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Productive Specialisation and Growth in the EU15: Exploring an Education Based Sectoral Taxonomy

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ABSTRACT
This paper analyses the relationship between productive specialisation and economic growth in the 15 older European Union member states between 1970 and 2005. The sectoral taxonomy proposed by (Peneder, 2007) is used to classify the different sectors of activity according to the educational levels of the respective workforce and establish a comparison between the manufacturing and the services sector, based on their potential contribution to productivity improvements. The empirical model corresponds to a growth regression where the employment share of the different sectors is the main explanatory variable taken alongside other control variables identified in the empirical growth literature as robust growth determinants and is estimated with the fixed effects method. The results indicate that a higher weight of manufacturing activities that use mostly very low and low educated workers presents a negative association with growth. Services activities that require low educated workers make a negative growth contribution. Manufacturing activities with high and medium-high educational requirements have a positive growth influence, while in the case of services only activities that require highly-educated workers show a positive correlation with growth. The policy advice that can be extrapolated from this study contemplates the design of industrial policies that promote manufacturing activities such as chemicals, telecommunications and transports equipment, and services such as financial intermediation, audit, tax consulting, engineering and legal activities, to promote growth

Key words: *Productive specialisation,; economic growth; sectoral taxonomy; education; European Union*

JEL Classification: J24; L60; L80; O14; O47

INTRODUCTION

In recent decades, the productive specialisation pattern of many countries has changed, characterized by what is known as deindustrialisation. The typical development pattern corresponding to a reduction of the importance of the agricultural sector and the associated increase in the weight of manufacturing has been followed by a reduction in the weight of manufacturing and an increase in the weight of services. This change in the productive specialisation pattern can have important consequences for the growth path of countries since different sectors present different potential for productivity improvements, the main driver of growth in modern knowledge based economies ((Baumol, 1967); (Silva & Teixeira, 2008)). Industrialisation has been associated with a sustained increase in economic growth due to its innovative nature, resulting in an increase in aggregate productivity. On the contrary, the services sector was considered as a low productivity sector and so a structural change pattern based on

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the increase of the relative weight of services could lead to a growth slowdown. More recently, several authors highlight that services activities are quite diversified in terms of their potential for productivity improvements, with some services sub-sectors rivalling with manufacturing (Eichengreen & Gupta, 2013). From a growth enhancing industrial policy perspective it is thus important to assess the contribution of the different sectors for economic growth.

The specific characteristics of each sector of activity, such as the associated physical and/or human capital intensities, participation in world markets, market size, etc., imply different potential for productivity improvements in each sector, and so it is important to distinguish the sectors according to a certain number of features to make the design of industrial policy more effective. (Peneder, 2007) proposes a taxonomy that classifies industries according to the educational composition of their workforce given that in knowledge-based economies human capital is a fundamental input of innovation activities and thus a major contributor to increases in productivity ((Romer, 1990); (Jones, 2005); (Teixeira & Fortuna, 2011)). The taxonomy proposed by (Peneder, 2007) distinguishes between seven types of industries according to the respective educational requirements, very high, high, medium-high, medium, medium-low, low, very low, confirming a tendency towards 'education-biased structural change' between industries.

This study analyses the relationship between productive specialisation and economic growth in the 15 older European Union member states between 1970 and 2005. The main objective is to examine the impact of structural change towards sectors with higher educational intensity on economic growth. In particular, we want to assess the growth impact (positive/negative/non-existent) of different manufacturing and service industries classified according to the educational composition of their workforce under the assumption that activities with higher educational requirements should promote growth due to their role as sources of aggregate productivity growth, while the opposite applies to activities that require less educated workers. The sectoral taxonomy proposed by (Peneder, 2007) is used to classify the different sectors of activity according to the educational levels of the respective workforce and establish a comparison between the manufacturing and the services sector, based on their potential contribution to productivity improvements. The empirical model corresponds to a growth regression where the employment share of the different sectors is the main explanatory variable taken alongside other control variables identified in the empirical growth literature as robust growth determinants. This model is estimated with the fixed effects method.

The remainder of this paper is organized as follows: the section after the Introduction contains a brief review of the related theoretical and empirical literature. Afterwards we present the sectoral taxonomy used. The next section presents the empirical model and estimation methodology, as well as the results obtained. In the final section we include the main conclusions.

