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# Increasing returns to scale, technological catch-up and research intensity: endogenising the Verdoorn coefficient

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This paper examines the importance of output growth and research intensity for productivity growth. Two hypotheses are tested. First, the paper investigates the impact of the two variables on productivity growth when simultaneously considered, assessing whether the basic Kaldorian and Schumpeterian models can be combined. Second, it examines whether research intensity impacts on the magnitude of returns to scale, assessing if countries with higher research intensity benefit from higher returns to scale. The tests reported in the paper provide strong evidence of the importance of demand growth for productivity growth, and on the existence of increasing returns to scale in manufacturing, while also recognizing the relevance of research intensity for productivity growth. Most importantly, the test results suggest that research intensity has a more relevant impact on the magnitude of returns to scale than on productivity growth directly.

*Key words:* Increasing returns, Productivity growth, Research intensity, Technological catch-up, Kaldor-Verdoorn's Law
*JEL classification:* O11, O30, O47

## 1. Introduction

Following Keynes's (1936) demand-led approach, Kaldorian works emphasise the importance of the growth of autonomous demand for productivity growth. The Dutch economist Petrus Verdoorn (1949) was the first to observe a positive relationship between output and productivity growth in the manufacturing sector. Nonetheless, it was Kaldor (1966) who brought attention to the relevance of this finding, pointing out that a positive impact of output growth on productivity growth indicates the existence of increasing returns to scale in the manufacturing sector. Furthermore, following Allyn Young (1928), Kaldor (1966) emphasised that a considerable part of

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this impact should be attributed to technical progress induced by expanding demand. After Kaldor's influential lecture in 1966, the relationship between output growth and productivity growth, known as Kaldor-Verdoorn's Law, was scrutinised and elaborated further (see McCombie, 2002). Most importantly, a large number of empirical works have found support for the law (e.g. McCombie and De Ridder, 1983, 1984; Angeriz *et al.*, 2008, 2009).

In parallel to the Kaldorian demand-led approach, however, Schumpeterian works emphasise the importance of supply-side factors for technical progress. The importance of research intensity for technical progress represents the main foundation of Schumpeterian models of economic growth (e.g. Romer, 1990; Aghion and Howitt, 1992, 1998; Ha and Howitt, 2007; Madsen, 2008). According to Schumpeter (1943), innovations create temporary monopolies, providing a strong incentive for firms to invest in research and development (R&D) in pursuit of innovations. Moreover, technological transfer is yet another determinant of productivity growth emphasised by Schumpeterian works (e.g. Posner, 1961; Verspagen, 1991; Griffith *et al.*, 2004; Vanderbussche *et al.*, 2006). Transposing Schumpeter's (1934, 1943) microeconomic ideas on innovation and imitation to a macroeconomic setting, these works stress that follower economies may benefit from their backwardness and increase productivity growth through technological absorption, given that absorbing (imitating) existing technology is less costly than investing in uncertain innovations. Thus, the existence of differences in productivity between countries opens up the opportunity for technological transfer from frontier to follower countries, providing an interesting explanation for conditional convergence.

Given the strong theoretical and empirical foundations of these two influential schools of thought, therefore, their combination should contribute to a better understanding of the dynamics involved in the process of productivity growth. In effect, the two approaches present a certain degree of complementarity. While Kaldorian theory emphasises the importance of demand growth for long-term growth, putting less stress on the importance of supply-side factors, the opposite holds true for Schumpeterian theory. Still, this difference does create an important difficulty, since bringing these theories together can subvert one of the two by attributing a final role to either demand or to supply alone. Indeed, perhaps because of this difficulty, in spite of the large number of Kaldorian and Schumpeterian works that have investigated the determinants of productivity growth, there have been only a few attempts to reconcile the two approaches (e.g. Léon-Ledesma, 2002).

The purpose of this paper, therefore, is to assess the impacts of output growth and research intensity on productivity growth. Two hypotheses are tested. First, the paper investigates whether the two variables have significant impacts on productivity growth when considered simultaneously, in order to determine if the basic Kaldorian and Schumpeterian models can be combined. Second, the paper examines whether research intensity impacts on the degree of returns to scale, assessing if countries with higher research intensity benefit from higher returns to scale. The intuition behind this hypothesis is that higher research intensity generates faster knowledge accumulation, which allows faster technical progress (or dynamic returns to scale) in response to output growth.

The empirical investigation reported in this paper is based on disaggregated data on patents and productivity not explored to date. The data used to calculate the growth rate of total factor productivity (TFP) comes from the EU KLEMS Database, and comprises 12 manufacturing industries in up to 15 OECD countries over the period

1976–2006. The data on patents used to calculate research intensity for each country, industry and year is from the United States Patent and Trademark Office (USPTO), and was aggregated by industry using the methodology developed by Lybbert and Zolas (2014). Thus, the investigation presented in this paper extends previous works carried out using EU KLEMS data by incorporating innovation indicators into the database, as suggested by O'Mahony and Timmer (2009, p. F396).

The remainder of the paper is organised as follows. Section 2 presents the model. Section 3 describes the empirical investigation and discusses the results. Section 4 presents the concluding remarks.

## 2. The Model

### 2.1. Kaldor-Verdoorn's Law

Kaldor-Verdoorn's Law postulates that faster output growth generates productivity growth due to increasing returns. The law can be derived from a production function such as

$$Y = A_0 e^{g_A t} K^{\alpha} L^{\beta} \tag{1}$$

where $Y$ is total value added, $K$ is the stock of capital, $L$ is labour, $A$ is a constant and $g_A$ is the rate of technological progress. Moreover, $\alpha$ and $\beta$ are respectively the output elasticities of capital and labour, so that $(\alpha + \beta) = \gamma[\alpha' + (1-\alpha')]$, where $\gamma$ is a measure of the degree of static returns to scale and $\alpha'$ is the share of capital in total value added (Angeriz *et al.*, 2009).

In contrast with the Schumpeterian growth models developed by Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1998), in the Kaldorian approach it is demand growth that determines technological progress. Hence, assuming that the growth of factor inputs is driven by demand growth (i.e. $[\alpha'\hat{K} + (1-\alpha')\hat{L}] = f(\hat{Y})$), a faster growth of weighted factor inputs induces a faster rate of technical progress, so that

$$g_A = \varphi + \eta[\alpha'\hat{K} + (1-\alpha')\hat{L}] \tag{2}$$

where $\varphi$ is the exogenous technical progress and $\eta$ is the elasticity of induced technological progress. The circumflex over the variables indicates growth rates.

Thus, substituting equation (2) into the production function (1), taking logarithms, differentiating with respect to time and rearranging gives the dynamic demand-side Kaldor-Verdoon Law:[1]

$$T\hat{F}P = \left(\frac{\varphi}{v}\right) + \left(1 - \frac{1}{v}\right)\hat{Y} \tag{3}$$

where $v = \gamma + \eta$. The growth rate of TFP is defined as $T\hat{F}P \equiv \hat{Y} - T\hat{F}I$, where $T\hat{F}I \equiv \alpha'\hat{K} + (1-\alpha')\hat{L}$ is the growth rate of Total Factor Inputs (TFI).

