Differences in Increasing Returns Between Technological Sectors: A Panel Data Investigation Using the EU KLEMS Database

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Differences in Increasing Returns Between Technological Sectors: A Panel Data Investigation Using the EU KLEMS Database

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Abstract:

Purpose: The aim of this paper is twofold: to investigate the existence of different degrees of returns to scale in low-tech and high-tech manufacturing industries; and to examine whether the degrees of returns to scale change through time.

Design/methodology/approach: The empirical investigation implemented in the paper uses data from the EU KLEMS Database, covering a sample of 12 manufacturing industries in 11 OECD countries over the period 1976-2006. The investigation employed two different estimation methods: Instrumental Variables and System GMM. The robustness of the results was assessed by employing two different specifications of Kaldor-Verdoorn's Law, by using lags and 5-year averages to smooth business cycle fluctuations, and by dividing the sample into two time periods.

Findings: The results reported in the paper provide strong evidence in support of the hypothesis of substantial increasing returns to scale in manufacturing. The investigation suggests that high-tech manufacturing industries exhibit larger degrees of returns to scale than low-tech manufacturing industries. Finally, the analysis revealed also that the magnitude of the returns to scale in manufacturing have increased in the last decades, driven by increases in the magnitude of returns to scale observed in high-tech industries.

Originality/value: No previous work has assessed the hypothesis that increasing returns to scale vary according to the technological content of industries. Moreover, no previous work has used System GMM or data from EU KLEMS to test Kaldor-Verdoorn's Law. Most importantly, the findings of the paper present new evidence on the degree of returns to scale in high-tech and low-tech manufacturing industries.

Keywords: Increasing Returns; Kaldor-Verdoorn's Law; Productivity Growth; Manufacturing sector.

Paper type: Research paper.

JEL: O11; O47; O40.

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1. Introduction

Kaldor's Cambridge Inaugural Lecture in 1966 represented the starting point of a long tradition of investigation into the existence of increasing returns to scale. In this lecture, Kaldor (1966) presented evidence of the positive impact of output growth on the growth rate of productivity, which was interpreted as an indication of the existence of increasing returns to scale, broadly defined, in manufacturing. Kaldor called this relationship Verdoorn's Law, in reference to the Dutch economist Petrus Verdoorn (1949), who was one of the first to observe this empirical regularity. However, the relationship is often called Kaldor-Verdoorn's Law, given the importance of Kaldor's contributions to this debate.

The purpose of this paper is twofold. Firstly, the paper investigates whether or not the degree of increasing returns to scale varies according to the technological level of industries, by estimating Kaldor-Verdoorn's Law for low-tech and high-tech manufacturing industries. To date, as far as we are aware, Kaldor-Verdoorn's Law has not been tested adopting a technological classification of industries. In the Schumpeterian literature, technological classifications of industries are often used to stress differences in the dynamics of production, innovation and growth in different sectors (e.g. Pavit, 1984; Lall, 2000). Nonetheless, in spite of the interesting results found in the studies that follow this approach, only recently have Kaldorian studies started to carry out empirical investigations using technological classifications (e.g. Gouvêa and Lima, 2010; Romero *et al.*, 2011; Gouvêa and Lima, 2013; Romero and McCombie, 2016). Secondly, following Millemaci and Ofria's (2014) investigation, the paper examines whether the degree of increasing returns to scale varies through time, estimating Kaldor-Verdoorn's Law for different time periods.

The tests reported in this paper provide also a contribution in terms of the method used to estimate Kaldor-Verdoorn's Law. This study has used cross-country-industry panel data to test the law, whereas it is usually estimated by cross-country or cross-region regressions. Using cross-country-industry panels to estimate Kaldor-Verdoorn's Law considerably increases the number of observations available, improving the efficiency and consistency of the regressions. Furthermore, the tests reported in this paper employ modern panel data techniques not previously explored in this literature, using the specification proposed by Millemaci and Ofria (2014).

The remainder of the paper is organized as follows. Section 2 presents Kaldor-Verdoorn's Law. Section 3 discusses the empirical evidence regarding the law. Section 4 presents the empirical investigation, discusses the database, the estimation model and method, and the results. Section 5 concludes the paper.