PRODUCTIVE SPECIALISATION AND ECONOMIC GROWTH: AN OVERVIEW OF THE LITERATURE WITH A FOCUS ON SECTORAL DISAGGREGATION

In recent decades, the study of structural change, understood as a change in sectoral composition and thus resulting in a change in the productive specialisation pattern of a country, has regained interest within the growth literature given the potential growth impact of these changes and in particular on the ability of a country to sustain its long run growth rate of output. This resurgence of interest is particularly related to the importance of technological change and innovation, considered the main engines of economic growth ((Romer, 1990); (Jones, 2005)).

The sectors of activity that make up an economy have very different characteristics with respect to technological features, the relative intensity of physical and human capital and economies of scale ((Marelli, 2004)). As a result of these differences, the contribution of each sector to aggregate economic growth can be quite different. The modern economy we live in is the result of the industrialization process that occurred in many countries over the last couple of centuries

((Rodrik, 2013)). The industrial revolution ignited economic growth in Europe and other western countries, but more recently the weight of manufacturing has declined and it is being replaced by the services sector as the dominant sector of activity. This process of structural change raises concerns for the sustainability of economic growth, since manufacturing generally records higher productivity levels as it is a technologically more dynamic sector and produces tradable goods, among others.

The growing importance of the services sector has thus been regarded with concern. (Baumol, 1967) argued that this sector suffers from the cost disease since the productivity of the services sector is limited when compared to that manufacturing. This results from the fact that the potential for replacing labour by capital is more limited and so productivity improvements are less likely to occur in certain activities of the services sector such as education, health or art. These activities were thus called "stagnant services". However, later Baumol recognized that it is necessary to distinguish between various types of services in terms of their potential for productivity gains due to the importance of innovation and technology in some services sub-sectors. Thus, the services sector as a whole should be subdivided into traditional and modern services. Within the traditional services are included activities such as housing, barber shops, beauty salons, that is, labour intensive activities that make a small contribution to productivity growth. At the same time, modern services include activities such as banking, insurance and communications, which require a higher level of human capital and make a strong contribution to productivity growth ((Baumol, Blakman, & Wolff, 1985); (Maroto-Sánchez & Cuadrado-Roura, 2009)). In any case, according to some authors (Pugno, 2006), even the traditional (stagnant) personal services can make a positive growth contribution since services such as education, health or culture may contribute to human capital formation and in this way offset the negative contribution to overall growth due to its low productivity[2].

Recent empirical studies investigate how structural change has contributed to economic growth through increases in aggregate productivity using different sectoral taxonomies. (Peneder, 2003a) estimates how the share of manufacturing activities classified according to three different taxonomies affects either the level of real GDP per capita or its growth rate in a sample of 28 OECD countries over the period 1990-1998. Taxonomy I distinguishes activities according to factor input combinations resulting in five categories (mainstream; labour intensive; capital intensive; marketing driven; technology driven). Taxonomy II distinguishes among four categories according to skills requirements (low-skill; medium-skill blue-collar; medium-skill white-collar; high-skill). Taxonomy III is based on the use of external service inputs including also four categories (high inputs from transport services; high inputs from retail and advertising services; high inputs from information and knowledge based services). The results obtained indicate that technology driven and high skill manufacturing activities have a quantitatively important positive and statistically significant influence on the level and growth rate of real GDP per capita. The findings point also to a negative influence of an increasing share of services on the aggregate growth of GDP per capita, as well as on its level, and are thus consistent with Baumol's predictions. However, the impact is weak and the author stresses that it might be the case that opposite signs effects are netting out, and that in any case there might be a positive contribution from certain types of services industries that systematically achieve higher rates of productivity growth. Following up on this idea, (Maroto-Sánchez & Cuadrado-Roura, 2009) assess the impact of tertiarisation on overall productivity growth for a sample of 37 OECD countries over the period 1980-2005. The heterogeneity of the services sector is taken into account by differentiating the structural variables for market services and non-market services. The estimated coefficients are positive in both cases but the productivity growth impact of market services is quite stronger.

[2] Several authors also highlight the possibility that tertiarisation is a consequence not a cause of economic growth due to higher demand as income grows or more investment in R&D and education as a country develops. See (Peneder, 2003a).

Adopting two different classifications of industries, one that takes into account the industries' skill requirements, and a classification based on technological characteristics, (E.G. Silva & Teixeira, 2011) assess the importance of structural change for productivity growth in a sample of 10 countries described by the authors as 'relatively less developed' in the late 1970s but that exhibited different paths of structural change from then onwards with some promoting more skilled and technology-intensive activities. The main idea is to test whether these differing paths can explain the different growth performances registered over the period 1980-2003. The evidence suggests that a change towards the high-skill industries and science-based industries shares influences positively labour productivity growth. In contrast, an increase in the value added share of supplier-dominated industries results in a decline in labour productivity growth.

