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Auteurs

Andrea Borsato, André Lorentz

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Bureau d'Économie Théorique et Appliquée BETA

www.beta-economics.fr

@beta_economics

Contact :
jaoulgrammare@beta-cnrs.unistra.fr

The Kaldor-Verdoorn Law's at the Age of Robots and AI

Andrea Borsato and André Lorentz *

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Abstract

This paper contributes to the literature around the Kaldor-Verdoorn's law and analyses the impact of robotisation on the channel through which the law shapes labour-productivity growth. We start with a simple evolutionary interpretation of the law that combines Kaldorian and Post-Keynesian arguments with the neo-Schumpeterian theory of innovation and technological change. Then we apply a GMM estimator to a panel of 17 industries in 25 OECD capitalist economies for the period 1990-2018. After elaborating on the general evidence of the Kaldor-Verdoorn's law in the sample, we investigate the effect of increasing robotisation. The estimates suggest that for industries with a higher-than-average robot density, the increasing adoption of robots weakens, at least, the meso-economic channel that relates productivity growth to mechanisation. Yet, the higher degree of robotisation strengthens the mechanism that links labour productivity growth at the industrial level to the macro-level dynamic increasing returns to scale that emerge from a general expansion of economic activities through the many interactions between sectors. Such results are in agreement with the empirical literature that suggests different impacts from robotisation on the basis of the level of economic activity considered.

JEL Classification: J23, O33, O47.

Keywords: Labour productivity, Kaldor-Verdoorn's law, Robotisation, GMM.

*Université de Strasbourg, Université de Lorraine, CNRS BETA, 67000 Strasbourg. Contact the corresponding author at: Andrea Borsato, Office 323 Avenue de la Forêt-Noire, 67000 Strasbourg, France. E-mail address: aborsato@unistra.fr.

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1 Introduction

The Kaldor-Verdoorn's law is a cornerstone of Post-Keynesian economics (Lavoie 2022). Introduced by Verdoorn (1949) and re-evoked by Kaldor (1966), this law considers a dynamic relationship between the growth rate of output and improvements in labour-productivity growth, with a direction of causality from the former to the latter, without excluding possible feedback mechanisms. Ever since Kaldor's reappraisal, this relationship has been investigated by several generations of economists from both a theoretical and empirical perspective (McCombie, Pugno and Soro 2002). Regardless of the many ways scholars have specified it, the law can be thought of as a stylized fact generally confirmed for developed as well as developing countries, with respect to some stage of their development at least. Yet, the structural change from a manufacturing to service economy led scholars to reconsider its overall validity. The lack of economies of scale and the different division of labour in the service sector are believed as key mechanisms behind the detachment between increases of demand and gains in productivity experienced since the Eighties (Boyer and Petit 1981, 1988, Petit 1988, 1999, Petit and Soete 2001).

At the same time, economies have experienced a new wave of innovations that radically changed production methods since the Nineties. The pool of technologies around the Fourth Industrial Revolution have a major impact on businesses. From a supply-side perspective, new technologies disrupt global value chains and lead to a profound revision of the organization of production and the means to satisfy consumer needs. Moreover, the very process of innovative search benefits from world-wide digital platforms and this feature may increase the speed with which value is created and new products enter the market. By the same token, new digital technologies affect the customers on the demand side, through their engagement, their needs for transparency or simply by enhancing the range of needs to be met (Schwab 2016). Nevertheless, last developments in robotics and AI-based technologies made people worried about future prospects of widespread technological unemployment, since the extent and the ways digital technologies in general, and robots and AI in particular, could impact are broader than previous waves of innovations (Domini, Grazzi, Moschella and Treibich 2021).[1] The empirical evidence on this latter issue is rather inconclusive because we are still in the initial phase of implementation of such potentially breakthrough technologies (Acemoglu, Autor, Hazell and Restrepo 2020, Acemoglu, Lelarge and Restrepo 2020, Domini et al. 2021, Graetz and Michaels 2018, Klenert, Fernandez-Macias and Antón 2020).

In this paper we want to investigate if, and in which way, the increasing robotisation ex-

[1]For details, see the European Commission Special Eurobarometer 460 at https://digital-strategy.ec.europa.eu/en/news/attitudes-towards-impact-digitisation-and-automation-daily-life.

perienced by many industries (Fig. 1) has an impact on the supposed channels through which the Kaldor-Verdoorn's law shapes the dynamics of labour-productivity growth. We first offer a simple and evolutionary view of the law inspired by Llerena and Lorentz (2004), Lorentz and Llerena (2004) that combines both the traditional Kaldorian and Post-Keynesian arguments with the evolutionary literature on innovation and technical change *à la* Nelson and Winter (1982). We then collect data on labour productivity, capital-labour ratio, GDP, and robot adoption for a panel of 17 industries in 25 OECD countries for the period 1990-2018. After checking for the presence of mechanisms *à la* Kaldor-Verdoorn in the dynamics of productivity, we analyse through a GMM approach in which way the increasing robotisation affects the channels behind the Kaldor-Verdoorn's law. The results are contrasting and somewhat puzzling. Industries whose robot density is lower than cross-country sector average still benefit from a cumulative-causation process in their productivity dynamics. By contrast, industries with a robot density higher than the corresponding cross-country sector average suffer from a weakening of the meso-economic channel that links productivity achievements to the growth in mechanisation (i.e., the capital-to-labour ratio). At the same time, their higher robot density sustains the macro-level channel that associates changes in labour productivity with GDP growth. The evidence of technological unemployment depends on the specification of the underlying econometric model. This overall evidence is in agreement with the empirical literature that finds a positive relationship between robots adoption and employment at firm and industry level (Domini et al. 2021, Graetz and Michaels 2018, Klenert et al. 2020) but with a macroeconomic impact of uncertain magnitude and direction (Acemoglu, Autor, Hazell and Restrepo 2020, Acemoglu, Lelarge and Restrepo 2020, Bordot 2022).

The paper is organised as follows: Section II recalls the Kaldorian thought and relates our work to the literature; Section III offers an evolutionary interpretation of Kaldorian insights and presents econometric estimates; Section IV concludes.