2. The Model

The model investigated in this paper is an extension of the original Kaldor-Verdoorn Law, and incorporates the effect of technological transfer on the growth rate of productivity. The model can be described using the following production function and technical progress relationship:

$$Y = Ae^{g_A t} K^{\alpha} L^{\beta} \qquad (1)$$

$$g_A = \varphi + \eta[\alpha' \hat{K} + (1-\alpha')\hat{L}] - \sigma G_{t-1} \qquad (2)$$

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. The parameters α and β are respectively the output elasticities of capital and labour, so that $(\alpha+\beta) = \gamma[\alpha' + (1-\alpha')]$, where γ is a measure of the degree of static returns to scale and α' is the share of capital in total value added (Angeriz *et al.*, 2009).[1] Furthermore, φ is the rate of exogenous technical progress, η is the elasticity of induced technological progress, and G=ln(TFP/TFP_F) is the technology gap, with the subscript F denoting the frontier or most technological advanced economy, and where TFP is the level of total factor productivity.[2] Finally, the circumflex over the variables denotes growth rates.

Hence, substituting the technical progress equation (2) into the production function given by equation (1), taking logarithms, differentiating with respect to time and rearranging gives the *dynamic* demand-oriented Kaldor-Verdoorn Law:[3]

[1] Note that the rate of induced technical change is ultimately a function of the growth of output, given that the growth of inputs is driven by the growth of demand, i.e. $[\alpha' \hat{K}_{ijt} + (1-\alpha')\hat{L}_{ijt}] = f(\hat{Y}_{ijt})$.

[2] This form of measuring the technology gap is now widely used in the growth literature (e.g. León-Ledesma, 2002; Griffith *et al.*, 2004; Acemoglu *et al.*, 2006; Madsen, 2008), and is sometimes called proximity, or distance, to the frontier.

[3] See McCombie and Spreafico (2015) for an alternative interpretation of Kaldor-Verdoorn's law.

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

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).

This specification is different from the original specification of Kaldor-Verdoorn's Law, which has labour productivity growth as the dependent variable. In other words, the original Kaldor-Verdoorn's law is given by $\hat{P} = a + b\hat{Y}$, where $\hat{P}$ is the growth of labour productivity and b is the Verdoorn coefficient. The law given by equation (3) takes explicit account of capital accumulation. According to Wolfe (1968), the exclusion of the growth rate of capital stock as a determinant of labour productivity growth in Kaldor's (1966), due to data limitations at the time, estimates of Kaldor-Verdoorn's Law might be biases upwards. Kaldor omitted the effect of capital accumulation on productivity growth by assuming the stability of the capital-output ratio (i.e., $\hat{K} = \hat{Y}$), which is one of his stylized facts. Under this assumption, when productivity growth is regressed on output growth, a statistically significant coefficient on the growth of output is sufficient to indicate the presence of increasing returns to scale.

Nonetheless, as McCombie (1983: 418) argued, if $\hat{K} \neq \hat{Y}$, the correct specification of the Kaldor-Verdoorn Law must incorporate the growth rate of capital stock. Alternatively, however, using TFP growth instead of labour productivity growth solves this problem. This is because TFP growth explicitly captures the contribution of the growth of the capital stock. In addition, this method also avoids multicolinearity between the growth rates of output and of capital stock if both are specified as regressors. Moreover, it also solves the problem of the likely endogeneity of the growth of the capital stock, as this is determined by the growth of the output.

3. Empirical Evidence on Kaldor-Verdoorn's Law

Petrus Verdoorn and Nicholas Kaldor were the first to test the relationship between productivity growth and output growth. Verdoorn (1949) estimated this relationship for a sample of 13 OECD countries and found the coefficient of output growth equal to 0.573, which indicates the existence of considerably large increasing returns to scale, equal to $1/(1-b) = 2.341$. Kaldor (1966), in turn, tested the law using different specifications for a sample of 12 OECD countries over the period 1953-64, and found a coefficient of 0.484 linking productivity and output growth in manufacturing, indicating increasing returns of 1.937. In addition, Kaldor (1966) also assessed the existence of increasing returns to scale in non-manufacturing sectors, and found that non-manufacturing sectors are subject to constant or decreasing returns to scale.[4]