Using data for 28 manufacturing industries from 44 countries over the period 1980-1999, (Ciccone & Papaioannou, 2009) provide evidence of the importance of human capital availability for structural change. The authors find a positive and statistically significant correlation between initial schooling levels and value added and employment growth in schooling-intensive industries, stronger for more open economies. Faster educational attainment growth also seems to lead to faster shifts in production towards human capital-intensive industries. It is thus also likely that the availability of high levels of human capital, by facilitating technology adoption in education-intensive sectors, leads to faster growth. (Peneder, 2007) also presents evidence that the activities with a very high educational intensity, and also most industries with a high or intermediate level, were the ones that registered the highest growth rates in terms of value added and employment in a sample of 24 OECD countries over the period 1992-2000.

The studies reviewed indicate that it is possible to gain additional insights on the role of structural change for economic growth by disaggregating the main sectors activity. In this study we apply the sectoral taxonomy proposed by (Peneder, 2007) in order to distinguish the growth impact of different manufacturing and services activities divided according to the educational composition of the respective workforce.

SECTORAL TAXONOMIES AND PRODUCTIVITY GAINS: THE TAXONOMY OF PENEDER (2007)

The impact of structural change and thus productive specialisation on economic growth has been mainly analysed taking into account the sectors of activity at a very aggregated level, in some cases considering only the three main groups of activities: the primary sector, which includes activities that extract raw materials such as agriculture, livestock and fishing, the secondary sector, which transforms raw materials provided by the primary sector into tangible goods/products and includes activities such as manufacturing, construction and utilities, and the tertiary or services sector, which includes activities that produce intangible goods, that is services instead of products. It comprises a wide range of activities going from warehousing and transportation services, information services, financial intermediation, professional, technical and scientific services, education, health care and social assistance and arts, entertainment, and recreation services. This taxonomy does not, however, take into account the characteristics of the different activities that can contribute to greater productivity gains, namely the educational composition of the workforce and the innovation potential of the different subsectors, measured according to different features. Nevertheless, modern growth theory identifies productivity gains as the main driver of long run output growth and human capital and innovation as its primary sources ((Romer, 1990); (Hall & Jones, 1999); (Jones, 2005)). Thus, the consideration of sectoral taxonomies that accommodate these characteristics allows us to identify, in a more consistent way with the predictions of economic growth models, the impact of structural change on the behaviour of output in the long run.

The diversity of the characteristics of each sector, such as the intensity / quality of the factors used, technological regimes, economies of scale, inter-sectoral linkages or type of competition

((Peneder, 2003b); (Marelli, 2004)) imply different sectoral innovation potential and require a more disaggregated classification in order to achieve results that are more useful for policy makers. In what follows, we briefly present the sectoral taxonomy adopted in this study that will allow us to distinguish different activities according to their potential for productivity improvements assuming that higher human capital requirements lead to higher productivity gains.

(Peneder, 2003b) reviews the existing (to date) major industry classifications used in empirical research in terms of their aim, scope and methods of identification, highlighting their advantages and limitations, so that researchers can make an educated selection of the most appropriate classification for the purposes of their studies. According to the author, a taxonomy differs from a typology in that it is an empirical classification produced from quantitative identification undergirded in adequate statistical tools, such as cluster analysis, instead of the simpler but more subjective cut-off approach in which a differentiating threshold is defined exogenously by the researcher. A useful taxonomy must guarantee stability between countries and over time, "(…) reflecting systematic relationships for data which otherwise are difficult to compare." ((Peneder, 2003b); p. 126)

Obeying the general principles for the construction of a good taxonomy identified in (Peneder, 2003b), the taxonomy proposed by (Peneder, 2007) classifies 49 manufacturing and service industries according to the educational intensity required from the respective workforce[3], distinguishing between seven categories, on a scale that starts with activities with very high educational requirements and ends with activities with very low educational requirements (very high, high, medium-high, medium/intermediate, medium-low, low, very low). According to the author, "It provides an empirical tool that allows the researcher to add analytic structure to micro-level studies of firm behaviour, as well as aggregate international and comparative studies—applicable whenever sector dependent characteristics of educational intensity, or its according productive capabilities in the human resource base, are thought to be of importance." (p. 207). Since education data at the firm/sectoral level is not easily available in a comparable format across countries, the author first applies the statistical cluster analysis to each country for which there is detailed education data separately (the USA, Germany, France, the UK, and Austria) in order to identify the activities that belong to each of the seven educational categories that resulted from the identification method used. Statistical cluster analysis is a statistical identification method that classifies observations based on their relative similarities according to a multidimensional array of variables and produces different segments/categories of data (seven in this case) by allowing for maximum homogeneity within and maximum distance between segments ((Peneder, 2003b)). The five separate national taxonomies were then synthesized into one common consensus classification to be used in cross-country analysis, which would otherwise not be possible due to lack of comparable sectoral data on educational intensity (see Table 1, pp. 198-99, in (Peneder, 2007)). The subsequent quantitative validation of the taxonomy by means of ANOVA type regressions revealed considerable robustness to variations over time and between countries.