[1] In the Kaldorian literature there is a long-lasting debate about the direction of normalization of equation (3). This debate is not pursued here. For a detailed discussion of this debate, see McCombie (2002) and McCombie and Roberts (2007).

Equation (3) indicates that productivity growth is determined by the growth of value added, which is in turn driven by the growth of demand. Thus, if $\gamma > 1$ (i.e. $\beta > 1 - \alpha$), there are *static* increasing returns to scale, while if $\eta > 0$ there are *dynamic* increasing returns to scale. Consequently, if $\gamma > 1$, or $\eta_i > 0$, or both, then the second term between parentheses in the right side of equation (3) is positive, which indicates the existence of increasing returns to scale. This specification is different from the original specification of Kaldor-Verdoorn's Law, given by $\hat{P} = a + b\hat{Y}$ (where $\hat{P}$ is the growth of labour productivity and $b$ is the Verdoorn coefficient), due to the fact that equation (3) takes explicit account of capital accumulation. Nonetheless, the interpretation of the two relationships is similar, and should in fact present the same results in terms of the magnitude of returns to scale. Hence, it is possible to consider that the second term between parentheses in the right side of equation (3) as analogous to the original Verdoorn coefficient.

### *2.2. Expanded Kaldor-Verdoorn's Law*

Notwithstanding the importance of demand for productivity growth, other factors might influence the speed of productivity growth across countries and industries. A number of supply-side factors can be considered possible explanations for productivity growth. Just to mention a few examples, there is a large literature that emphasises the importance of institutions for economic growth (e.g. Acemoglu *et al.*, 2001), while there are also works that discuss the importance of the rise of information and communication technology (ICT) for productivity growth (e.g. O'Mahony and Timmer, 2009). Nonetheless, although it is important to take these debates into account, and seek to control for the effect of such variables, this paper's investigation focuses on the main factors emphasised in the Schumpeterian literature.

The Schumpeterian literature places considerable emphasis on the role played by innovation in income growth (e.g. Nelson, 1993; Fagerberg, 1994; Freeman, 1995).[2] In Schumpeterian growth models, research intensity is the main determinant of productivity growth (see Madsen, 2008).[3] The share of resources devoted to research, therefore, becomes the key determinant of productivity growth in this approach. It is important to note, however, that research intensity cannot increase indefinitely, given that resources must be divided between research and production (see Ha and Howitt, 2007). Consequently, when research intensity is held fixed, technical progress can only increase if the efficiency of research increases. Yet, according to the Schumpeterian literature, the growth rate of technical progress can be indefinitely positive, given that knowledge accumulation is assumed to face constant marginal returns (Romer, 1990). This generates increasing returns to scale, pushing economies towards divergence. As

[2] It is important to stress that Schumpeter's (1934, 1943) works have inspired research from different perspectives. On the one hand, Nelson and Winter (1982), Dosi (1982) and others have explored Schumpeter's ideas using an evolutionary framework. On the other hand, Grossman and Helpman (1991), Aghion and Howitt (1992, 1998) and others have explored Schumpeter's ideas using growth models with endogenous technical progress. Still, in spite of the sharp differences in the microeconomic foundations of these traditions, the macroeconomic application of Schumpeter's insights is considerably similar between the two (see Verspagen, 2005, p. 504). In terms of the macroeconomic analysis of the determinants of innovation and growth, authors from both streams emphasise the importance of technology transfer (e.g. Griffith *et al.*, 2004; Verspagen, 1991), finance (e.g. Levine *et al.*, 2000; Fagerberg and Srholec, 2008), research and development (R&D) (e.g. Madsen, 2008; Cohen and Levinthal, 1990; Fagerberg *et al.*, 2007; Archibugi and Coco, 2005) and institutions (e.g. Acemolgu *et al.*, 2006; Lundval, 1992; Nelson, 1993; Metcalfe and Ramlogan, 2008).

[3] Note that Schumpeterian models are different from the semi-endogenous models (e.g. Jones, 1995), which assume a relationship between inputs devoted to R&D and productivity growth.

Young (1998) argued, however, product proliferation can offset these scale effects, which means knowledge accumulation may not necessarily translate into productivity growth.

The Schumpeterian literature also stresses the importance of technological transfer for productivity growth (e.g. Nelson and Phelps, 1966; Fagerberg, 1987, 1988; Griffith *et al.*, 2004; Acemoglu *et al.*, 2006). This literature emphasises that differences in productivity growth rates between countries can be partially explained by the existence of technology gaps, which allow backward countries to absorb foreign technology and grow at higher rates than advanced countries.[4] Indeed, controlling for technological transfer is now commonplace in the Kaldorian literature (e.g. León-Ledesma, 2002; Angeriz *et al.*, 2008, 2009), given that it is crucial to avoid spurious correlation between output growth and productivity growth (see McCombie, 1983; Bairam, 1987).

A straightforward way of incorporating the Schumpeterian insights discussed above into the model presented in the previous section is to introduce research intensity and the technology gap as determinants of autonomous technical progress, so that equation (2) becomes

$$g_A = \varphi + \eta[\alpha'\hat{K} + (1-\alpha')\hat{L}] + \mu T - \sigma G_{t-1} \tag{4}$$

where $T$ is research intensity and $G=TFP/TFP_F$ is the technology gap, where the subscript $F$ denotes the leading economy in each particular industry.

Thus, substituting equation (4) into equation (1) yields an expanded Kaldor-Verdoorn's Law:

$$T\hat{F}P = \left(\frac{\varphi}{v}\right) + \delta\hat{Y} + \left(\frac{\mu}{v}\right)T - \left(\frac{\sigma}{v}\right)G_{t-1} \tag{5}$$

where $\delta = (1 - 1/v)$.

Nonetheless, if research intensity fosters technical progress, then higher research intensity should also increase the response of technical progress to output growth, influencing the magnitude of returns to scale. The Verdoorn coefficient is a measure of encompassing returns to scale, including induced technical progress, internal economies of scale and the division of labour broadly defined. Thus, a higher value of the coefficient reflects a greater effect of the growth of output in raising (inducing) the growth of productivity. Consequently, assuming that research intensity makes the industry's productivity growth more responsive to demand growth, the Verdoorn coefficient becomes positively related to the degree of research intensity. Formally, this means that the Verdoorn coefficient $\delta$ in equation (5) becomes endogenous, given by

$$\delta = \rho + \varepsilon T \tag{6}$$

Thus, substituting (6) into (5) yields

$$T\hat{F}P = \left(\frac{\varphi}{v}\right) - \left(\frac{\sigma}{v}\right)G_{t-1} + \rho\hat{Y} + \left(\frac{\mu}{v}\right)T + \varepsilon T\hat{Y} \tag{7}$$

[4] Recent studies have been exploring the impact of different variables on the speed of technological catch up (e.g. Griffith *et al.*, 2004; Acemoglu *et al.*, 2006; Vanderbussche *et al.*, 2006).