Following the seminal estimates of Verdoorn and Kaldor, a number of works have tested Kaldor-Verdoorn's Law using different samples and different econometric techniques. McCombie and de Ridder (1983) and León-Ledesma (2002), for instance, have tested the validity of law using US cross-regional and cross-country data respectively while using instrumental variables to control for simultaneity. Other works have used time-series data to test the law. According to McCombie and de Ridder (1983), however, using time-series data might be problematic due to the existence of employment rigidities (due to contracts and institutional factors) in the downward phase of the business cycle. This can induce a spurious reduction in productivity that reflects Okun's Law. Thus, to avoid this problem, McCombie and Ridder (1984: 385) suggested adjusting the data for short-term fluctuations. This estimation strategy was used by McCombie and de Ridder (1983), Harris and Liu (1999) and Oliveira *et al.*, (2006). Millemaci and Ofria (2014), however, used time-series techniques to estimate the law for 11 OECD countries using lags of productivity and output growth to control for short-term fluctuations. Finally, in addition to time-series and cross-country analyses, a large number of studies have used regional data to investigate the validity of Kaldor-Verdoorn's Law (e.g. McCombie and Ridder, 1984; León-Ledesma, 1999; 2000; Hansen and Zhang, 1996). In comparison with cross-country regressions, using cross-region data not only increases the number of observations available, but it also reduces differences in autonomous productivity growth stemming from technological transfer. Moreover, several of the works that employed regional data have used models that control for spatial autocorrelation (e.g. Bernat, 1996; Fingleton and McCombie, 1998; Angeriz *et al.*, 2008; Alexiadis and Tsagdis; 2010). Most importantly, the results of all the

[4] See McCombie (2002) for a broad review of the critiques directed to Kaldor-Verdoorn's Law.

studies mentioned above suggest the existence of substantial increasing returns to scale in manufacturing.[5]

Although there is now an extensive literature on Kaldor-Verdoorn's Law, there are relatively few studies that inquire into the existence of increasing returns at a more disaggregated levels of analysis. McCombie and de Ridder (1983), for instance, estimated Kaldor-Verdoorn's Law for different sectors using both regional data from US and country data from 12 OECD countries. They found that manufacturing presents increasing returns to scale, while agriculture, mining, services and the economy as a whole present constant returns to scale. McCombie (1985) estimated the law using state data for US manufacturing at the two-digit standard industrial classification level and found virtually all industries exhibited large increasing returns to scale. Leon-Ledesma (2000), in turn, estimated Kaldor-Verdoorn's Law for different sectors using regional data from Spain. His results suggested the existence of constant returns to scale in construction and agriculture (with a very poor fit for the latter), and of increasing returns in manufacturing and total value added. Inconclusive evidence of increasing returns was found for services. More recently, Angeriz *et al.* (2009) estimated Kaldor-Verdoorn's Law for six different sectors across European regions. They found evidence of increasing returns to scale in all sectors, although finding differences in the degree of increasing returns. Likewise, Tharnpanich and McCombie (2014) found evidence of increasing returns in different sectors using regional data from Thailand.

4. Empirical Investigation

4.1. Data description

This paper reports estimates of Verdoorn's Law using data from the EU KLEMS Database (version of March 2011) over the period 1976-2006. This database provides disaggregated data on value added, number of hours worked by persons engaged, and capital stock for 25 European countries, plus the United States and Japan. The EU KLEMS is based on data from national statistical institutes and other

[5] An extensive coverage of the empirical works on Kaldor-Verdoorn's Law is found in McCombie, Pugno and Soro (2002).

additional sources, and has been constructed paying careful attention to several of the problems that involve measuring output and productivity at the industry level.[6]

The results reported in this paper were obtained using a sample of 11 OECD countries (Australia, Austria, Denmark, Finland, Germany, Italy, Japan, Netherlands, Spain, USA, and the United Kingdom), for which data on value added, capital stock, and number of hours worked by persons engaged is consistently available for 12 manufacturing industries over the period 1976-2006 (see O'Mahoney and Timmer, 2009: F400). Capital stock is the most incomplete variable in the database (O'Mahoney and Timmer, 2009: 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. The first sample, henceforth called low-tech industries, comprises 5 low-tech industries (Food, Textiles, Wood, Paper and Other Manufactures) plus 3 medium-low-tech industries (Plastics, Minerals and Metals). The second sample, henceforth called high-tech industries, comprises 3 medium-high industries (Chemicals, Machinery and Transport) plus the high-tech industry (Electrical).[7]

Data on real value added and capital stocks in 1995 US dollars, labour shares, and number of hours worked by persons engaged were used to calculate TFP growth rates and technology gaps.[8] 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]

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[6] See Timmer *et al.* (2007) and O'Mahoney and Timmer (2009) for detailed descriptions of the EU KLEMS Database.