In this study, we group, for each EU15 member state, manufacturing and services activities according to the former seven categories, distinguishing between manufacturing and services in order to compare the results for these two main sectors of economic activity. Table A.1 in the Appendix describes the manufacturing activities according to the ISIC Rev. 3 classification at the two digit level that belong to each of the categories in the sectoral taxonomy proposed by

[3] Other popular sectoral taxonomies that distinguish sectors according to their potential for productivity improvements include (Pavitt, 1984) perfected by (Tidd, Bessant, & Pavitt, 2005), which is based on the innovative intensity of each sector and the use of inter-sectoral knowledge, and (Robinson, Stokes, Stuivenwold, & Ark, 2003), based on the production and use of ICTs by each activity. See also (Peneder, 2003a,b).

(Peneder, 2007). Table A.2 in the Appendix does the same for services activities. Notice that there are no manufacturing activities in the very high educational intensity category.

EMPIRICAL MODEL AND RESULTS

For the analysis of the relationship between productive specialisation and economic growth we use data on real GDP per capita growth, computed with data on real GDP and population taken from the Penn World Table (PWT) 9.0, while productive specialisation is measured as the share of different activities in total value added, computed with data from the EU KLEMS. The period covered starts in 1970 and ends in 2005 for econometric and data availability reasons. Recently, EU KLEMS has released data for a more recent period that goes up to 2015, but it only starts in 1995. Using this more recent data would thus involve the loss of a considerable number of degree of freedom in the econometric analysis that follows, making the results less robust. Additionally, this more recent data is not directly comparable to the data used in the paper since it uses ISIC Rev. 4 (NACE 2) classification of economic activities while the data in the paper refers to the ISIC Rev. 3 (NACE 1) the one used by (Peneder, 2007) as the basis for his sectoral taxonomy, making the more recent EU KLEMS sectoral data based on ISIC Rev. 4 more difficult to translate into the original taxonomy.

We estimate what is known as a growth regression since the dependent variable in our empirical model is the growth rate of real GDP per capita and the main explanatory variable refers to productive specialisation defined according to the sectoral taxonomy of (Peneder, 2007), included alongside a set of control variables identified as relevant growth determinants in the theoretical and empirical growth literature ((Peneder, 2003a); (Moral-Benito, 2012)). The data used refers to a 35 years period (1970-2005) and were taken from the EU KLEMS (Jäger, 2017) and the PWT (Feenstra, Inklaar, & Timmer, 2015) databases and the Barro and Lee education data set ((Barro & Lee, 2013)). The estimations were carried out with the econometric package GRETL.

The empirical model is given by equation (1):

$$\Delta lnGDPrpc_{i,\tau} = \alpha + \rho SPEC_{i,t-1} + \lambda lnGDPrpc_{i,t-1} + \beta Educ_{i,t-1} + \gamma GFCF_{i,t} + \delta OPEN_{i,t} + \theta GOV_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $\Delta lnGDPrpc_{i,\tau}$ is the annual average growth rate of real GDP per capita measured for each 5-year (τ) sub-period from 1970-2005, with *GDPrpc* corresponding to real GDP per capita, α is a constant; i= 1,2,…, N (with N = 15, the fifteen EU member states in our sample); τ = 1,2,…,7 (with τ = 7) are the 5-year sub-periods (1970-75; 1975-80;…; 2000-05); *SPEC* is the value added share of each sectoral category defined by (Peneder, 2007), included each at a time; $lnGDPrpc_{i,t-1}$ is the log of the initial value of real GDP per capita for each 5-year sub-period; $Educ_{i,t-1}$ is average years of total schooling of the population aged 25 and above measured at the beginning of each 5-year sub-period taken from (Barro & Lee, 2013); *GFCF* is the investment rate – gross fixed capital formation as a percentage of GDP measured as the average value for each 5-year sub-period; *OPEN* refers to openness measured as the GDP ratio of imports plus exports corresponding to the average value for each 5-year sub-period; *GOV* is public consumption as a percentage of GDP measured as the average value for each 5-year sub-period; and ε is the error term. All the control variables except for *Educ* were computed with data taken from the PWT.