Equation (7) indicates that productivity growth depends not only on output growth and on the technology gap, but that it also depends on the interaction between output growth and research intensity. Hence, this means that countries with higher levels of research intensity benefit from higher increasing returns when output grows.

In this model, therefore, research intensity is assumed to be an exogenous variable. Schmookler (1966) has found evidence of a strong relationship between investment in capital goods user industries and patent applications by capital goods producing industries, which suggests that patenting is a function of effective demand ('demand pull' hypothesis). However, this finding is not free from problems. For example, in a re-examination of Schmookler's findings using data from the Dutch economy, Kleinknecht and Verspagen (1990, p. 394) found evidence of a mutual dependence between demand and innovations, which suggests that not only demand may favour innovation, but also innovation may induce extra demand. Moreover, in León-Ledemsma's (2002) tests, demand has no significant contemporaneous impact on research intensity. Consequently, although the relationship between demand and research intensity deserves further investigation, it is reasonable to consider that research intensity has an exogenous impact on the magnitude of returns to scale.

## 3. Empirical Investigation

### 3.1. Econometric Specification

Similarly to Griffith *et al.* (2004), the regressions reported in this chapter were estimated using panel data models for industries $i$ in countries $j$ at time $t$.[5] A preliminary investigation was carried out to assess the basic Kaldorian and Schumpeterian models, and then equations (5) and (7) were tested. The estimated regressions were

$$T\hat{F}P_{ijt} = \beta_0 + \beta_1\hat{Y}_{ijt} + u_{ijt} \tag{8}$$

$$T\hat{F}P_{ijt} = \beta_0 - \beta_1 \ln G_{ijt-1} + \beta_3 T_{ijt} + u_{ijt} \tag{9}$$

$$T\hat{F}P_{ijt} = \beta_0 - \beta_1 \ln G_{ijt-1} + \beta_2\hat{Y}_{ijt} + \beta_3 T_{ijt} + u_{ijt} \tag{10}$$

$$T\hat{F}P_{ijt} = \beta_0 - \beta_1 \ln G_{ijt-1} + \beta_2\hat{Y}_{ijt} + \beta_3 T_{ijt} + \beta_4 T_{ijt}\hat{Y}_{ijt} + u_{ijt} \tag{11}$$

There are three econometric issues involved in estimating these equations. First, it is necessary to control for unobserved fixed effects (FE). Second, it is also necessary to control for possible measurement errors in the variables, especially TFP and research intensity. Third, it is necessary to deal with endogeneity due to simultaneity between the dependent variable and (i) the technology gap, given that $T\hat{F}P_{ijt} = \ln TFP_{ijt} - \ln TFP_{ijt-1}$ and $\ln G_{ijt-1} = \ln TFP_{ijt-1} - \ln TFP_{Fjt-1}$; (ii) the growth rate of value added, given that

[5] Note that when country-sector panels are regressed, the equation estimated is actually similar to Fabricant's (1942) Law, instead of Kaldor-Verdoorn's Law. The difference between the two is that the former assesses the relationship between output and productivity growth across industries, while the later assesses this relationship across countries. This estimation strategy eliminates endogeneity problems, since it holds constant country- and industry-specific characteristics.

$\hat{TFP}_{ijt} = \hat{Y}_{ijt} - \hat{TFI}_{ijt}$; (iii) research intensity, since higher productivity growth can generate more resources to be invested on research.[6]

In the tests reported in this paper, these problems were addressed employing the System Generalised Method of Moments (SYS-GMM) approach of Blundell and Bond (2000). This method, which has been used in a number of studies (e.g. Baltagi *et al.*, 2000; Griffith *et al.*, 2006), employs a system of equations in levels and in differences to estimate the parameters, using as instruments the lags of the variables in differences and in levels, respectively (see Roodman, 2009A, p. 114). This estimator is a Two-Step Feasible Efficient System GMM estimator, which controls for fixed effects via first differences. The two-step approach is used to obtain a feasible efficient GMM estimator, given that GMM is inefficient in the presence of heteroskedasticity. In the first step a Two-Stage Least Square (2SLS) is regressed. The residuals from the first stage are then employed to form the weighting matrix that is used to eliminate heteroskedasticity, while in the second step the parameters are estimated satisfying the orthogonality conditions of the instruments, i.e. minimising the $L$ moment conditions $E[Z_{ijt}u_{ijt}] = 0$, where $Z$ is the matrix that contains the $L$ included and excluded instruments. However, the identification of the parameters using the System GMM estimator not only requires overidentification, tested using Hansen's J test, but requires also no autocorrelation, which is tested using Arellano and Bond's (1991) Autoregressive (AR) Test.[7]

### 3.2. *Data description*

Kaldor-Verdoorn's Law was estimated using data from the EU KLEMS Database. The sample used comprises up to 15 OECD countries (Australia, Austria, Czech Republic, Denmark, Finland, Germany, Italy, Japan, the Netherlands, Portugal, Slovenia, Spain, Sweden, the USA, and the UK), for which data on value added, capital stock, and number of hours worked by persons engaged in production is consistently available for 12 manufacturing industries over the period 1976–2006 (see O'Mahony and Timmer, 2009). Capital stock is the most restrictive variable in the database (O'Mahony and Timmer, 2009, p. F401), and therefore guides the selection of the countries and time periods adopted in this paper's investigation. To assess the consistency of the data, the value-added accounting identity was checked for each industry, year and country (see Felipe *et al.*, 2008).

The 12 industries were split into two samples following the OECD technological classification (OECD, 2003). The first sample, henceforth called low-tech industries, comprises five low-tech industries (Food, Textiles, Wood, Paper and Other Manufactures) plus three medium-low-tech industries (Plastics, Minerals and Metals). The second sample, henceforth called high-tech industries, comprises three

[6] Kaldor advocated the importance of mechanisms of cumulative causation in the process of economic growth. In this paper's estimates, however, simultaneity between different variables is addressed using instrumental variables to isolate the effect of one particular variable over the other. An alternative to this approach would be to use simultaneous equations. However, using instruments allows to control for additional econometric problems. In this case, therefore, the effects of cumulative causation have to be analysed via the mechanisms of the model. Yet, in theory, unbiased estimates found using different methods should be similar.

[7] As Roodman (2009A, p. 119) argues, 'negative first-order serial correlation is expected in differences and evidence of it is uninformative'. Hence, the relevant test is the AR(2) or higher, depending on the first lag used as instrument (Roodman, 2009A, pp. 108, 124).

medium-high industries (Chemicals, Machinery and Transport) plus the high-tech industry (Electrical).[8] Table A1, in the appendix, presents this classification.