[7] The Fuels industry was excluded from the investigation, given that TFP movements in this industry present high spikes, possibly resulting from measurement errors or abrupt changes in oil prices.

[8] TFPs have been calculated dividing capital stocks 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 also differ. No assumptions were made about the rate of return 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.

[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: 50-1), using the formula:

The technology gap, in turn, was calculated as:[10]

$$\ln G_{ijt} = \ln\left(\frac{Y_{ijt}}{Y_{Fjt}}\right) - \frac{1}{2}(\alpha_{ijt} + \alpha_{Fjt})\ln\left(\frac{K_{ijt}}{K_{Fjt}}\right) - \left(1 - \frac{1}{2}(\alpha_{ijt} + \alpha_{Fjt})\right)\ln\left(\frac{L_{ijt}}{L_{Fjt}}\right) \quad (4)$$

Table 1 reports the average growth rates of productivity and output by 5-year periods, in low-tech and high-tech industries. This table presents three important pieces of information. First, the table shows that, taking into account the average growth rates of productivity and output for the sample as a whole, the growth rates of both observed in the high-tech industries are about twice as large as the rates observed in the low-tech industries. This observation is the main driver of this paper's analysis. Secondly, the table shows that in both sectors there was a considerable reduction in the average output and productivity growth rates during the 1990s. Third, the table shows also that during the 2000s, the average output and productivity growth rates increased to levels similar to the period 1976-1989.

< Table 1 >

4.2. Estimation model and methods

Following equation (3), the structural equation to be estimated is:

$$T\hat{F}P_{ijt} = \beta_0 - \beta_1 \ln G_{ijt-1} + \beta_2 \hat{Y}_{ijt} + u_{ijt} \quad (5)$$

where u is the error term, i denotes industries, j denotes countries, and t denotes time periods. It is interesting to note that when country-industry panels are regressed, as in the model represented in equation (5), the equation estimated is actually an

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$PPP_{ijt} \equiv (P_{ijt} / P_{USjt}) * PPP_{ij1997}$, 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 are used assuming that they better account for the relative prices of capital goods than the value added PPPs.

[10] Analogous measures of the technology gap are used by Bernard and Jones (1996), Griffith *et al.* (2004), Acemolgu *et al.* (2006), and Madsen (2008). The log-level approach is adopted in this paper to follow the more common approach used in the literature.

amalgamation of Fabricant's (1942) Law and Kaldor-Verdoorn's Law. The difference between the two is that the former estimates the relationship between productivity growth and output growth across *industries*, whereas the latter carries out the same assessment, but across countries (or regions). In practice, however, the results found using both specifications are similar (see also Salter, 1960).[11]

There are two econometric issues involved in estimating equation (5). First, it is necessary to control for unobserved country and industry fixed effects (FE). Second, it is necessary to deal with the possible endogeneity due to simultaneity between productivity growth and output growth, and between productivity growth and the lagged technology gap, given that $\ln G_{ijt-1} = \ln TFP_{ijt-1} - \ln TFP_{Fijt-1}$, while $T\hat{F}P_{ijt} = \ln TFP_{ijt} - \ln TFP_{ijt-1}$.

Moreover, as discussed in the previous section, when estimating Kaldor-Verdoorn's law using time-series data, it is important to separate the long-term effect of demand growth on productivity growth, from the short-term effects of business cycle fluctuations (Okun's Law). One way of avoiding this problem is to take 5-year averages to smooth business-cycle fluctuations. Alternatively, it is also possible to introduce one-period lags of the variables into the regression model, as done by Millemaci and Ofria (2014), so that the structural equation (3) becomes:

$$T\hat{F}P_{ijt} = \beta_0 - \beta_1 G_{ijt-1} + \beta_2 \hat{Y}_{ijt} - \beta_3 \hat{Y}_{ijt-1} + \beta_4 T\hat{F}P_{ijt-1} + u_{ijt} \qquad (6)$$