The initial value of GDP per capita is included in the regression to capture the convergence hypothesis from exogenous and technological diffusion growth models according to which initially poorer countries/more distant from the technological frontier are expected to grow faster and so the respective coefficient is expected to be negative ((Islam 1995; 2003). According to (Solow, 1956), higher investment rates lead to higher physical capital accumulation and the increased availability of this input fosters growth, at least in the medium run. The estimated coefficient for the variable GFCF is thus expected to be positive. Models in the tradition of Solow (1957) that include additionally human capital ((Mankiw, Romer, & Weil, 1992)) but also endogenous growth models ((Lucas, 1988); (Romer, 1990); (Jones, 2005)) attribute a fundamental role to education, either as an input into final goods production, allowing workers to produce more, but also as an input into innovation and imitation activities allowing for productivity improvements and thus faster growth. The estimated coefficient for the variable Educ is thus expected to be positive. More open economies have access to larger markets and new technologies and thus become more efficient and productive, so the coefficient of OPEN is expected to be positive ((Gries & Redlin, 2012)). According to (Barro, 1990), public consumption (GOV) is expected to hamper growth since it deviates resources from more efficient/productive activities (θ is expected to be negative).

Table A.3 in the Appendix contains descriptive statistics for the variables in the model. Overall it is possible to see that there is considerable variation across countries and over time for the variables under analysis. As far as our dependent variable is concerned, the growth rate of real GDP per capita, a more in depth inspection of the data (available from the authors) revealed that there is some evidence of convergence among the EU15, with the initially poorer countries (Greece, Portugal, Spain, Ireland) recording higher than average growth rates. As for the main explanatory variables, the value added shares of the different manufacturing and services activities classified according to (Peneder, 2007), overall the activities that increased the respective value added share are those that need more human capital. This is true for both manufacturing and services, although the relative weight of these categories is higher for services. Additionally, the countries with the higher levels of real GDP per capita are also the ones that recorded a higher weight of activities that require more educated workers. The countries with lower initial levels of real GDP per capita also recorded a higher weight of manufacturing and services activities classified as very low and low by (Peneder, 2007).

The empirical model described in equation (1) is a static panel data model that will be estimated using the fixed effects method. Fixed effects is more adequate when, although there are common variables that affect the behaviour of the countries under analysis, there are also characteristics intrinsic to each country that influence the respective behaviour that are different across countries, while remaining constant over time ((Adkins, 2010); (Rodríguez-Pose & Tselios, 2009)).

Table 1 contains the results obtained with the fixed effects method considering as the main explanatory variable the value added share of each category in (Peneder, 2007) for the manufacturing sector[4] [5]. The findings confirm the expected influence of initial income, with the estimated coefficient of lnGDPrpc statistically significant and negative, supporting in this way the convergence hypothesis: initially poorer countries such as Greece, Portugal and Spain are approaching the income levels of the richer countries in the sample, such as Germany, Sweden or Denmark. Regarding educational attainment levels, the results confirm the importance of human capital for growth with the estimated coefficient always positive as expected and statistically significant. The control variables GFCF, GOV and OPEN present more varied results. The estimated coefficient for the investment rate is always positive as expected but only statistically significant (at 10%) when considering manufacturing activities with high educational requirements. The variable public consumption presents a negative and statistically significant influence on the growth rate of real GDP per capita, indicating that it is probably the source of inefficiencies in the group of countries under analysis. As for openness, although the estimated coefficient is also always positive as expected it is never statistically significant.

The results for the value added shares of the different sectors defined by (Peneder, 2007), confirm the expected negative influence of specialisation in manufacturing activities with rather

[4] As described in section 3, for the manufacturing sector there are no activities in the very high educational requirements category, which is why we only consider six categories.
[5] The model was also estimated using the employment shares of the different categories as the main explanatory variables. The results are identical to the ones obtained when using the value added shares.

low educational requirements, in particular very low and medium-low, and positive for the remaining categories. The estimated coefficients are statistically significant at the 10% level for the categories medium-low and medium-high, at the 5% level for the category very low and at 1% for the category high, and are not significant for the categories low and medium. Overall, these findings indicate that the countries in our sample stand to gain in terms of economic growth from moving their productive specialisation pattern away from manufacturing activities with low educational requirements.

