 (0.57)		.004 (2.37)	
Sectors' technology intensity								
% of workers in *high tech* sectors	.049 (2.22)		.054 (2.29)		.044 (1.90)		.045 (1.80)	
% of workers in *medium-high tech* sectors	-.003 (-1.47)		.001 (0.31)		-.002 (-1.22)		.001 (0.46)	
% of workers in *medium-low tech* sectors	.004 (1.76)		.006 (2.84)		.004 (1.71)		.005 (2.55)	
% of workers in *low tech* sectors	-.003 (-1.52)		-.000 (-0.30)		-.003 (-1.66)		-.001 (-0.49)	
Interaction between workers' human capital and macro-sectors of work								
% workers in Services with at least upper-secondary education		.004 (0.88)		.007 (2.26)		.007 (1.49)		.010 (2.75)
Interaction between workers' human capital and sectors' technology intensity								
% of workers in *high tech* sectors with at least upper-secondary education		.079 (1.62)		.082 (1.64)		.079 (1.52)		.079 (1.50)
% of workers in *medium-high tech* sectors with at least upper-secondary education		-.011 (-1.58)		-.004 (-0.83)		-.003 (-0.51)		.001 (0.27)
% of workers in *medium-low tech* sectors with at least upper-secondary education		.017 (2.90)		.019 (3.08)		.022 (3.24)		.022 (3.23)
% of workers in *low tech* sectors with at least upper-secondary education		-.019 (-2.10)		-.016 (-1.84)		-.014 (-1.54)		-0.11 (-1.25)
ρ	.157 (2.89)	.111 (1.65)			.158 (2.69)	.084 (1.24)		
λ			-.003 (-1.98)	-.002 (-1.16)			-.002 (-1.34)	-.001 (-0.56)
Observations	34	34	34	34	34	34	34	34
Variance ratio	0.75	0.71	0.83	0.76	0.73	0.70	0.76	0.72

Note: z-statistics in parenthesis. All models include constants. Robust estimates.

In order to choose which model best fits the data – either spatial autoregressive or spatial error or OLS –, we need to discuss separately on one hand, specifications numbered with 4, and on the other, those numbered with 5. In models where employment regional distribution is detailed at the sector level (by technological intensity), correction for spatial dependence is needed; in that case, the regressive-spatial autoregressive model, regressed with explicative variables defined in terms of worker-months, is preferable. Those estimation results (Model 4a') highlight the significant and positive relevance for growth of the relative dimension of the sector with the highest technological intensity. In contrast, when specifying the proportion of human capital employed by sector, according to technological intensity, spatial dependence weakens; the significance of spatial correction decreases both in the model measuring employment in terms of number of workers and in the model with employment corrected for months of work. In this last case, correction for spatial dependence is absolutely irrelevant. If we compare those results with outcomes from OLS regressions (in the previous section), we may conclude that the OLS model is likely to represent the relationships between human capital and its use in technology and growth when we define employment in terms of worker-months. If we are less precise in the definition of employment, not correcting for actual months of work, then spatial dependence correction is important. The result shared by both models is the significance of the coefficient of the variable that measures the human capital employed in medium-low technology sectors. The autoregressive model shows, unlike the OLS model, a mild significance of human capital employed in high-tech and a clear insignificance of human capital employed in the service sector.

6. Conclusions

In this article we study in detail and at a sub-regional scale the origin of gaps in value added growth by looking at the role of human capital in promoting overall economic growth and by analysing its role in specific sectors, according to and in combination with differences in technological intensity. The results clearly show how, in the Veneto region, the sector that significantly explains the growth path is the medium-low technological intensity one. On the other hand, the productive "specialization" which has potentially the greatest impact on LLSs growth is the one in high-technology sectors. However, although the high technology-intensive sector is significant as a whole, the human capital employed in it does not explain growth significantly, unlike what happens with the intensity of human capital employed in the firms in medium-low sector. This result seems to be indicative of an insufficient use of highly educated workers in this sector.