Data on real value added and capital stocks in 1995 US dollars, labour shares, and number of hours worked by persons engaged in production were used to calculate TFP growth rates. Variables in constant 1995 prices were transformed from national currencies to 1995 US dollars using industry-specific PPPs from the Groningen Growth and Development Centre (GGDC) Productivity Level Database (Inklaar and Timmer, 2008).[9]

TFPs were calculated using the log-level index number approach, which is more commonly used in the literature, while capital stocks were divided into two types of assets: information and communication technology (ICT) assets, and Non-ICT assets. The difference between the measures of ICT and Non-ICT assets is twofold: (i) the investment prices used for each asset are different; and (ii) the depreciation rates used for each asset are different as well. No assumptions were made about the returns of each asset, so that the total capital stock of each country is simply calculated as the weighted average of the two types of assets, where the weights are their respective shares in capital compensation. As McCombie (2002, p. 71) argues, this form of weighting does not necessarily imply that factors are paid according to their marginal productivities. Instead, these weights are only used for practical reasons without a particular theoretical justification. Using two different types of capital, however, should generate more accurate measures of capital stocks, especially due to the fact that the depreciation rate of ICT assets is higher than the depreciation rate of Non-ICT assets. Nonetheless, the average correlation between the capital stock calculated using this separation and the capital stock calculated based on gross fixed capital formation for all assets is still very high (0.943).[10] Hence, TFP growth was calculated as

$$T\hat{F}P_{ijt} = \ln\left(\frac{Y_{ijt}}{Y_{ijt-1}}\right) - \frac{1}{2}(\alpha_{ijt} + \alpha_{ijt-1})\ln\left(\frac{K_{ijt}}{K_{ijt-1}}\right) - \frac{1}{2}(\alpha_{ijt}^{ICT} + \alpha_{ijt-1}^{ICT})\ \ln\left(\frac{K_{ijt}^{ICT}}{K_{ijt-1}^{ICT}}\right) \tag{12}$$

$$-\left(1 - \frac{1}{2}(\alpha_{ijt} + \alpha_{ijt-1} + \alpha_{ijt}^{ICT} + \alpha_{ijt-1}^{ICT})\right)\ln\left(\frac{L_{ijt}}{L_{ijt-1}}\right)$$

[8] The Fuels industry was excluded from the investigation, given that TFP movements in this industry present extremely high volatility, possibly due to measurement errors.

[9] Industry-specific PPPs are available for the benchmark year of 1997 (see Inklaar and Timmer, 2008). Thus, PPPs for the year 1995 were calculated following Timmer *et al.* (2007, pp. 50–51), using the formula $PPP_{ijt} \equiv (P_{ijt} / P_{USjt}) \star PPP_{ij1997}$, where $P$ are price indexes with base year 1997, and $PPP_{ij1997}$ is the benchmark PPP. Capital stocks were transformed to US dollars using capital PPPs, which implies assuming that capital efficiency is equal across countries, since PPPs compare the prices of the same good. Although this is a stringent assumption, capital PPPs were used assuming they better represent the relative prices of capital goods than value-added PPPs.

[10] Although it would be important to take into account differences in labour quality as well, data on different types of labour categories (e.g. gender, age, education) has not yet been made available in the EU KLEMS Database. Although this data was used in the calculations of TFP provided by the EU KLEMS project, these estimates assume that relative marginal products equal relative wages, which is a hypothesis avoided in this paper.

Similarly, the technology gap was calculated as[11]

$$\ln G_{ijt} = \ln\left(\frac{Y_{ijt}}{Y_{Fjt}}\right) - \frac{1}{2}(\alpha_{ijt} + \alpha_{Fjt})\ln\left(\frac{K_{ijt}}{K_{Fjt}}\right) - \left(1 - \frac{1}{2}(\alpha_{ijt} + \alpha_{Fjt})\right)\ln\left(\frac{L_{ijt}}{L_{Fjt}}\right) \tag{13}$$

Finally, the ratio of patents to the number of millions of hours worked by persons engaged in production was used as a measure of research intensity in each industry $i$, country $j$ and period $t$.[12] It is common to use patent data gathered from a single patent office to avoid differences in patent legislations between countries (see Soete, 1981; Nagaoca *et al.*, 2010). USPTO is normally the most common choice, given that the USA has the biggest market in the world, so that most high-value patents are registered there. Patents registered at the USPTO were gathered individually, and the first four digits of the respective International Patent Classification (IPC) codes were extracted from each patent registration along with the country of origin of the first author of the patent and the year the patent was granted.[13] Collecting information from each individual patent from the USPTO allowed employing the correspondence table between the IPC 2-digits and the International Standard Industrial Classification (ISIC) (Revision 3) 2-digits developed by Lybbert and Zolas (2014) to find the number of patents from each country in each of the industries of the KLEMS Database. The number of hours worked by persons engaged in production (in millions) used to calculate research intensity is from the EU KLEMS Database.

### 3.3. *Main results*

Table 1 presents the results of the basic Kaldorian and Schumpeterian models, as in equations (8) and (9). Columns (i) to (iii) present the results found using OLS, while columns (iv) to (vi) present the estimates found employing SYS-GMM. In all the models Hansen's J test indicates the instruments are valid at the 10% level of significance, while Arellano and Bond's (1991) AR test indicates that there is no autocorrelation in the lags used as instruments. All the variables are significant and have the anticipated signs. As expected, the technology gap has a negative impact on TFP growth. This impact, however, is small in all the models, and only significant in three of the six regressions, indicating that the gap is not very relevant in the sample analysed.

Columns (i) and (iv) report tests of the basic Schumpeterian model. The results indicate that research intensity has a positive and significant impact on TFP growth. The magnitude of the variable is slightly lower than the 0.03 to 0.09 coefficients commonly found in the literature (see Griliches, 1990; Madsen, 2008; Chang *et al.*, 2013).

Columns (ii) and (v), in turn, report tests of the basic Kaldorian model. The results indicate that output growth has a positive and significant impact on TFP growth. Verdoorn (1949) estimated the relationship between productivity and output growth

[11] This form of measuring the technology gap is widely used in the growth literature (e.g. León-Ledesma, 2002; Griffith *et al.*, 2004; Acemoglu *et al.*, 2006).

[12] See Griliches (1990) and OECD (2008) for detailed discussions on patent data.

[13] There are 4,860,384 patents registered at the USPTO between 1976 and 2012. Using this methodology of data collection led to a sample of 4,187,766 patents, which represents around 86% of the total number of patents registered at the USPTO. The difference between the two numbers is due to patents that did not present the information required for the analysis (IPC, country and year). Patents granted is a better indicator when data from USPTO is used, given that the number of patent applications only started to be disclosed in 1999 in USA (see Nagaoca *et al.*, 2010, p. 1087).