2 Relation with the literature

2.1 Theoretical premises

The dissatisfaction raised by the explanation of the growth process in terms of a neoclassical aggregate production function (Solow 1956, 1957, Swan 1956) prompted Kaldor to enter the debate with an alternative approach based on three pillars: firstly, economic growth is a historical process with some regularities; secondly, technical and structural changes in production should be thought of as endogenous processes; thirdly, growth is demand driven[2]. In a first series of papers, Kaldor formalized these ideas by means of a *technical progress function* (Kaldor 1957, 1961, Kaldor and Mirrlees 1962). Stated in its simplest form, the technical progress function is a dynamic relationship that relates the growth in productivity, $\dot{a}_t$, to the growth of the capital-labour ratio, $\dot{k}_t$:

$$\dot{a}_t = f\left(\dot{k}_t\right) \qquad f_k' > 0; f_k'' < 0 \tag{1}$$

in which f_k' and f_k'' are first and second derivative with respect to k. In the steady state, the growth of labour productivity coincides with the growth in the capital-labour ratio, implying a constant capital-output ratio. The model helps consider the capitalist economies as a two-stage growth process, in which the first is characterised by the stagnant growth path of early capitalism whereas the second envisages the self-sustained growth pattern of mature economies. Yet, this representation of endogenous productivity gains relies on another black-box to be open, overlooking the very mechanisms through which mechanisation generates productivity gains.

Well aware of this issue, Kaldor tried to fine-tune his ideas in a paper with Mirrlees (Kaldor and Mirrlees 1962). They propose a framework in which labour-productivity growth is determined by the productivity embodied in the newly installed equipment and so by the growth rate of gross investments:

$$\dot{a}_t = f\left(\dot{i}_t\right) \tag{2}$$

in which $\dot{i}_t$ is the ratio between investments in the new capital vintage and labour. However, neither this formulation was reliable since the steady-state constancy of the investment share in output leads back to the previous version of the technical progress function.
Unsatisfied by these outcomes, Kaldor undertook a revision of his approach to economic growth that led to the content of the Inaugural Lecture at Cambridge in 1966 on the causes of UK slowdown in growth (Kaldor 1966). This Lecture represents a crucial step in his analysis since Kaldor expounded three laws of capitalist development based on four key concepts: dynamics increasing returns to scale in manufacturing, demand-led growth, intersectoral structural linkages, and import-export determinants of economic growth. Among the three laws, we are interested in the Kaldorian interpretation of Verdoorn's law, according to which "a faster growth in output increases productivity growth as a result of increasing returns, broadly defined to also include induced technical progress" (McCombie and Spreafico 2015, p. 1122):

[2]See Lorentz (2016) for a discussion on the evolution of Kaldor's writings on technological change and economic growth.

$$\dot{a}_t = \lambda_{0t} + \lambda_1 \cdot \dot{y}_t \tag{3}$$

in which λ_{0t} is the exogenous technical progress, $\dot{y}_t$ is output growth and λ_1 the Verdoorn's coefficient. When re-interpreting this law, Kaldor was heavily inspired by **?** and Young (1928), and considered the macro-level relationship between output and productivity as *dynamic* rather than *static*, "primarily because technological progress enters to it, and is not just a reflection of the economies of large scale production" (Kaldor 1966). The structure of production and aggregate demand are viewed as in symbiosis in which efficiency gains from increasing returns to scale affect and respond to the increase of production in terms of consumption, investments, and intermediate demand for inputs fuelled by income growth. All these elements represent the core of his cumulative causation mechanisms, according to which "economic growth is a self-reinforcing phenomenon generating the necessary resources to self-sustain in the long run" (Lorentz, Ciarli, Savona and Valente 2022, p. 7). Then, increasing returns act and manifest as a general expansion of economic activities through the interactions between sectors (Thirlwall 2015). An increased demand stimulates firms investments and production, engendering productivity growth. It is important to notice, nonetheless, that such cumulative causation mechanism does not imply that economic growth perpetuates itself, for on the growth path there exist strong inter-dependencies between the ways productivity gains are achieved and the ways they are used (Petit 1999).

2.2 Empirical estimates

Kaldor's arguments have risen an amount of empirical research that counts dozens of works, from the preliminary inspections by Verdoorn (1949), Kaldor (1966) and Vaciago (1975) to current specifications, e.g., Antenucci, Deleidi and Paternesi Meloni (2020), Deleidi, Fontanari and Gahn (2022), Deleidi, Paternesi Meloni, Salvati and Tosi (2021).[3] More precisely, economists concerned with development issues focused their empirical investigations on the influence of structural change in determining aggregate productivity and output growth in both developing and mature countries (Bah 2011), whether Kaldorian principles can be detected in countries at different stages of development (Dasgupta and Singh 2005, Felipe, Leon-Ledesma, Lanzafame and Estrada 2007, McMillan and Rodrik 2011, Page 2012, Wells and Thirlwall 2003), or which one between manufacturing and services triggers productivity growth the most (Di Meglio et al. 2018, Felipe and Mehta 2016, Tregenna 2011). In addition to this, recent works can be distinguished according to the several econometric methodologies applied. Bianchi (2002), Castiglione (2011), Deleidi and Paternesi Meloni

[3] Empirical estimations of the Kaldor-Verdoorn's law and the technical progress function became quite sophisticated as time went by. For an overall survey on both the theoretical foundations and empirical findings, we suggest Llerena and Lorentz (2004), McCombie et al. (2002), and Di Meglio, Gallego, Maroto and Savona (2018).

(2019), Deleidi, Paternesi Meloni and Stirati (2020), Harris and Lau (1998), Millemaci and Ofria (2014), Ofria (2009) implement time-series econometrics often based on the cointegration approach. Panel-data econometrics is instead crucial in the analysis of Angeriz, McCombie and Roberts (2008), Knell (2004), León-Ledesma (1999, 2000), Magacho and McCombie (2017, 2018), Tridico and Pariboni (2018). Conversely, Antenucci et al. (2020), Deleidi et al. (2022, 2021) implement panel vector autoregressions techniques to estimate both the Kaldorian technical progress function and the Verdoorn's law at country and regional level. Albeit the great heterogeneity in the approaches, most works show that Kaldorian laws generally hold for manufacturing and business service sectors, confirming Verdoorn's law as a stylised fact for most countries along their development stages, with some notable exception pointing to inherent instabilities behind the law (Boyer and Petit 1981).[4]

3 Any effect from robotisation and AI?

3.1 An evolutionary intepretation of the law

The cumulative-causation framework in which Kaldor-Verdoorn's law is usually integrated presents a circular vision of the growth process that relies on quite a schematic representation of the mechanisms that drive technical change. The latter indeed seems to occur in a deterministic and automatic way without a proper conception of the process behind (Llerena and Lorentz 2004). This gap can be filled by the evolutionary literature on technical change *à la* Nelson and Winter (1982), in which the emphasis is on the emergence and diffusion of technologies within the economic systems.[5] The intriguing union between Kaldorian theories and evolutionary economics of innovation and technical change is far more evident, though sometimes tacit, when we turn to modelling such thought. For instance, the way with which technical change occurs in evolutionary models through firms R&D activities resembles a stochastic version of Kaldor's technical progress function. Additionally, analysing the cumulative-causation process in which growth is exports-led and exports are driven by competitiveness and increasing returns reveals a mechanism very much alike the selection process based on a replicator dynamics.[6] Such rationales suggest a *dynamic* interpretation of the Kaldor-Verdoorn's law in which the growth in labour productivity at firm

[4]A typical value for the Verdoorn's coefficient is around 0.5 but well below unity, meaning that an increase in the growth rate of production manages to raise both productivity growth and employment rates.