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Appendix

Table A1. Technological and human capital intensity in Venetian LLSs

Local Labour Systems	% of Human Capital			% in High Tech.			% in Medium-high Tech.			% in Medium-low Tech.			% in Low Tech		
	2001	2005	2007	2001	2005	2007	2001	2005	2007	2001	2005	2007	2001	2005	2007
Adria	21.2	20.1	26.9	0.0	0.0	0.0	7.2	8.2	6.9	22.3	16.9	18.6	29.2	29.8	18.5
Agordo	24.8	27.1	27.6	0.0	0.0	0.0	40.5	33.3	34.3	2.4	1.4	1.2	1.3	1.4	1.0
Arzignano	21.8	24.7	25.8	0.5	0.4	0.3	8.7	8.3	8.2	16.0	13.2	13.5	29.5	24.2	22.0
Asiago	25.8	29.1	27.1	0.0	0.0	0.0	0.3	0.2	0.2	2.7	1.8	1.7	10.2	6.0	5.9
Auronzo Di Cadore	22.7	22.9	23.1	0.0	0.0	0.0	25.9	13.3	10.7	3.7	3.4	3.2	4.4	4.7	5.0
Badia Polesine	21.8	23.4	30.6	1.3	2.4	1.3	5.1	7.2	3.7	15.4	17.7	13.5	36.1	25.7	22.0
Bassano Del Grappa	31.2	38.2	39.6	0.0	0.1	0.1	5.9	5.2	5.1	29.4	23.7	21.2	15.0	11.2	10.2
Belluno	30.6	32.6	32.6	0.9	1.8	2.1	31.3	24.7	23.8	10.8	10.5	8.7	5.1	4.3	3.3
Bovolone	21.8	25.4	26.9	1.6	1.1	0.8	8.1	6.5	5.8	19.6	17.2	15.1	16.8	11.8	11.0
Castelfranco Veneto	25.9	28.4	29.7	0.4	0.4	0.3	9.4	7.8	7.2	17.6	14.2	13.6	22.6	17.4	15.0
Conegliano	25.1	26.9	27.2	0.2	0.1	0.1	13.8	10.7	10.3	27.8	21.6	20.8	17.6	13.6	11.7
Cortina D'ampezzo	28.0	26.5	26.3	0.0	0.0	0.0	0.5	0.5	0.4	1.0	1.1	1.4	2.5	2.5	2.6
Este	29.6	32.4	32.4	0.1	0.1	0.1	6.6	7.0	7.1	20.1	18.6	18.0	19.8	12.2	10.2
Feltre	25.7	27.5	28.3	0.1	0.1	0.1	29.1	24.5	23.0	10.6	8.5	8.5	9.4	6.1	3.9
Grezzana	22.0	27.6	29.4	0.0	0.0	0.0	1.4	1.1	1.3	23.4	17.8	18.9	11.8	8.3	7.9
Legnago	29.7	30.6	33.2	0.9	0.6	0.6	13.6	13.1	12.5	19.0	15.0	14.5	16.0	11.1	9.4
Malcesine	19.3	22.4	20.7	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.3	0.3	0.3	0.4	0.4
Montagnana	24.0	26.7	28.4	0.1	0.0	0.1	5.7	5.9	5.7	23.8	19.7	18.2	24.0	17.8	16.5
Montebelluna	24.0	27.5	28.7	0.0	0.0	0.0	7.8	6.6	6.9	18.6	16.9	15.2	37.0	26.9	24.2
Padova	40.3	40.1	41.7	0.6	0.8	0.5	6.3	6.8	5.3	9.4	10.2	8.0	8.8	9.0	6.0
Pieve Di Cadore	28.7	31.0	31.1	0.0	0.0	0.0	49.4	38.7	32.3	5.8	3.2	3.5	1.8	2.7	3.1
Pieve Di Soligo	20.2	24.2	25.4	0.1	0.1	0.3	9.3	6.1	4.9	40.2	32.5	31.7	17.0	12.5	11.2
Porto Viro	14.8	17.8	23.0	0.0	0.0	0.1	4.8	5.1	2.6	9.6	13.9	10.8	24.2	23.1	16.9
Portogruaro	24.5	25.7	25.8	0.8	0.3	0.3	8.1	4.3	3.8	16.2	13.9	12.8	20.4	15.2	13.7
Rovigo	31.9	27.9	39.9	0.9	1.1	0.9	8.3	13.2	8.3	21.7	20.3	16.4	13.2	9.7	8.0
San Bonifacio	25.4	26.7	28.7	0.9	0.9	0.8	11.9	8.7	8.4	12.6	11.8	11.9	20.7	14.7	11.5
San Donà Di Piave	24.5	26.5	26.7	0.1	0.1	0.1	4.3	4.3	4.0	11.0	9.2	7.9	8.0	5.9	5.1
San Giovanni Ilarione	14.6	17.2	20.6	0.0	0.1	0.0	1.2	0.9	1.6	5.6	5.2	6.3	52.3	40.6	36.0
Schio	26.1	29.5	31.1	0.5	0.3	0.6	13.8	14.4	14.6	21.0	19.4	19.5	20.1	13.4	11.0
Thiene	26.8	29.8	31.6	0.4	0.4	0.3	9.9	8.4	9.3	20.1	19.1	18.8	22.0	15.8	14.9
Treviso	27.3	30.6	31.9	0.4	0.5	0.4	10.7	8.0	7.7	16.2	13.4	12.3	21.9	15.8	13.0
Venezia	33.3	34.0	34.6	0.2	0.3	0.2	5.4	3.7	3.0	8.9	7.1	6.6	9.1	6.8	6.0
Verona	31.5	34.2	36.0	0.9	0.6	0.6	3.1	2.8	2.8	6.9	5.7	5.5	12.3	9.4	8.0
Vicenza	29.2	32.8	33.4	0.4	0.7	0.5	7.8	6.6	7.0	19.1	14.9	13.5	9.1	7.5	6.7

**Note: Percentage of workers in sectors with different technological intensity and percentage of workers with at least an upper-secondary education diploma. (in percentage of total workers in Industry and Services)*

Keywords: regional growth, human capita, technological intensity, spatial analysis