**Table 1.** *Basic Kaldorian and Schumpeterian approaches*

| Model | OLS | OLS | OLS | SYS-GMM | SYS-GMM | SYS-GMM |
|---|---|---|---|---|---|---|
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
| Lag of Gap | -0.00302 | -0.00348*** | -0.00204* | -0.0213 | -0.0838* | -0.0368 |
| | (0.00173) | (0.00101) | (0.00100) | (0.0417) | (0.0328) | (0.0209) |
| Research intensity | 0.0129*** | | | 0.0195* | | |
| | (0.00242) | | | (0.00888) | | |
| Output growth | | 0.728*** | 0.766*** | | 0.666*** | 0.667*** |
| | | (0.0132) | (0.0133) | | (0.116) | (0.103) |
| Lag of Output growth | | | -0.340*** | | | -0.461*** |
| | | | (0.0263) | | | (0.0754) |
| Lag of TFP growth | | | 0.263*** | | | 0.501*** |
| | | | (0.0319) | | | (0.0902) |
| Constant | 0.0204*** | 0.00893*** | 0.00717** | 0.00000160 | -0.0496 | -0.0241 |
| | (0.00364) | (0.00213) | (0.00236) | (0.0328) | (0.0264) | (0.0168) |
| No. Observations | 3948 | 3948 | 3816 | 3948 | 3948 | 3816 |
| Adj. R-Squared | 0.064 | 0.655 | 0.700 | | | |
| No. Instruments/ Lags | | | | 39/2–5 | 63/5–20 | 45/3–6 |
| Arellano-Bond AR Test | | | | 0.297 | 0.348 | 0.253 |
| Hansen J Test | | | | 0.514 | 0.087 | 0.568 |
| Increasing returns ($v$) | | 3.676 | 2.370 | | 2.994 | 1.703 |

*Note*: The dependent variable is the growth rate of TFP. Research intensity is measured by the number of patents per millions of hours worked by persons engaged. The figures reported for the tests are $p$-values. The Arellano-Bond AR test reported refers to the test applied to the first lag used as instrument. Time dummies and robust standard errors were used in all the regressions. The sample comprises 11 OECD countries, 12 industries, over 1976–2006. Significance: *=5%; **=1%; ***=0.1%.

*Source*: Authors' elaboration.

and found the coefficient equal to 0.573, which indicates the existence of considerably large increasing returns to scale, equal to 1/(1–b)=2.341 (see Section 2.1). Kaldor (1966), in turn, found a coefficient of 0.484, which suggests increasing returns of 1.937. The magnitudes of the coefficients of columns (ii) and (v) (0.728 and 0.666) are higher than Verdoorn's (1949) and Kaldor's (1966) estimates, as well as Tharnpanish and McCombie's (2014), indicating returns to scale equal to 3.676 and 2.994, respectively. Nonetheless, these figures are similar to the estimates found in some previous works (e.g. Angeriz *et al.*, 2008, 2009). Thus, following Millemaci and Ofria (2014) and Romero and McCombie (in press), the first lag of output growth and of TFP growth were introduced to capture short-term effects. This reduces the magnitude of the Verdoorn coefficient to 0.578 and 0.412, and the returns to scale to 2.37 and 1.7, respectively, which are figures closer to the original estimates of Verdoorn (1949) and Kaldor (1966).[14]

Table 2, in turn, presents the results of regressing equations (10) and (11) using both OLS and SYS-GMM. The OLS results, presented in columns (i) to (iv), provide benchmark results to be compared with the estimates found using the robust SYS-GMM, which are presented in columns (v) to (viii).

Columns (i) and (v) report the estimates of equation (10). These results indicate that both output growth and research intensity are significant determinants of TFP growth, even when endogeneity due to fixed effects and simultaneity is controlled for. In the SYS-GMM regression, the Hansen test and the Arellano-Bond AR test indicate the validity of the instruments used. Interestingly, the returns to scale found using SYS-GMM and introducing research intensity (1.377) are much lower than the returns to scale found using OLS (3.636). One possible explanation for this finding is that movements in research intensity capture short-term fluctuation of output, bringing the returns to scale to a magnitude similar to the one found when controlling for short-term movements in output and TFP growth, as presented in columns (iii) and (vi) of Table 1.

Columns (ii) and (vi) report the estimates of equation (11). Output growth and the interaction term between output growth and research intensity are significant, while research intensity alone is not significant in the SYS-GMM regression. This corroborates the initial hypothesis, suggesting that the effect of research intensity on productivity growth is indeed stronger when combined with output growth. In other words, this finding indicates that although output growth generates productivity growth through increasing returns to scale, when the country has higher research intensity, the magnitude of the increasing returns is higher. In these regressions, the long-term coefficient that links output growth to productivity growth can be calculated using equation (6). Thus, taking into account that in the sample used the average number of patents per millions of hours worked is 0.333, using this number and the coefficients estimated it is possible to calculate the Verdoorn coefficient $\delta$ using equation (6). From this coefficient it is possible to calculate the degree of returns to scale $v$, given that $\delta = (1 - 1/v)$. The degree of returns to scale found in column (vi) of Table 2 (1.802) is similar to the degree found in column (vi) of Table 1, and not too distant from the seminal estimates of Kaldor (1966).

Columns (iii), (iv), (vii) and (viii) report the results of estimating equation (11), but dividing the sample of sectors into low-tech and high-tech industries, following the OECD classification. In both the OLS and the SYS-GMM regressions, the

[14] Note that the Verdoorn coefficient is now calculated as $n = (1 - 1/v) = (\beta_2 - \beta_3)/(1 - \beta_4)$, where $\beta_3$ and $\beta_4$ are the coefficients of the lags of output and productivity growth, respectively (see Millemaci and Ofria, 2014).