[5]By the way, most contributions in this neo-Schumpeterian literature consider the macro-dynamics as a simple aggregation process of dynamics at the microeconomic level. The absence of macro-constraints on the micro-dynamics is exactly where the Kaldorian approach might complete the evolutionary modelling of economic growth. Recent attempts are Lorentz (2005, 2018) and Lorentz et al. (2022), among the others.

[6]These, and further, points of convergence between the two approaches must not move divergences to the background. Kaldorians consider economic dynamics as a top-down process in which the *macro* directly determines the *micro via* Verdoorn's law. Conversely, the evolutionary approach adopts a bottom-up framework with micro dynamics and behaviours shaping the aggregate dimension. Further details in Llerena and Lorentz (2004).

or sector level respond positively to micro and macro stimuli:

$$\dot{a}_{it} = f\left(\dot{k}_{it}, \ldots, \dot{k}_{it-z}; \dot{Y}_t, \ldots, \dot{Y}_{t-z}\right) \tag{4}$$

in which $\dot{Y}_t$ is the GDP growth rate and z an unspecified time lag.
Microeconomic stimuli in Eq. (4) are summarized by the growth in the capital-labour ratio, $\dot{k}_{it}$. The related technical progress function implies that the resources generated are invested in production capacities with a scale of production both larger and more efficient due to the accumulation of new generations of capital goods. On the other hand, the GDP growth rate summarizes the arguments *à la* Young (1928) that refer to the macro-level extension of the idea of division of labour already found in the Classicals. By the way, this macro-level division of labour engenders a self-sustaining growth process which constitutes the main engine for productivity achievements.[7]

Taking for granted this theoretical framework, we find interesting to join it with the empirical literature on the innovation-employment nexus. Most empirical studies suggest a positive relationship between innovation and employment growth at the firm level, in particular when attention is paid to high-growth and high-tech enterprises (Calvino and Virgillito 2018). Moreover, if benefits in terms of employment rates out of product innovations tend to be confirmed at sector level too, the analyses focusing on the job-displacement effects of process innovations provide mixed results.[8]
Yet, few of these empirical works deal with the influence of robots and recent automation technologies on productivity gains and employment. Results are generally mixed and provide unambiguous interpretations in no way. To be precise, previous studies fall into two camps. Works in the first group usually find no effects of robots on total employment or negative effects with reference to low-skilled workers (Acemoglu, Lelarge and Restrepo 2020, Graetz and Michaels 2018, Kromann, Malchow-Møller, Skaksen and Sørensen 2020). The second camp instead finds positive or neutral effects from robots adoption on total employment (Acemoglu, Autor, Hazell and Restrepo 2020, Domini et al. 2021, Klenert et al. 2020). However, as argued also by Bordot (2022), this bulk of research lacks a proper theoretical and practical framework for answering the question of the net effect of technological progress on employment at the aggregate level. Furthermore, no work focuses on the evo-

[7] In this respect, the micro and macro aspects here envisaged represent the phenotypes of dynamic increasing returns to scale. In addition to this, GDP is a proxy for aggregate demand, the factor that in Kaldor's view links the increase of production capacities with income growth. Then, demand induces a chain reaction along the economy in which "the increase in demand for any commodities [. . .] reflects the increasing in supply of other commodities, and vice versa" (Kaldor 1966, p. 19).

[8] Calvino and Virgillito (2018) and Vivarelli (2014) offer comprehensive literature reviews on the innovation-employment nexus, distinguishing firm-level and industry-level empirical studies, and providing some stylized facts.

lutionary Kaldorian channels that might exist between demand and productivity gains. The following analysis is a first step in tackling this issue.

3.2 Data, descriptive statistics and methodology

We collect time series data about 17 industries in 25 OECD countries from 1990 to 2018. The main sources of data are the World Robotics - Industrial Robotics (WRIR) database of the International Federation of Robotics (IFR) and the OECD STAN database. The WRIR database presents statistics about production, imports, exports and domestic installations of industrial robots since 1990, defined as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (World Robotics, ch. 1, p. 29).[9] This source provides us with data on the operational stock of robots, that measures the number of robots currently employed at industry level. IFR statistical departments assume an average service life of about twelve years with immediate withdrawal afterwards.[10]

The STAN database provides indicators on industrial performance at quite a detailed level of activity from 1970 onward, from which we took data on labour productivity, capital stock and employment. More precisely, labour productivity (a) is defined in terms of value added over hours worked by total engaged. The (net) capital stock is the value of all vintages of assets to owners where valuation reflects market prices for new and used assets, thus considering some form of depreciation. Employment is expressed in total hours worked by person engaged. Data on expenditure-side real GDP are from the Penn World Table 10.0.

This set of variables allows for the computation of the capital-labour ratio (k), defined as net capital stock in total hours worked, and the share of operational robots in net capital. The variable we are most interested in is a measure of robot density (d), that tells us how much the sector i in country j is *robotised* if compared to the yearly cross-country sectoral average. This variable takes value 1 if the ratio between the stock of robots and net capital is above the average and 0 otherwise.[11] We present descriptive statistics on our variables of interest in Fig. 1 to Fig. 3 and in Tab. 1 to Tab. 6. For what concerns to robots, we consider three different measures that provide insights on the widespread adoption of this automation

[9] For a clarification of all the adjectives in this definition, we remind to the documentation at `https://ifr.org/industrial-robots`.