Table 1. Estimation results with the manufacturing sector divided according to Peneder (2007)

	Very Low	**Low**	**Medium-low**	**Medium**	**Medium-high**	**High**
Constant	0.2907*** (0.0780)	0.2460*** (0.0774)	0.2508*** (0.0766)	0.2521*** (0.0769)	0.2566*** (0.0016)	0.2653*** (0.0718)
lnGDPrpc	- 0.0269*** (0.0085)	- 0.0233*** (0.0087)	−0.0226*** (0.0085)	−0.0234*** (0.0085)	−0.0240*** (0.0085)	−0.0267*** (0.0080)
SPEC	- 0.2969** (0.1169)	0.0288 (0.0370)	−0.3580* (0.2140)	0.0619 (0.0417)	0.1224* (0.0712)	1.2467*** (0.2754)
Educ	0.0035** (0.0015)	0.0037** (0.0016)	0.0035** (0.0015)	0.0027* (0.0016)	0.0027* (0.0016)	0.0027* (0.0014)
GFCF	0.0136 (0.0320)	0.0187 (0.0335)	0.0163 (0.0327)	0.0147 (0.0328)	0.0229 (0.0330)	0.0549* (0.0298)
GOV	−0.1863*** (0.0499)	−0.1653*** (0.0510)	−0.1841*** (0.0511)	−0.1493*** (0.0521)	-0.1479*** (0.0516)	−0.0723 (0.0483)
OPEN	0.0017 (0.0038)	0.0024 (0.0039)	0.0035 (0.0039)	0.0020 (0.0038)	0.0016 (0.0038)	-0.0033 (0.0038)
R^2	0.2463	0.2009	0.2194	0.2145	0.2207	0.3801
AIC	-603.7688	-59.6269	-600.0875	-599.4232	-600.2586	−585.7840
HQ	-589.7881	-583.6463	-586.0107	-585.4425	-586.2780	−572.1917
No. Obs.	105	105	105	105	105	105

*Notes: ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors in parenthesis.*

Source: authors' computations using Gretl

Table 2 contains the results of the estimation of equation (1) considering the value added shares of the different services activities grouped according to the seven categories in (Peneder, 2007). In any of the estimated models, initial GDP presents a negative coefficient that is statistically significant at the 1% level. The variable Educ presents a positive coefficient as expected and is statistically significant at the 5% level. The estimated coefficient for public consumption is negative and presents statistical significance at the 1% level for all equations. On the other hand, the estimated coefficients for GFCF and OPEN are not statistically significant for any of the categories in the Peneder taxonomy.

The variable SPEC, measured as the value added share of the services activities corresponding to each of the seven categories in (Peneder, 2007), shows a negative sign for the categories very low, low and medium-low and a positive sign for the medium, medium-high, high and very high categories. These results are in line with the theoretical predictions since the latter three categories are the ones that require a more educated workforce, which may indicate that when countries are specialized in activities in the services sector that require skilled labour the growth rate of the country will be higher, and the opposite applies to the low educational requirements categories. However, the variable is only statistically significant (at 1%) in the very low category and in the high category.

Combining the analysis of the different results in Tables 1 and 2, we find that both in the manufacturing and services sectors the activities included in the very low category that includes the activities that require the less educated workers present a negative and statistically significant correlation with real GDP per capita growth. On the other hand, the activities included in the high category present a positive correlation with real GDP per capita growth, a category that includes activities with high levels of human capital. Besides these common results, manufacturing activities included in the low category present a negative correlation with growth while those included in the medium high category present a positive correlation.

Additionally, as far as comparing manufacturing and services activities is concerned, the results indicate that a productive specialisation pattern towards manufacturing activities classified as very low and low is more harmful for growth than specialisation in the equivalent categories but in services activities. On the other hand, there are also more categories requiring more skilled workers in the manufacturing industry that positively influence growth, relative to services activities. Finally, a somewhat unexpected result refers to the finding that services activities classified in the very high category do not show a statistical significant relationship with growth.