**Table 2.** *Expanded Kaldor-Verdoorn Law*

| Model | OLS | OLS | OLS | OLS | SYS-GMM | SYS-GMM | SYS-GMM | SYS-GMM |
|---|---|---|---|---|---|---|---|---|
| Sample | All industries | All industries | Low-Tech industries | High-Tech industries | All industries | All industries | Low-Tech industries | High-Tech industries |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) | (viii) |
| Lag of Gap | -0.00364*** | -0.00371*** | -0.000389 | -0.00827*** | -0.0509 | -0.0329 | -0.0240 | -0.0261 |
| | (0.00100) | (0.00100) | (0.000588) | (0.00193) | (0.0437) | (0.0205) | (0.0154) | (0.0247) |
| Output growth | 0.725*** | 0.706*** | 0.680*** | 0.726*** | 0.274* | 0.369*** | 0.266** | 0.426* |
| | (0.0132) | (0.0167) | (0.0163) | (0.0211) | (0.110) | (0.0906) | (0.0956) | (0.181) |
| Research intensity | 0.00440*** | 0.00289* | 0.0104*** | -0.00181 | 0.0167+ | 0.00404 | 0.00639 | -0.00487 |
| | (0.00125) | (0.00140) | (0.00184) | (0.00161) | (0.00863) | (0.00678) | (0.00745) | (0.00952) |
| Research intensity*Output growth | | 0.0496** | 0.0566* | 0.0980*** | | 0.228** | 0.330*** | 0.295* |
| | | (0.0183) | (0.0272) | (0.0195) | | (0.0758) | (0.0578) | (0.144) |
| Constant | 0.00635** | 0.00656** | -0.00596*** | -0.00416 | -0.0305 | -0.0136 | -0.0201 | -0.0130 |
| | (0.00221) | (0.00220) | (0.00163) | (0.00418) | (0.0374) | (0.0176) | (0.0124) | (0.0287) |
| No. Observations | 3948 | 3948 | 6909 | 1316 | 3948 | 3948 | 6909 | 1316 |
| Adj. R-Squared | 0.656 | 0.657 | 0.561 | 0.746 | | | | |
| No. Instruments/Lags | | | | | 41/2–4 | 109/2–20 | 53/2–6 | 41/2–3 |
| Arellano-Bond AR Test | | | | | 0.756 | 0.945 | 0.035 | 0.522 |
| Hansen J Test | | | | | 0.073 | 0.074 | 0.037 | 0.301 |
| Long-term coefficient ($\delta$) | 0.725 | 0.723 | 0.697 | 0.778 | 0.274 | 0.445 | 0.362 | 0.583 |
| Increasing returns ($v$) | 3.636 | 3.606 | 3.296 | 4.509 | 1.377 | 1.802 | 1.568 | 2.399 |

*Note*: The dependent variable is the growth rate of TFP. Research intensity is measured by the number of patents per millions of hours worked by persons engaged. The figures reported for the tests are *p*-values. The Arellano-Bond AR test reported refers to the test applied to the first lag used as instrument. Time dummies and robust standard errors are used in all regressions. The sample comprises 11 OECD countries, 12 industries, over 1976–2006. Significance: +=10%; *=5%; **=1%; ***=0.1%.

*Source*: Authors' elaboration.

magnitude of the Verdoorn coefficient is higher for high-tech industries (0.68 and 0.726 for OLS, and 0.266 and 0.426 for SYS-GMM, respectively). This shows that returns to scale are higher in high-tech industries for other reasons than its higher level of research intensity, which is being controlled for. Nonetheless, for the coefficient of the interaction between research intensity and output growth, the magnitude is higher for high-tech industries when using OLS (0.056 and 0.098, respectively), but similar when using SYS-GMM (0.330 and 0.295, respectively). Hence, this result shows that although high-tech industries enjoy higher returns to scale, the effect of research intensity on productivity growth is roughly the same in both low-tech and high-tech industries. Still, for low-tech industries, Hansen's J test rejects the validity of the instruments at the 5% level.

Finally, using the parameters reported in columns (vii) and (viii) and the average number of patents per millions of hours worked of the countries analysed as the proxy for research intensity, it is possible to estimate the changes in the magnitude of increasing returns through time following equation (6). Research intensity increased from an average number of patents per millions of hours worked of 0.09 in 1976 to 0.40 in 2006 in the low-tech sector, while in the high-tech sector it went from 0.22 to 1.08. This led to changes in returns to scale in these two sectors from 1.420 to 1.661, and from 1.965 to 3.937, respectively. Thus, this investigation reveals that not only the degree of returns to scale is higher in the high-tech sector than in the low-tech sector, but that the difference in the returns to scale between the two sectors has been widening through time. Hence, these figures corroborate the findings of Romero and McCombie (in press), which suggested that the degree of returns to scale in manufacturing has increased from the 1970s and 1980s to the 1990s and 2000s, mainly due to an increase in the scale economies observed in high-tech industries. Yet, this paper's analysis indicates that such increase has resulted from increases in the level of research intensity in the high-tech sector.

### *3.4. Robustness assessment*

*3.4.1 Influential outliers.* In order to assess whether the results presented in the previous sections were driven by influential outliers, SYS-GMM models were re-estimated excluding one and two industries at a time, and also excluding one country at a time. All the regressions generated results similar to the ones reported in column (vi) of Table 2.[15]

*3.4.2 Four-year averages.* Kaldor-Verdoorn's Law is normally estimated using five-year averages to remove short-term fluctuations and avoid that the estimates capture Okun's Law, which reflects the short-term correlation between productivity and output growth that stems from the existence of employment rigidities (due to contracts and institutional factors) in the downward phase of the business cycle. The first three columns of Table 3 report estimates of equation (11) using four-year averages.[16] Column (i) shows that using four-year averages increases the magnitude of the Verdoorn coefficient, while research intensity alone and its interaction with output growth are no longer significant. Still, columns (ii) and (iii) indicate that for low-tech industries,

[15] These results are available from the authors.

[16] Four-year averages are used instead of five-year averages in order to increase the number of time periods available in the panel.

**Table 3.** *Expanded Kaldor-Verdoorn Law: robustness analysis*

| Sample | All Industries | Low-Tech Industries | High-Tech Industries | All Industries | All Industries | All Industries | All Industries | All Industries | All Industries | All Industries / Alternative Sample |
|---|---|---|---|---|---|---|---|---|---|---|
| Robustness Test | 4-year Averages | 4-year Averages | 4-year Averages | R&D/Value Added | R&D/Value Added | Different Lags | Alternative Sample | Additional Variable | Additional Variable | Additional Variable |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) | (viii) | (ix) | (x) |
| Lag of Gap | -0.0287* | -0.0221 | -0.0296* | -0.0549 | -0.0404* | -0.0552** | -0.00676 | -0.0104 | -0.0492** | -0.0237 |
| | (0.0132) | (0.0276) | (0.0137) | (0.0450) | (0.0196) | (0.0165) | (0.0159) | (0.0160) | (0.0164) | (0.0196) |
| Output growth | 0.527** | 0.762** | 0.572* | | 0.399*** | 0.552*** | 0.265* | 0.316*** | 0.563*** | 0.448** |
| | (0.168) | (0.254) | (0.216) | | (0.0748) | (0.113) | (0.131) | (0.0640) | (0.0668) | (0.153) |
| Research intensity | 0.000971 | 0.0171* | -0.00888 | 0.225* | -0.000945 | 0.00435 | -0.00325 | | | |
| | (0.00813) | (0.00852) | (0.00536) | (0.113) | (0.0735) | (0.00909) | (0.00599) | | | |
| Research intensity*Output growth | 0.142 | -0.0164 | 0.283** | | 1.047* | 0.194* | 0.221** | 0.167*** | 0.107* | 0.149+ |
| | (0.135) | (0.142) | (0.102) | | (0.504) | (0.0877) | (0.0842) | (0.0493) | (0.0489) | (0.0791) |
| Lag of Human capital | | | | | | | | -0.000688 | | |
| | | | | | | | | (0.000756) | | |
| Government size | | | | | | | | | 0.00451** | |
| | | | | | | | | | (0.00138) | |
| Property Rights | | | | | | | | | | -0.0000148 |
| | | | | | | | | | | (0.000869) |
| Constant | -0.00750 | -0.0246 | -0.0106 | -0.0290 | -0.0161 | -0.0359* | 0.0151 | 0.0195 | -0.117*** | -0.00313 |
| | (0.00959) | (0.0175) | (0.0139) | (0.0319) | (0.0155) | (0.0147) | (0.0151) | (0.0129) | (0.0307) | (0.0792) |
| No. Observations | 924 | 1617 | 308 | 3502 | 3502 | 3948 | 1716 | 3948 | 3948 | 1584 |
| No. Instruments/Lags | 23/2–4 | 22/5–7 | 19/2–3 | 45/2–8 | 129/2–25 | 97/3–18 | 38/2–7 | 133/2–26 | 133/2–26 | 26/2–4 |