Interestingly, this specification is similar to the transformation of Kaldor-Verdoorn's Law proposed by Roberts (2007). Examining the convergence properties of Dixon and Thirlwall's (1975) model of growth, Roberts observes that the model predicts too fast a rate of convergence. He shows that introducing the lagged productivity growth to capture the adjustment between short-term and long-term productivity growth rates brings the expected convergence rate closer to levels

[11] The existence of increasing returns to scale can be investigated using different methodologies, such as Data Envelopment Analysis (e.g. Banker and Thrall, 1992; Angeriz *et al.* 2006), or by estimating production functions and assessing the magnitude of the sum of the elasticities of factor inputs (e.g. Perälä, 2008). This paper follows Kaldor's (1966) approach and estimates returns to scale assessing the impact of output growth on productivity growth. Kaldor used this approach to avoid separating changes in the stock of capital from changes in technology. According to him, such attempt is problematic, given that as capital is accumulated, more productive vintages of capital are incorporated, entangling capital accumulation and technical progress. Moreover, the rate of technical change is also determined by the rate of growth of output through learning-by-doing.

normally found in the literature. Likewise, the introduction of the lagged output growth in equation (6) aims to capture the adjustment between short-term and long-term output growth rates.

In equation (6), however, it is necessary to control also for the endogeneity of the lagged variables. Not only the lagged dependent variable is endogenous (see Roodman, 2009: 104), but it is important to note that lagged output growth can also be correlated with the dependent variable, given that $T\hat{F}P_{ijt} = \ln TFP_{ijt} - \ln TFP_{ijt-1}$, while $\hat{Y}_{t-1}$ can be determined by $\ln TFP_{ijt-1}$.

As discussed in the previous sections, in the empirical literature, the partial effect of output growth on labour productivity growth, which measures the degree of increasing returns to scale, is called the Verdoorn coefficient. As shown by McCombie (2002), similar results are found using either labour productivity growth or TFP growth as the dependent variable. Following Millemaci and Ofria (2014), however, using equation (6) as the reference model, the long-term elasticity of productivity growth in relation to output growth (*n =1–1/v*, in equation (3)) is given by the expression:

$$n = (1 - 1/v) = (\beta_2 - \beta_3)/(1 - \beta_4) \quad (7)$$

In this paper's estimations, two different methods were used to cope with the issues discussed above. First, a benchmark model was regressed employing the Durbin ranking method to instrument the endogenous variables in equation (5), while using data in non-overlapping 5-year averages to avoid short-term fluctuations. The Durbin ranking method, used by Angeriz *et al.* (2009: 141), consists in ranking the observations of the endogenous variable, and then using this ranking as an instrument. The estimator used was a Two-Step Feasible Efficient Generalized Method of Moments (GMM) estimator with FE (see Baum *et al.*, 2007), henceforth called IV-FE. Secondly, the System-GMM approach of Blundell and Bond (2000) was employed. This method, which has been used in a number of studies (e.g. Baltagi *et al.*, 2000; Griffith *et al.*, 2006; Hausman *et al.*, 2007), employs a system of equations in levels and differences to estimate the parameters using as instruments the lags of the variables in differences and levels, respectively, while controlling for FE (see

Roodman, 2009a: 86). This method was used to regress equation (5) using data in 5-year averages, and to regress equation (6) using data without taking averages.

To guarantee the consistency of the System-GMM estimator, three assumptions must be fulfilled: (i) the error term must not be serially correlated; (ii) the instruments introduced must be valid; and (iii) the correlation between the instruments and the fixed effects must be null. The Arellano and Bond (1991) AR test was used to assess the first assumption, while Hansen's J test of over-identification was employed to assess the second one.[12] In all the System-GMM regressions the number of instruments was kept small to avoid spurious significance due to instrument proliferation (Roodman, 2009a; 2009b). The number of lags adopted in each model was guided by the analysis of the validity of the instruments, following Arellano-Bond's AR Test and Hansen's J Test. Attention was also paid to the stability of the results found with different lags.