Table 2. Estimation results with the services sector divided according to Peneder (2007)

	Very Low	**Low**	**Medium-low**	**Medium**	**Medium-high**	**High**	**Very High**
Constant	0.2627*** (0.0771)	0.2433*** (0.0774)	0.2618*** (0.0781)	0.2667*** (0.0867)	0.2523*** (0.0778)	0.2670 (0.1070)	0.257*** 0.0783)
lnGDPrpc	-0.0237*** (0.0085)	- 0.0225*** (0.0086)	−0.0234*** (0.0086)	−0.0253*** (0.0099)	−0.024*** (0.0087)	−0.025*** (0.0115)	- 0.024*** (0.0087)
SPEC	- 0.0940* (0.0534)	-0.0493 (0.06230)	−0.1356 (0.0970)	0.0257 (0.0448)	0.0342 (0.0382)	0.0784*** (0.0508)	0.06566 (0.0670)
Educ	0.0032** (0.0015)	0.0032** (0.0016)	0.0036** (0.0016)	0.0037** (0.0017)	0.0034** (0.0016)	0.0046* (0.0021)	0.0036** (0.0016)
GFCF	0.0099 (0.0327)	0.0152 (0.0330)	0.0152 (0.0329)	0.0160 (0.0332)	0.0157 (0.0330)	0.0430 (0.0443)	0.0152 (0.0330)
GOV	−0.1729*** (0.0502)	−0.1570*** (0.0529)	−0.1743*** (0.0541)	−0.1776*** (0.0533)	-0.180*** (0.0524)	−0.2227*** (0.0587)	- 0.181*** (0.0524)
OPEN	0.0039 (0.0039)	0.0034 (0.0042)	0.0021 (0.0042)	0.0021 (0.0039)	0.0040 (0.0044)	-0.0075 (0.0058)	0.0014 (0.0039)
R^2	0.2218	0.2011	0.2179	0.1985	0.2026	0.2757	0.2040
AIC	−600.4149	-597.6532	-597.8808	-597.3178	-597.852	-470.3560	- 598.033
HQ	−586.4342	-583.6726	-582.8247	-583.3371	-583.872	-457.7947	- 584.052
No. Obs.	105	105	105	105	105	105	105

*Notes: ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors in parenthesis.*

Source: authors' computations using Gretl

From an industrial policy perspective, the main policy advice that can be extrapolated from this study contemplates the design of industrial policies that promote manufacturing activities such as chemicals, telecommunications and transports equipment, and services such as financial intermediation, audit, tax consulting, engineering and legal activities, in order to promote growth. This industrial policy orientation involves also coordination with educational policy, promoting higher educational attainment levels in the EU, in order to guarantee that the expansion of the former sectors is not constrained by a lack of supply of skilled/more educated workers.

CONCLUSION

This study analyses the relationship between productive structure and economic growth for a sample composed of the fifteen older EU member states over the period 1970-2005 taking into account the innovation potential of different groups of activities. To identify these groups we use the sectoral taxonomy proposed by (Peneder, 2007) based on the educational requirements of the respective workforce.

When analysing real GDP per capita levels in the EU15, we concluded that countries such as Portugal, Greece, Spain, Ireland and Finland with lower than average levels are also the countries that recorded a higher relative weight of activities classified as very low and low in terms of educational requirements, both in the manufacturing and services sectors. From 1970 until 2005, the period covered in this study, the EU15 has experienced changes in its productive structure, with the activities that need more educated workers gaining importance. This is true for both manufacturing and services activities, although in the latter the activities that require more human capital have a higher weight relative to the services activities classified as very low and low.

We thus investigated the relationship between productive structure and economic growth for the EU15 countries by estimating a growth regression in a panel data context using the fixed effects method. The results support the idea that countries with a productive specialisation pattern based on activities that require mainly low skilled labour tend to record lower growth rates. In particular, manufacturing and services activities classified as very low according to the sectoral taxonomy of (Peneder, 2007) present a negative and statistically significant correlation with the growth rate of real GDP per capita, while manufacturing and services activities classified as high present a positive correlation. For the remaining categories the estimated coefficients present the expected signs but are not statistically significant. The exceptions are manufacturing activities classified as medium-low, with a negative and statistically significant coefficient, and as medium-high with a positive and statistically significant coefficient.

The implications of these key findings for the design of a growth enhancing industrial policy are the support of activities that require more educated workers, in particular manufacturing activities corresponding to chemical, telecommunications and transports, classified as medium-high and high according to (Peneder, 2007), and services activities corresponding to financial intermediation and computers, classified as high in terms of education requirements. This industrial policy orientation involves also coordination with educational policy, promoting higher educational attainment levels in the EU, in order to guarantee that the expansion of the former sectors is not constrained by a lack of supply of skilled/more educated workers.