[10] We should keep two important caveats in mind. On the one hand, considering the impact of the quantity of industrial robots as a stock variable may conceal the evidence that robots became more and more integrated over time such that a single robot today could perform tasks carried out by several robots yesterday (Kromann et al. 2020). In this case, the stock of robots underestimates the degree of automation in sectors where investments have been relatively high as it overestimates the automation in sectors with low investment rates. On the other hand, industrial robots can be a rough approximate variable when it comes to analysing the effect of such new technologies on the economy as a whole. (Klenert et al. 2020). These caveats apply to our analyses as well as to the abovementioned empirical studies.

[11] IFR computes an indicator of robot density as the number of operational industrial robots relative to the number of employees. We consider this measure in the robustness check.

technology. The first measure is the operational stock of robots. Top graphs in Fig. 1 and Tab. 1 clearly point to a great increase in the adoption of robots common to all industries, averaged across countries. Obviously, this increase presents sector-specific magnitude and dynamics. As expected, the automotive industry (D29) employs the largest stock of robots. Starting with an average of 1700 units in the early Nineties, the operational stock increases by a factor of seven, peaking to an average of 12 thousand units after 2013. Other industries that have widely adopted robots since data are available are the producers of fabricated metals (D25), electrical and electronic devises (D26T27), and rubber and plastics products (D22), with an average stock around 2000 units in the period 2013-2018. In particular, the industry producing plastics products began to adopt robots in early 2000s only and exhibited a rapid increase in the years after the 2007 financial crisis.

However, focusing on the operational stock of robots only can be misleading if not framed into the industry-specific technological structure. Therefore, we compute the robots-to-capital ratio and the robots-to-hours worked ratio. Data on the former are in the central plots of Fig. 1 and in Tab. 2. It is important to note that this ratio does not express robots share of capital, but just the number of robots employed with a given capital stock. Results do not change significantly from the above. The automotive sector and those producing plastics products and fabricated metals present the largest increases of this ratio throughout the period, reaching an average value of about 34%, 20% and 13%, respectively. All the other industries never display a ratio above 4% on average, though it rises through time.

The outcomes are roughly confirmed by the robots-to-hours ratio in Tab. 3 and bottom graphs in Fig. 1. The predominance of the automotive industry is clear when we observe that a ratio of about 10 in the years between 2007 and 2013 is larger than the average value assumed by all the other industries in the next six years, with the sole exception of the plastics industry.

To sum up, these simple statistics point to the widespread diffusion of robots throughout the economies. The average adoption pattern proceeded slowly for most sectors until the early 2000s and then has rapidly increased since 2003-2004. The automotive industry is leader in the ranking and displays a rather exponential increase in the pattern of adoption.

As a second step, we calculate growth statistics for labour productivity (top panels in Fig. 2 and Tab. 4), the capital-labour ratio (bottom panels in Fig. 2 and Tab. 5) and GDP (Fig. 3 and Tab. 6). About productivity growth, data envisage a stylized fact shared by each sector. In other terms, though sectors follow their own productivity trajectory, their growth rates in labour productivity could be described by a hump-shaped pattern. For instance, if we considered the electronic industry, we would observe an average growth of about 7.5% in the early 1990s that peaks to 8% the following decade. Yet, this average growth rate

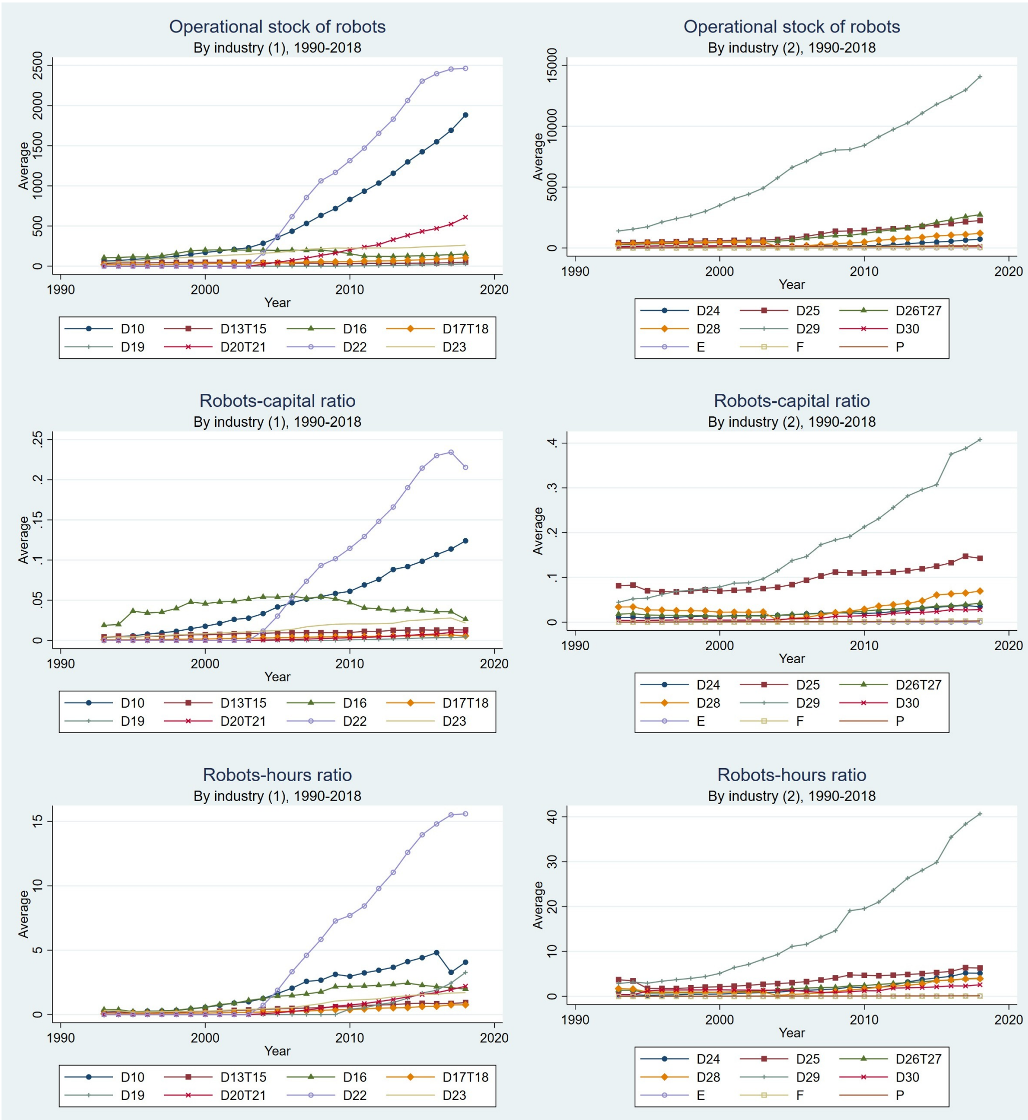

Figure 1. Statistics on robots by industry, 1990-2018

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN and IFR data.