4.3. Results

Table 2 reports the results of regressing equations (5) and (6) using IV-FE and System-GMM. An important advantage of System-GMM in relation to IV-FE using the Durbin ranking method to generate instruments, is that in the former case it is possible to test the validity of the instruments using Hansen's J Test of over-identification, while in the latter case it is not possible to do so, given that the estimated equation is perfectly identified. In all the System-GMM regressions, Arellano and Bond's AR test for autocorrelation did not reject the null hypothesis of no autocorrelation in any of the regressions at the 5% significance level, while Hansen's J test did not reject the null hypothesis of the validity of the instruments at the 5% significance level.

Columns (i) and (ii) of Table 2 report the results found estimating equation (5) using IV-FE and System-GMM, respectively. In both these regressions the data are 5-year averages. The results found for total manufacturing reported in column (i) are similar to the estimates found by Verdoorn (1949), Kaldor (1966), Angeriz *et al.* (2009) and Alexiadis and Tsagdis (2010), with an estimate of "encompassing" returns

[12] As Roodman (2009a: 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 up, depending on the first lag used as instrument (Roodman, 2009a: 108; 124).

to scale of 2.288. The estimates reported in column (ii), however, imply considerably larger returns to scale (3.135), although similar to the findings of Angeriz *et al.* (2008). The coefficient of output growth (the Verdoorn coefficient) is highly significant, while the technology gap is only significant in the System-GMM estimation, most likely because of the superiority of this instrumenting strategy.

Column (iii) reports the results found estimating equation (6) using System-GMM, with data in 5-year averages. As expected the lags are not significant, given that short-term variations have been removed through averaging. Nevertheless, the coefficients are similar to the ones found in column (i).

< Table 2 >

Columns (iv) to (vi) report the estimates of equation (6) found using System-GMM, with data not averaged. For total manufacturing, the degree of returns to scale is similar to the estimates found in columns (i) and (iii). The results shown in columns (v) and (vi), however, indicate that low-tech industries present lower increasing returns than high-tech industries (1.423 as opposed to 2.990). Interestingly, in these regressions, the technology gap is not significant, possibly because the lag of output growth already captures the effect of technological diffusion. The lag of TFP growth, in turn, is possibly capturing short-term inertial growth in productivity, streaming from ongoing increases in productivity.

Table 1 shows, however, that the average rate of growth of productivity has experienced some changes over the last decades, decreasing from the 1970s and 1980s to the 1990s, and then increasing again in the 2000s. Thus, in order to analyse whether these changes have any counterpart in the degree of increasing returns to scale, regressions were performed dividing the data into two periods, namely, 1976-1991 and 1992-2006. Although TFP growth has increased in the 2000s, using only data from 1999 onwards would reduce too much the number of years available in the sample. The periods adopted, therefore, divide the sample in two time periods of 15 years each. Moreover, Alexiadis and Tsagidis (2010) divide their sample in two similar periods (1977-91 and 1992-2005) due to the transition to the European single market.

< Table 3 >

Table 3 reports the results of the regressions dividing the period of analysis. This table shows that high-tech industries have higher economies of scale than low-tech industries in both sub-periods. The magnitude of the returns to scale in manufacturing in the first period is lower than the original estimates of Verdoorn (1949) and Kaldor (1966). The degree of returns to scale in manufacturing increases from one period to the other, going from 1.477 to 1.956, which is similar to estimates found in the literature. Most interestingly, while the returns to scale in low-tech industries remained roughly the same (1.273 to 1.222), the degree of returns to scale in high-tech industries increased considerably (1.974 to 2.334). Thus, the increase in the magnitude of returns to scale in the more recent period seems to be driven by the increase in the returns to scale in high-tech industries.[13]

The analysis carried out in this section, therefore, suggests once again that high-tech manufacturing industries exhibit higher returns to scale than low-tech manufacturing industries. Moreover, it is interesting to note that although the magnitude of the Verdoorn coefficient is similar to the coefficients found in previous studies, taking into account the short-term variation of the variables brings the degrees of returns to scale closer to values that correspond to the original Verdoorn coefficient of around 0.5 for manufacturing as a whole during the period 1976-2006. In addition, the lack of significance of the technology gap suggests that technological transfer is possibly being captured by the lag of output growth. Finally, the results also suggest that the degree of returns to scale in manufacturing have increased in the last decades, and that this can be attributed to the increase in the returns to scale in the high-tech industries.