The robustness of the previous conclusions needs in any case to be further checked in future studies that address issues related to the use of econometric methodologies for panel data that control in other ways for endogeneity issues or non-linearities, for instance. Additionally, the economic policy implications derived would benefit from the analysis of the situation in specific countries as the results obtained apply to the representative/average country, not taking into account potential heterogeneity among the fifteen EU countries analysed coming from sources other than the fixed effects considered. Finally, a comparison with the results obtained through the use of alternative sectoral taxonomies could also bring additional insights.

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APPENDIX

Table A.1. Manufacturing activities divided according to the taxonomy of Peneder (2007)

ISIC revision 3	Subsectors	Classification of Peneder (2007)
17 18 19 20	Textiles Wearing Apparel, Dressing And Dying Of Fur Leather, leather and footwear Wood and products made of wood and cork	Very low
15-16 26 27 28	Food and beverages; Tobacco Other non-metallic mineral Basic metals Fabricated metal	Low
25 36-37	Rubber and plastics Manufacturing nec; recycling	Medium-low
21 22 23 29 31-313 34	Pulp, paper and paper Printing, publishing and reproduction Coke, refined petroleum and nuclear fuel Machinery, nec Electrical machinery and apparatus, nec Insulated wire Motor vehicles, trailers and semi-trailers	Medium
24 321 322 323 33-331 351 353 352þ359	Chemicals and chemical products Electronic valves and tubes Telecommunication equipment Radio and television receivers Medical, precision and optical instruments Scientific instruments Other transport equipment Building and repairing of ships and boats Aircraft and spacecraft Railroad equipment and transport equipment nec	Medium-high
30	Office, accounting and computing machinery	High

Source: authors based on Peneder (2007), Table 1, pp. 198-99.

Table A.2. Services activities divided according to the taxonomy of Peneder (2007)

ISIC revision 3	Subsectors	Classification of Peneder (2007)
55 95	Hotels and restaurants; Private households with employed persons;	Very low
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel;	Low
52 60 61	Retail trade, except of motor vehicles and motorcycles; repair of household goods; Inland transport; Water transport;	Medium-low
51 63 64 70 71	Wholesale trade and commission trade, except of motor vehicles and motorcycles; Supporting and auxiliary transport activities; activities of travel agencies; Post and telecommunications; Real estate activities; Renting of machinery and equipment;	Medium

ISIC revision 3	Subsectors	Classification of Peneder (2007)
66 67 75 85 90-93	Insurance and pension funding, except compulsory social security; Activities related to financial intermediation; Public administration and defense; compulsory social security; Health and social work; Other community, social and personal services;	Medium-high
65 741-3 49	Financial intermediation, except insurance and pension funding; Legal, technical and advertising; Other business activities;	High
72 73 80 99	Computer and related activities; Research and development; Education: Extra-territorial organizations and bodies.	Very high

Source: authors based on Peneder (2007), Table 1, pp. 198-99.

Table A.3. Descriptive statistics for the variables in the empirical model

Variable	Mean	Median	Std. Dev.	Min.	Max.
ΔlnGDPrpc	2.36%	2.30%	1.40%	-0.93%	8.54%
GDPrpc (USD)	24900	24100	7400	9960	48100
Educ (years)	8.43	8.49	1.87	2.72	11.9
GFCF	27.50%	26.80%	4.49%	19.10%	46.00%
OPEN	73.80%	60.90%	42.90%	15.30%	202.00%
GOV	16.90%	16.70%	3.20%	9.05%	25.90%
SPEC_very_low_manuf	1.99%	1.72%	1.27%	0.06%	6.49%
SPEC_low_manuf	7.04%	6.60%	3.88%	2.81%	32.3%
SPEC_medium_low_manuf	1.40%	1.34%	0.66%	0.32%	3.38%
SPEC_medium_manuf	6.86%	6.05%	3.94%	2.28%	29.9%
SPEC_medium_high_manuf	2.70%	2.20%	2.38%	0.48%	16.9%
SPEC_high_manuf	0.22%	0.07%	0.56%	0.00%	3.85%
SPEC_very_low_serv	4.17%	3.36%	2.99%	1.30%	20.5%
SPEC_low_serv	2.61%	1.88%	2.73%	1.15%	20.1%
SPEC_medium_low_serv	7.67%	7.67%	2.23%	2.03%	21.4%
SPEC_medium_serv	17.40%	18.20%	3.96%	1.94%	23.8%
SPEC_medium_high_serv	17.50%	17.80%	4.51%	1.63%	36.9%
SPEC_high_serv	6.79%	6.72%	4.19%	1.06%	23.9%
SPEC_very_high_serv	6.58%	6.54%	2.26%	1.35%	20.0%

Source: authors' computations

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