Industry	1990-96	1996-01	2001-07	2007-13	2013-18
D10	78.570	139.293	284.860	834.206	1500.713
	(14.475)	(36.380)	(127.782)	(223.490)	264.521
D13T15	39.150	46.133	43.177	35.114	40.447
	(3.517)	(2.817)	(4.510)	(1.831)	(5.207)
D16	111.100	166.353	199.371	157.457	134.860
	(5.184)	(38.226)	(2.403)	(36.056)	(11.519)
D17T18	18.350	26.560	41.291	59.366	84.353
	(0.289)	(6.122)	(5.800)	(5.769)	(14.089)
D19	0.000	0.000	0.000	2.971	18.007
	(0.000)	(0.000)	(0.000)	(3.350)	(7.041)
D20T21	0.000	0.000	35.326	206.126	458.360
	(0.000)	(0.000)	(40.496)	(79.949)	(99.770)
D22	0.000	0.000	287.091	1336.383	2252.467
	(0.000)	(0.000)	(341.634)	(341.617)	(253.927)
D23	60.223	106.153	163.817	222.314	242.787
	(13.578)	(19.816)	(27.891)	(6.260)	(13.790)
D24	152.070	176.567	181.206	224.486	534.687
	(11.813)	(11.265)	(8.504)	(59.480)	(140.146)
D25	469.050	567.240	790.600	1449.754	1958.553
	(28.940)	(44.377)	(200.041)	(167.282)	(223.319)
D26T27	321.760	420.460	628.600	1241.971	2200.807
	(28.298)	(50.184)	(170.597)	(268.623)	(425.610)
D28	374.480	455.040	319.040	526.560	1007.633
	(42.456)	(36.614)	(182.628)	(198.396)	(152.713)
D29	1706.590	2961.273	5805.783	8778.480	12098.353
	(315.462)	(713.581)	(1414.294)	(958.360)	(1357.265)
D30	130.818	171.613	149.789	93.086	120.453
	(38.712)	(5.048)	(17.022)	(9.837)	(17.296)
E	0.000	0.360	2.097	5.531	11.033
	(0.000)	(0.311)	(0.775)	(1.705)	(3.142)
F	0.390	5.027	14.634	33.509	53.080
	(0.384)	(2.874)	(5.454)	(7.514)	(6.897)
P	8.250	62.313	117.931	130.669	175.360
	(6.251)	(27.967)	(16.601)	(10.100)	(29.236)

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on IFR data.

Table 1. Operational stock of robots by industry: average and standard deviation

Industry	1990-96	1996-01	2001-07	2007-13	2013-18
D10	0.005	0.014	0.033	0.065	0.104
	(0.002)	(0.005)	(0.011)	(0.013)	(0.014)
D13T15	0.005	0.006	0.009	0.011	0.013
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
D16	0.027	0.042	0.052	0.046	0.035
	(0.009)	(0.006)	(0.003)	(0.007)	(0.004)
D17T18	0.001	0.001	0.003	0.005	0.006
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
D19	0.000	0.000	0.000	0.001	0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
D20T21	0.000	0.000	0.001	0.003	0.008
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
D22	0.000	0.000	0.024	0.118	0.208
	(0.000)	(0.000)	(0.029)	(0.032)	(0.026)
D23	0.005	0.007	0.012	0.020	0.025
	(0.000)	(0.002)	(0.003)	(0.002)	(0.003)
D24	0.010	0.013	0.016	0.022	0.033
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
D25	0.076	0.070	0.083	0.110	0.130
	(0.007)	(0.002)	(0.012)	(0.004)	(0.013)
D26T27	0.017	0.015	0.016	0.025	0.036
	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)
D28	0.031	0.025	0.015	0.030	0.058
	(0.004)	(0.002)	(0.008)	(0.010)	(0.011)
D29	0.053	0.074	0.121	0.219	0.343
	(0.007)	(0.009)	(0.033)	(0.040)	(0.054)
D30	0.004	0.005	0.006	0.015	0.025
	(0.000)	(0.000)	(0.002)	(0.004)	(0.003)
E	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F	0.000	0.000	0.000	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
P	0.000	0.001	0.001	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN and IFR data.

Table 2. Robots-to-capital ratio by industry: average and standard deviation

Industry	1990-96	1996-01	2001-07	2007-13	2013-18
D10	0.221	0.430	1.255	3.096	4.058
	(0.044)	(0.181)	(0.677)	(0.395)	(0.540)
D13T15	0.144	0.190	0.396	0.637	0.853
	(0.040)	(0.062)	(0.084)	(0.103)	(0.050)
D16	0.307	0.443	1.214	2.078	2.215
	(0.085)	(0.205)	(0.311)	(0.284)	(0.170)
D17T18	0.069	0.107	0.204	0.399	0.637
	(0.015)	(0.018)	(0.055)	(0.087)	(0.100)
D19	0.000	0.000	0.000	0.379	1.912
	(0.000)	(0.000)	(0.000)	(0.391)	(0.844)
D20T21	0.000	0.000	0.111	0.749	1.656
	(0.000)	(0.000)	(0.134)	(0.290)	(0.374)
D22	0.000	0.000	1.504	7.811	13.923
	(0.000)	(0.000)	(1.846)	(2.211)	(1.797)
D23	0.254	0.251	0.465	1.067	1.556
	(0.063)	(0.037)	(0.128)	(0.231)	(0.125)
D24	0.314	0.452	1.037	2.118	4.314
	(0.081)	(0.122)	(0.328)	(0.579)	(0.789)
D25	2.668	1.983	2.893	4.489	5.582
	(1.051)	(0.214)	(0.475)	(0.443)	(0.639)
D26T27	1.053	0.848	1.485	2.470	3.565
	(0.359)	(0.101)	(0.368)	(0.418)	(0.382)
D28	1.325	0.933	0.694	1.678	3.374
	(0.416)	(0.021)	(0.302)	(0.621)	(0.611)
D29	3.090	4.505	9.585	19.638	33.131
	(0.240)	(1.112)	(2.503)	(4.641)	(5.867)
D30	0.845	1.432	1.266	1.289	2.203
	(0.542)	(0.016)	(0.203)	(0.431)	(0.253)
E	0.000	0.003	0.012	0.024	0.059
	(0.000)	(0.003)	(0.002)	(0.008)	(0.022)
F	0.000	0.004	0.009	0.030	0.053
	(0.001)	(0.002)	(0.004)	(0.012)	(0.005)
P	0.012	0.040	0.073	0.094	0.127
	(0.003)	(0.017)	(0.010)	(0.013)	(0.011)

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN and IFR data.