Hence, the findings reported in this paper contrast with the results found by Millemaci and Ofria (2014), which suggest that the Verdoorn coefficient has been stable during the period 1973-2006 for 11 OECD countries individually considered. Still, the results of the present paper are reinforced not only by the quality and size of the data used, but also by the different robustness tests discussed above. These

[13] In order to assess the robustness of the results reported in Table 3, the econometric investigation was repeated adopting an expanded sample of countries. In the EU KLEMS Database, in addition to the 11 countries used in the investigation presented Table 3, the data required to estimate equation (6) is available for 4 additional countries (Czech Rep., Portugal, Slovenia, and Sweden) over the period 1995-2006. The results found using this expanded sample are similar to the results reported in Table 3 for the period 1992-2006. Regression results are available from the authors upon request.

contrasting results indicate the importance of carrying out further research on the variations of the Verdoorn coefficient through time. An interesting possibility for further research is the use of long panels, which explores time-series techniques while providing more robust results than simple time-series analysis because of the higher number of observations in the panel.

To illustrate the importance of the differences in returns to scale between technological sectors reported in this paper, suppose the output of each technological sector in two countries is growing at the same 2% rate per annum. However, suppose one of the countries, called developed, produces 70% of high-tech goods and 30% of low-tech goods, while the opposite holds for the other country, called underdeveloped. Given the estimates presented in this section, this difference in the productive structure implies that productivity growth in the developed country will be 4%, while productivity growth in the underdeveloped country will be only 3.1%. Taking into account the sample of countries analysed in this paper and calculating aggregate productivity growth as the weighted average of TFP growth in each sector, Japan is the country with the highest average rate of productivity growth (3.07%) and is also the country with the highest average share of high-tech production (51.4%). In contrast, Australia has the lowest average productivity growth (1.05%) and also the lowest share of high-tech production (23%). Evidently, other factors influence productivity growth, such as technological transfer. In spite of that, the Spearman rank correlation between average aggregate productivity growth and average share of high-tech production in the sample analysed is relatively high, at 0.64, and significant. Consequently, the results presented in this paper indicate that it is crucial for developing countries to elaborate policies to foster structural change towards high-tech industries in order to increase productivity growth.

Nonetheless, it is not an easy task to shift production towards high-tech industries. The production of such goods requires a considerable amount of productive capabilities, which demand time and resources to be formed (Lall, 2000). The Brazilian steel company Usiminas, for example, indicates learning to produce low-tech products can already take a couple of decades (see Dahlman *et al.*, 1987). Even more complex and costly, therefore, is the learning process involved in the efficient production of high-tech goods. In the case of the Brazilian aircraft company Embraer, 25 years of heavy state investments were required to achieve a competitive level of production. Moreover, analysing the development of the production of integrated circuits, hydraulic excavators and other machine tools in South Korea, Jacobsson (1993) showed that the time and the costs involved in learning to produce such high-tech products has been increasing.

5. Concluding remarks

This paper investigated the existence of different degrees of returns to scale in low-tech and high-tech manufacturing industries, using data from the EU KLEMS Database. The results reported in the paper provide strong evidence in support of the existence of substantial increasing returns to scale in manufacturing, corroborating previous findings. Most importantly, the investigation presented in this paper suggests that high-tech manufacturing industries exhibit higher degrees of returns to scale than low-tech manufacturing industries. Consequently, this result has an important policy implication: fostering structural change towards high-tech industries is crucial to increase productivity growth. The results also indicate that the technology gap is significant when the simple Kaldor-Verdoorn Law is estimated, but not when lagged output and productivity growth are introduced to control for short-term fluctuations. This suggests that lagged output growth is possibly capturing the effect of technological transfer in this specification. Finally, the analysis also revealed that the magnitudes of the returns to scale in manufacturing as a whole have increased in the last decades, driven by increases in the returns to scale observed in high-tech industries.

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Table 1

Average output and productivity growth by technological sector

	Low-Tech Industries		High-Tech Industries	
Periods	TFP Growth	Output Growth	TFP Growth	Output Growth
1976-1979	0.028	0.031	0.027	0.033
1980-1984	0.019	0.005	0.034	0.028
1985-1989	0.017	0.028	0.036	0.048
1990-1994	0.009	0.004	0.023	0.014
1995-1999	0.007	0.013	0.021	0.038
2000-2006	0.015	0.003	0.034	0.032
Average	0.016	0.014	0.029	0.032

Source: Authors' elaboration.