**Table 3.** *Continued*

| Sample | All Industries | Low-Tech Industries | High-Tech Industries | All Industries | All Industries | All Industries | All Industries | All Industries | All Industries | All Industries / Alternative Sample |
|---|---|---|---|---|---|---|---|---|---|---|
| Robustness Test | 4-year Averages | 4-year Averages | 4-year Averages | R&D/Value Added | R&D/Value Added | Different Lags | Alternative Sample | Additional Variable | Additional Variable | Additional Variable |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) | (viii) | (ix) | (x) |
| Arellano-Bond AR Test | 0.225 | 0.927 | 0.527 | 0.379 | 0.718 | 0.174 | 0.307 | 0.878 | 0.993 | 0.342 |
| Hansen J Test | 0.060 | 0.040 | 0.412 | 0.942 | 0.183 | 0.099 | 0.253 | 0.143 | 0.079 | 0.099 |
| Long-term coefficient (n) | 0.527 | 0.762 | 0.723 | - | 0.437 | 0.617 | 0.273 | 0.372 | 0.599 | 0.498 |
| Increasing returns (v) | 2.114 | 4.202 | 3.608 | - | 1.775 | 2.608 | 1.375 | 1.591 | 2.491 | 1.991 |

*Note*: The dependent variable is the growth rate of TFP. All the estimates were regressed using System GMM. Research intensity is measured by the number of patents per hours worked. The figures reported for the tests are *p*-values. The Arellano-Bond AR test reported refers to the test applied to the first lag used as instrument. Time dummies and robust standard errors are used in all the regressions. The sample comprises 11 OECD countries, 12 industries, over 1976–2006. The Alternative sample comprises 14 OECD countries (not including Czech Rep.), 12 industries, over 1995–2006. Significance: +=10%; *=5%; **=1%; ***=0.1%.

*Source*: Authors' elaboration.

although the interaction between research intensity and output growth is still not significant, research intensity is, the opposite applying to high-tech industries. Hence, the results presented in the first three columns of Table 3 provide some support to the results reported in Table 2. Yet, it seems that using four-year averages tends to increase the magnitude of the Verdoorn coefficient and reduce the effect of research intensity on productivity growth.

*3.4.3 Alterative measure.* Table 3 also presents estimates using the ratio of R&D expenditure to value added as an alternative measure of research intensity. The R&D data used in these tests was gathered from the OECD Analytical Business Enterprise Research and Development (ANBERD) Database, for the period 1976–2006. Data from 1987 to 2006 is available classified according to ISIC Rev. 3, while from 1976 to 1986 data is at ISIC Rev. 2. Nonetheless, at the level of aggregation used this does not represent a problem, and it is straightforward to make the data compatible. The correspondence between the two classifications becomes more complex only at higher levels of disaggregation.

R&D to output has been used in a number of studies to measure research intensity, and although the results normally indicate that the variable has a positive impact on productivity growth, the estimated coefficients vary considerably. Zachariadis (2004) found that research intensity has a positive and significant impact on productivity growth, but the estimated effect varies from 0.47 to 1.69 using data for the economy as a whole, and from 0.24 to 0.32 using industry-level data. Griffith *et al.* (2004) found similar results using industry-level data, with coefficients varying from 0.34 to 0.86. In another study, Madsen (2008) examines a number of different measures of research intensity, including patents per capita and R&D to GDP ratio. For the latter measure, a positive and significant coefficient of 0.007 was found.

The regression reported in column (iv) of Table 3 replicates the test of the basic Schumpeterian models presented in Table 1. The result is similar to previous studies, and indicates that research intensity has a positive and significant effect on productivity growth. Column (v) shows that when output growth is introduced in the regression research intensity is no longer significant. Multicolinearity between the two variables does not seem to pose a problem, since the correlation between them is 0.21. The interaction term, however, has a positive and significant impact on productivity growth. The magnitude of the estimated coefficient is higher than found in the tests that employed patents per millions of hours worked as a measure of research intensity. However, this is because the level of the variables is different. In the sample, the average number of patents per millions of hours worked is 0.333, while the average R&D to value added ratio is 0.036. Consequently, using this average to calculate the returns to scale following equation (6), given that $\delta = (1 - 1/v)$, the implied degree of returns to scale found using R&D to value added ratio (1.776) is indeed very similar to the degree found using patents per millions of hours worked (1.802). Thus, these tests provide additional support to the results reported in Table 2.

*3.4.4 Different lags as instruments.* As Roodman (2009B) emphasised, SYS-GMM generates a large number of instruments and this instrument proliferation weakens the capacity of the Hansen J test to detect violation of the orthogonality hypothesis. One form of solving this problem, as Roodman (2009B) stressed, is to limit the lags used as instruments. Nonetheless, it is often the case that using different lags as instruments leads to marked changes in the estimated parameters, while Arellano and Bond's AR test and Hansen's J test still indicate the validity of the instruments. In this case, it is difficult to assess what is the preferred specification.

Column (vi) shows the results found using SYS-GMM but instrumenting with lags that are different from those used in the tests reported in Table 2. The results are similar to the benchmark regression reported in column (vi) of Table 2, although the returns to scale found are higher (2.611) then in the other regressions, but still similar to Verdoorn's (1949) original estimates.

*3.4.5 Alternative sample.* As mentioned in Section 3.2, from 1995 onwards the basic data from EU KLEMS is available for four additional countries: Czech Republic, Portugal, Slovenia and Sweden. In the tests reported thus far, a sample of 11 OECD countries over the period 1976–2006 has been used.