Table 3. Robots-to-hours worked ratio by industry: average and standard deviation

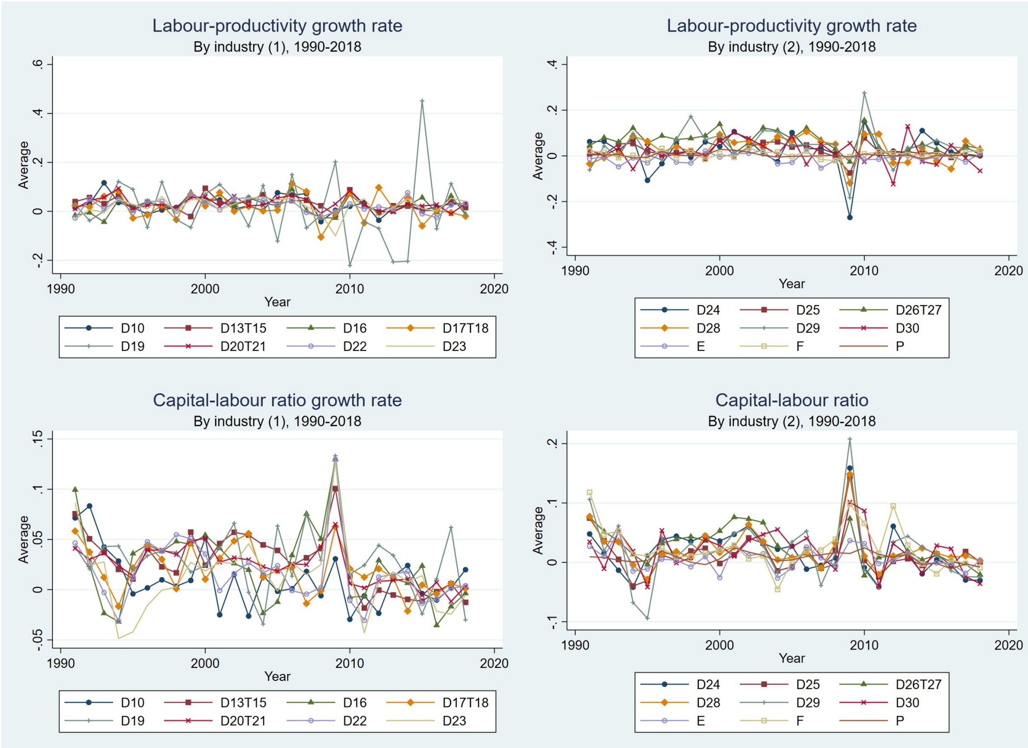

Figure 2. Statistics on labour productivity and capital-labour ratio by industry, 1990-2018

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN data.

halves in the years between 2007 and 2013 (4.1%) and then reduces to an average 3% since 2013.

A similar trend is envisaged by the growth performance in the capital-labour ratio. Nonetheless, the decline in growth is stronger than productivity's and there is the evidence of a null, when not negative, growth path after 2007 and most after 2013. For example, the automotive industry goes from an average growth of about 3% in the capital-labour ratio in the period 2007-2013 to a third of it subsequently.

Finally, the last set of descriptive statistics in Fig. 3 and Tab. 6 is about average GDP growth. Here again, the growth performance can be very heterogeneous across countries, but as a general remark we point to the overall decrease in average growth post-2007 and post-2013 since in very few cases the related performance could match the pre-crisis one. This assertion holds especially for most advanced economies.

From what said so far, we identify a relationship that ties labour-productivity dynamics

Industry	1990-96	1996-01	2001-07	2007-13	2013-18
D10	0.034	0.029	0.037	0.010	0.021
	(0.044)	(0.030)	(0.031)	(0.040)	(0.011)
D13T15	0.039	0.029	0.042	0.027	0.018
	(0.020)	(0.038)	(0.013)	(0.034)	(0.014)
D16	0.006	0.042	0.043	0.005	0.021
	(0.035)	(0.026)	(0.030)	(0.033)	(0.033)
D17T18	0.024	0.024	0.043	0.015	-0.003
	(0.043)	(0.044)	(0.046)	(0.075)	(0.037)
D19	0.023	0.022	0.023	-0.060	0.011
	(0.073)	(0.087)	(0.106)	(0.141)	(0.247)
D20T21	0.040	0.034	0.043	0.025	0.016
	(0.032)	(0.019)	(0.019)	(0.033)	(0.018)
D22	0.020	0.033	0.032	0.005	0.018
	(0.032)	(0.026)	(0.023)	(0.018)	(0.036)
D23	0.010	0.029	0.039	-0.002	0.029
	(0.028)	(0.027)	(0.020)	(0.050)	(0.022)
D24	0.014	0.037	0.046	-0.005	0.034
	(0.072)	(0.050)	(0.048)	(0.127)	(0.042)
D25	0.024	0.016	0.037	0.010	0.013
	(0.023)	(0.029)	(0.022)	(0.045)	(0.015)
D26T27	0.075	0.079	0.081	0.041	0.030
	(0.028)	(0.041)	(0.040)	(0.059)	(0.019)
D28	0.022	0.039	0.069	0.018	0.003
	(0.045)	(0.032)	(0.021)	(0.080)	(0.046)
D29	0.011	0.068	0.058	0.029	0.039
	(0.055)	(0.065)	(0.036)	(0.139)	(0.017)
D30	0.007	0.032	0.047	0.017	0.006
	(0.036)	(0.042)	(0.049)	(0.078)	(0.071)
E	-0.014	-0.003	-0.007	-0.016	-0.006
	(0.023)	(0.023)	(0.032)	(0.018)	(0.014)
F	0.009	0.006	0.009	0.001	0.009
	(0.017)	(0.021)	(0.018)	(0.015)	(0.009)
P	0.003	0.013	0.005	0.002	-0.001
	(0.010)	(0.012)	(0.011)	(0.004)	(0.007)

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN data.