Table 2

Dynamic demand-side Kaldor-Verdoorn Law (1976-2006)

Dependent Variable	TFP Growth	TFP Growth	TFP Growth	TFP Growth	TFP Growth	TFP Growth
Method	IV-FE	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
Aggregation	5-year averages	5-year averages	5-year averages	Years	Years	Years
Sample	All Industries	All Industries	All Industries	All Industries	Low-Tech	High-Tech
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Lag of Technology Gap	-0.0111	-0.0420*	-0.0482*	-0.0365	-0.0515	-0.00409
	(0.00944)	(0.0162)	(0.0208)	(0.0223)	(0.0352)	(0.0162)
Output Growth	0.563***	0.681**	0.548**	0.734***	0.703***	0.825***
	(0.0339)	(0.211)	(0.194)	(0.0921)	(0.0974)	(0.217)
Lag of Output Growth			-0.222	-0.435***	-0.515***	-0.435**
			(0.211)	(0.0825)	(0.0787)	(0.130)
Lag of TFP Growth			0.237	0.494***	0.368+	0.414**
			(0.340)	(0.0916)	(0.209)	(0.133)
Constant		-0.0151	-0.0167	-0.0257	-0.0280	-0.00213
		(0.0110)	(0.0134)	(0.0181)	(0.0233)	(0.0225)
Observations	660	660	660	3816	2544	1272
No. Instruments/Lags	2	13/2-4	13/2	48/3-7	48/3-7	48/2-6
R-Squared	0.523					
Arellano-Bond AR Test		0.869	0.454	0.303	0.586	0.401
Hansen J Test		0.299	0.288	0.656	0.451	0.534
Long-term coefficient (*n*)	0.563	0.681	0.548	0.591	0.297	0.666
Increasing returns (*v*)	2.288	3.135	2.212	2.444	1.423	2.990

Note: 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. Significance: +=10%; *=5%; **=1%; ***=0.1%.
Source: Authors' elaboration.

Table 3

Dynamic demand-side Kaldor-Verdoorn Law in different time periods

Dependent Variable	TFP Growth	TFP Growth	TFP Growth	TFP Growth	TFP Growth	TFP Growth
Period	1976-1991			1992-2006		
Sample	All Industries (i)	Low-Tech (ii)	High-Tech (iii)	All Industries (iv)	Low-Tech (v)	High-Tech (vi)
Lag of Technology Gap	0.00133	-0.0111	0.0266	-0.00853	-0.00677	0.00402
	(0.0197)	(0.0114)	(0.0326)	(0.0187)	(0.0429)	(0.0142)
Output Growth	0.635***	0.667***	0.719***	0.695***	0.502***	0.748***
	(0.0789)	(0.105)	(0.0788)	(0.120)	(0.118)	(0.110)
Lag of Output Growth	-0.451***	-0.564***	-0.416*	-0.350***	-0.392**	-0.357***
	(0.0923)	(0.112)	(0.185)	(0.0889)	(0.133)	(0.0654)
Lag of TFP Growth	0.430***	0.520***	0.386+	0.294**	0.395*	0.316***
	(0.110)	(0.121)	(0.219)	(0.107)	(0.170)	(0.0854)
Constant	0.00412	-0.00695	0.0287	-0.00338	-0.00377	0.0127
	(0.0140)	(0.00827)	(0.0254)	(0.0153)	(0.0315)	(0.0128)
Observations	1836	1224	612	1980	1320	660
No. Instruments/Lags	52/2-12	37/2-7	52/2-12	54/2-12	54/2-12	42/2-8
Arellano-Bond AR Test	0.168	0.131	0.830	0.504	0.482	0.383
Hansen J Test	0.655	0.279	0.668	0.131	0640	0.445
Long-term coefficient (*n*)	0.323	0.215	0.493	0.489	0.182	0.572
Increasing returns (*v*)	1.477	1.273	1.974	1.956	1.222	2.334

Note: 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. Significance: +=10%; *=5%; **=1%; ***=0.1%.
Source: Authors' elaboration.