Column (vii) of Table 3 presents the results found adding Portugal, Slovenia and Sweden to the sample, but considering only the period 1995–2006. Czech Republic was excluded from the sample, given that additional tests revealed that this country is an influential outlier. This shows that further work is necessary to assess whether the investigated relationship holds for more comprehensive samples of countries. This caveat notwithstanding, the results reported in column (vii) are similar to the results found in Table 2. Both output growth and the interaction term are significant and present magnitudes similar to the previous tests.

*3.4.6 Additional variables.* Table 3 reports also tests assessing the robustness of the results to the inclusion of three additional variables that might explain productivity growth: (i) human capital; (ii) government size; and (iii) quality of property rights.

A number of works emphasise the importance of human capital for productivity growth (e.g. Barro, 1991; Mankiw *et al.*, 1992; Krueger and Lindahl, 2001; Barro and Lee, 2013). Furthermore, the importance of human capital is also stressed in the Schumpeterian approach. Following the seminal approach of Nelson and Phelps (1966), human capital is considered not only important to generate innovations, but also to allow the absorption of foreign knowledge (e.g. Verspagen, 1991; Griffith *et al.*, 2004). In the same spirit, R&D intensity is regarded relevant for the absorption of foreign technology as well (e.g. Cohen and Levinthal, 1990; Griffith *et al.*, 2004). There is evidence, however, that human capital is more important for countries closer to the technological frontier (Vanderbussche *et al.*, 2006).

In addition, several studies analyse the impact of the size of government on economic performance (e.g. Barro, 1991). The argument is normally that large governments generate inefficiencies, so that the higher the government expenditure in proportion to GDP, the lower the productivity growth.

Finally, a number of works have been exploring the relationship between the quality of institutions and productivity growth (e.g. La Porta *et al.*, 1999; Acemoglu *et al.*, 2001; Djankov *et al.*, 2002; Rodrik *et al.*, 2004). This literature explores the relationship between productivity growth and different institutions, such as property rights, type of legal system, corruption and bureaucracy. The quality of property rights, however, is the most important variable used in this literature. Furthermore, apart from type of legal system, which is usually not significant, the other variables are highly correlated, so that countries with good property rights normally feature low corruption and low bureaucracy as well.

The last three columns of Table 3, therefore, present the results of regressing equation (11), whereby each of these additional variables is introduced one at a time. Research intensity was dropped from these regressions, since it has been found to be not significant in most tests. The variables used in this analysis are the following. Human capital is the percentage of population with tertiary education, from Barro and Lee (2013).[17] Government size is the share of government expenditure in GPD, from World Development Indicators. Quality of property rights is measured by the Property Rights Index from the Heritage Foundation, used by La Porta *et al.* (1999). Given that this variable is only available from 1995 onwards, the alternative sample is used when testing the effect of this variable.

Columns (viii) to (x) of Table 3 show that the results reported in the previous sections do not change significantly when human capital, government size and property rights are introduced in the estimated equation. Interestingly, the only variable that is significant is government size, which actually has a positive impact on productivity growth. A possible explanation for this positive effect is that higher public investment might foster innovation, which contributes to productivity growth.

## 4. Concluding remarks

This paper investigated whether output growth and research intensity impact on productivity growth, testing two alternative hypotheses. First, the simultaneous impact of the two variables on productivity growth was tested. This allowed assessing if the basic Kaldorian and Schumpeterian models can be combined. Second, it was examined whether research intensity impacts on the magnitude of returns to scale, assessing if countries with higher research intensity benefit from higher returns to scale.

This inquiry revealed that higher research intensity generates higher productivity growth (dynamic return to scale) when associated with output growth. This result is interpreted as an indication that higher research intensity generates higher knowledge, which allows faster technical progress in response to output growth. Research intensity alone, however, is rarely significant when the impact of output growth on productivity growth is controlled for. The results reported in the paper are robust to (i) the use of different econometric methods; (ii) different samples; (iii) different measures of research intensity; (iv) different instruments to control for endogeneity; and also (v) the inclusion of additional variables in the estimated equations.

However, in spite of the fact that research intensity influences the magnitude of returns to scale both in low-tech and in high-tech industries, the exogenous part of the Verdoorn coefficient (in relation to research intensity) is still higher in high-tech than in low-tech industries. In other words, although research intensity has a positive impact on scale economies, differences in supply-side characteristics generate distinct returns to scale in low-tech and high-tech industries. These results complement and reinforce the results found by Romero and McCombie (in press).

The results reported in this paper generate three main policy implications. First, the results suggest that fostering increases in research intensity contributes to increasing productivity growth in response to output growth. Second, policies should also aim to

[17] Although it would be preferable to use data from the EU KLEMS Database to measure human capital in each sector, this data (used in the calculations of TFP provided by the EU KLEMS project) is not available for the general public.

sustain demand growth, given that this paper's results suggest that research intensity only fosters productivity growth when associated with demand growth. Third, fostering the production of high-tech products contributes to increase the economy's overall productivity growth, given that these industries present higher returns to scale.

To sum up, the tests reported in this paper provide strong evidence of the importance of demand growth for productivity growth and of the existence of increasing returns to scale in manufacturing, while also recognising the relevance of research intensity for productivity growth. Most importantly, the test results suggest that research intensity has a more relevant impact on the degree of returns to scale than directly on productivity growth. Moreover, the tests indicate that returns to scale are higher in high-tech industries than in low-tech industries, notwithstanding the fact that the impact of research intensity on the magnitude of scale economies is similar in both groups of industries.

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## Appendix

**Table A1.** *EU KLEMS Database: manufacturing industries for which data is available*

| ISIC (Rev. 3) categories [KLEMS Code] | Description | Resumed name | OECD Tech. Class. |
|---|---|---|---|
| 15 to 16 | Food products, beverages and Tabaco | Food | LTM |
| 17 to 19 | Textiles, textile products, leather and footwear | Textiles | LTM |
| 20 | Wood and products of wood and cork | Wood | LTM |
| 21 to 22 | Pulp, paper, paper products, printing and publishing | Paper | LTM |
| 23 | Coke, refined petroleum products and nuclear fuel | Fuels | MLTM |
| 24 | Chemicals and chemical products | Chemicals | MHTM |
| 25 | Rubber and plastics products | Plastics | MLTM |
| 26 | Other non-metallic mineral products | Minerals | MLTM |
| 27 to 28 | Basic metals and fabricated metal products | Metals | MLTM |
| 29 | Machinery, n.e.c. | Machinery | MHTM |
| 30 to 33 | Electrical and optical equipment | Electrical | HTM |
| 34 to 35 | Transport equipment | Transport | MHTM |
| 36 to 37 | Manufacturing n.e.c., recycling | Recycling | LTM |

*Note:* LTM = Low-Tech Manufacturing; MLTM = Medium-Low Tech Manufacturing; MHTM = Medium-High Tech Manufacturing; HTM = High-Tech Manufacturing.

*Source:* Author's elaboration based on O'Mahony and Timmer (2009, p. F400).