Table 4. Productivity growth rates by industry: average and standard deviation

Industry	1990-96	1996-01	2001-07	2007-13	2013-18
D10	0.037	0.008	-0.004	0.000	0.007
	(0.036)	(0.025)	(0.019)	(0.022)	(0.014)
D13T15	0.039	0.035	0.042	0.023	-0.006
	(0.023)	(0.016)	(0.012)	(0.040)	(0.007)
D16	0.025	0.045	0.023	0.040	-0.002
	(0.048)	(0.006)	(0.033)	(0.050)	(0.021)
D17T18	0.026	0.027	0.025	0.016	0.000
	(0.027)	(0.018)	(0.023)	(0.024)	(0.012)
D19	0.034	0.032	0.032	0.051	0.011
	(0.011)	(0.009)	(0.041)	(0.041)	(0.035)
D20T21	0.031	0.040	0.026	0.023	0.002
	(0.010)	(0.009)	(0.004)	(0.024)	(0.009)
D22	0.016	0.038	0.011	0.016	0.003
	(0.030)	(0.020)	(0.013)	(0.052)	(0.013)
D23	0.005	0.010	0.023	0.024	-0.002
	(0.051)	(0.017)	(0.014)	(0.051)	(0.018)
D24	0.010	0.041	0.025	0.027	-0.011
	(0.033)	(0.005)	(0.026)	(0.066)	(0.019)
D25	0.010	0.012	0.011	0.020	0.005
	(0.043)	(0.009)	(0.022)	(0.057)	(0.010)
D26T27	0.034	0.047	0.037	0.011	0.002
	(0.028)	(0.016)	(0.035)	(0.031)	(0.014)
D28	0.021	0.021	0.021	0.027	0.012
	(0.037	(0.013	(0.024	(0.056	(0.007)
D29	0.011	0.027	0.023	0.030	0.003
	(0.077)	(0.016)	(0.037)	(0.086)	(0.029)
D30	0.018	0.023	0.032	0.027	-0.002
	(0.038)	(0.021)	(0.018)	(0.051)	(0.027)
E	0.011	0.002	0.008	0.012	-0.001
	(0.025)	(0.018)	(0.020)	(0.016)	(0.011)
F	0.044	0.018	0.006	0.052	0.000
	(0.040)	(0.006)	(0.025)	(0.035)	(0.016)
P	0.007	0.009	0.012	0.015	-0.002
	(0.007)	(0.011)	(0.008)	(0.005)	(0.008)

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on OECD STAN data.

Table 5. Capital-to-labour ratio growth rates by industry: average and standard deviation

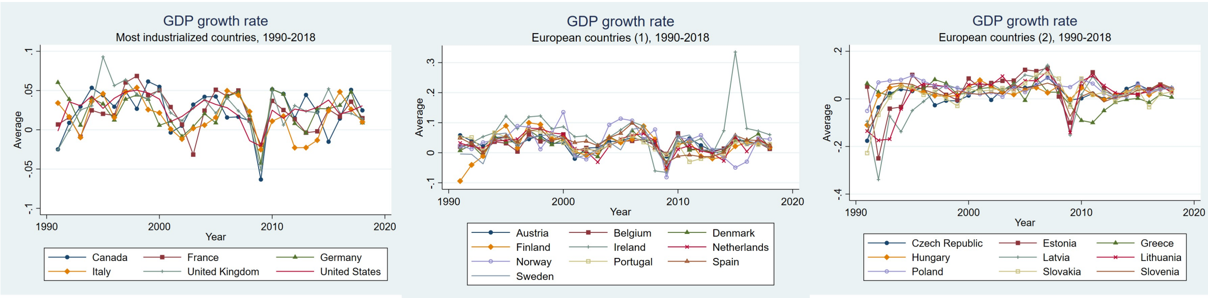

Figure 3. Statistics on GDP by country, 1990-2018

Note: Industry codes are from STAN ISIC rev. 4: Food products (D10), Textiles, wearing apparel, leather and related products (D13T15), Wood and products of wood and cork, except furniture (D16), Paper, printing and reproduction of recorded media (D17T18), Coke and refined petroleum products (D19), Chemical and pharmaceutical products (D20T21), Rubber and plastic products (D22), Other non-metallic mineral products (D23), Basic metals (D24), Fabricated metal products, except machinery and equipment (D25), Electrical, electronic and optical equipment (D26T27), Machinery and equipment (D28), Automotive (D29), Other transport equipment (D30), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Education (P). Source: Authors' own computations based on Penn World Table 10.0 data.

Country	**1990-96**		**1996-01**		**2001-07**		**2007-13**		**2013-18**	
Austria	0.045	(0.014)	0.041	(0.013)	0.025	(0.023)	0.029	(0.021)	0.015	(0.015)
Belgium	0.025	(0.014)	0.040	(0.021)	0.027	(0.021)	0.027	(0.024)	0.016	(0.016)
Canada	0.022	(0.031)	0.044	(0.014)	0.027	(0.022)	0.013	(0.037)	0.024	(0.024)
Czech Republic	-0.023	(0.091)	0.009	(0.028)	0.035	(0.022)	0.030	(0.035)	0.025	(0.020)
Denmark	0.022	(0.025)	0.045	(0.017)	0.027	(0.032)	0.028	(0.036)	0.025	(0.024)
Estonia	-0.035	(0.134)	0.050	(0.040)	0.084	(0.027)	0.052	(0.080)	0.019	(0.018)
Finland	0.002	(0.075)	0.066	(0.034)	0.025	(0.025)	0.025	(0.046)	0.025	(0.023)
France	0.012	(0.013)	0.044	(0.021)	0.025	(0.029)	0.023	(0.023)	0.015	(0.015)
Germany	0.036	(0.020)	0.029	(0.016)	0.012	(0.016)	0.024	(0.034)	0.018	(0.018)
Greece	0.042	(0.021)	0.047	(0.024)	0.042	(0.030)	-0.017	(0.069)	0.023	(0.013)
Hungary	0.010	(0.069)	0.026	(0.016)	0.045	(0.020)	0.027	(0.024)	0.020	(0.015)
Ireland	0.058	(0.041)	0.102	(0.022)	0.065	(0.025)	0.026	(0.066)	0.119	(0.118)
Italy	0.025	(0.022)	0.035	(0.016)	0.012	(0.020)	0.014	(0.029)	0.030	(0.027)
Latvia	-0.139	(0.117)	0.019	(0.041)	0.064	(0.024)	0.039	(0.095)	0.014	(0.016)
Lithuania	-0.096	(0.092)	0.047	(0.019)	0.067	(0.018)	0.047	(0.086)	0.018	(0.015)
Netherlands	0.030	(0.012)	0.063	(0.017)	0.025	(0.033)	0.022	(0.038)	0.031	(0.031)
Norway	0.033	(0.015)	0.073	(0.041)	0.061	(0.066)	0.043	(0.059)	0.043	(0.040)
Poland	0.054	(0.060)	0.057	(0.026)	0.031	(0.018)	0.060	(0.022)	0.022	(0.022)
Portugal	0.045	(0.023)	0.054	(0.018)	0.026	(0.019)	0.011	(0.031)	0.024	(0.020)
Slovakia	-0.037	(0.117)	0.018	(0.029)	0.051	(0.025)	0.056	(0.053)	0.028	(0.028)
Slovenia	-0.001	(0.091)	0.032	(0.016)	0.035	(0.017)	0.018	(0.049)	0.028	(0.022)
Spain	0.035	(0.022)	0.055	(0.017)	0.051	(0.025)	0.017	(0.049)	0.031	(0.027)
Sweden	0.016	(0.045)	0.050	(0.016)	0.022	(0.034)	0.036	(0.046)	0.020	(0.019)
United Kingdom	0.025	(0.044)	0.058	(0.019)	0.030	(0.014)	0.016	(0.033)	0.012	(0.013)
United States	0.027	(0.017)	0.042	(0.009)	0.027	(0.011)	0.011	(0.020)	0.006	(0.006)

Source: Authors' own computations based on Penn World Table 10.0 data.

Table 6. Real GDP growth rates by country: average and standard deviation

to a set of variables that includes the capital-labour ratio, GDP and the interaction terms between the latter and the dummy for robot density. Eq. (5) presents the econometric specification of the evolutionary Kaldor-Verdoorn's law:

$$
\begin{aligned}
\dot{a}_{ijt} &= c_0 + \sum_{z=0}^{4} \alpha_z \cdot \dot{a}_{ijt-z} + \sum_{z=0}^{4} \beta_z \cdot \dot{k}_{ijt-z} + \sum_{z=0}^{4} \delta_z \cdot \dot{Y}_{jt-z} \\
&+ \sum_{z=0}^{4} \varepsilon_z \cdot d_{ijt-z} \cdot \dot{k}_{ijt-z} + \sum_{z=0}^{4} \vartheta_z \cdot d_{ijt-z} \cdot \dot{Y}_{jt-z} + yr_t^* + u_{ijt}
\end{aligned} \tag{5}
$$

in which αs, βs, δs, εs and ϑs are the coefficients of interest, c_0 is the constant term, yr^* the time effects and u the disturbance.

Some clarification is necessary. Firstly, the theoretical framework in Subsection 3.1 entails a dynamic relationship between variables in growth terms.[12] Secondly, since the unit of analysis is the industry i in country j, we account for robotisation with a dummy variable, d_{ijt}, that takes value 1 whenever the ratio between stock of robots and net capital at time t is above the cross-country industry average, and zero otherwise. This simple dummy is a way to control for the impact of increasing robot density across time and space. Moreover, it appears in Eq. (5) as term of interaction with the key components of the Kaldor-Verdoorn's law, i.e., $\dot{k}$ and $\dot{Y}$. Thirdly, the lack of suitable lag choice criteria for a dynamic panel time-series constrains our choice to be based on a rule of thumb. The stationarity properties of the covariates, the yearly time unit, and the need to keep the model as parsimonious as possible suggest considering at most four lags in the dynamic process of adjustment to the long-run average steady state. Furthermore, the choice of a parsimonious model allows to contain problems of collinearity that emerge with the inclusion of many lags. Fourthly, the cumulative-causation framework implies the inherent endogeneity of the three main regressors, $\dot{k}$, $\dot{Y}$ and d. We account for this issue with the GMM estimator as developed by Arellano and Bond (1991) and Blundell, Bond and Windmeijer (2001).[13] Estimates are carried out with both the difference and the system GMM estimation procedures.[14]

3.3 Main empirical evidence

We begin our empirical exercise with the estimates reported in Tab. 7 and Tab. 8. These results constitute preliminary evidence on the general validity of the evolutionary Kaldor-

[12] The growth rates follow a stationary process according to Fisher-type panel unit root tests; details available upon request.

[13] The literature on the properties of GMM estimators is abundant. We suggest Bond (2002), Bontempi and Golinelli (2005), Judson and Owen (1999), Roodman (2009a), Wooldridge (2010).

[14] Although we present both onestep and twostep estimates, it is important to notice that onestep GMM estimates, even if robust, assume a pattern of homoskedasticity in the computation of the estimator. The twostep procedure, in contrast, takes heteroskedasticity patterns in strong consideration with important gains in terms of efficiency. We therefore believe that all the following twostep estimates are more reliable.

Verdoorn's law, without considering the impact of robots. Focusing on Tab. 7, the reported estimates refer to a parsimonious specification of Eq. (4) in which either one or two lags are considered for both regressors and dependent variable. We single out a threefold evidence. Firstly, the impact of a change in the capital-labour ratio is always positive when statistically significant and lower than one. Precisely, the coefficient of the contemporaneous regressor ranges between 0.27 and 0.49. In addition to this, the positive association between current growth in labour productivity and in the capital-labour ratio extends to the first and to the second lag of the latter, though the magnitude is smaller. Secondly, the macro-level arguments summarized by the growth in GDP find a weak significance. The coefficient of the contemporaneous relation is positive, statistically significant and with the expected magnitude in two specifications only and the term ranges between 0.18 and 0.44. Previous lags in GDP growth do not seem to be significantly associated with current changes in labour productivity. Thirdly, the influence of past changes in current productivity growth is negative and statistically significant. This finding is in agreement with a stationary variable that undertakes an adjustment process toward the long-run average value.

Such preliminary results look more complex and richer when switching to less parsimonious specifications as in Tab. 8. If, on the one hand, the inner adjustment dynamics of productivity growth is as previously observed and as expected, on the other hand, the impact of the growth in the capital-labour ratio is different. In other words, results point to a *cyclical* dynamics with both positive and negative correlations. The relationship between the growth rates of productivity and capital-labour ratio is positive at time t, $t-2$ and $t-4$, while it is negative in correspondence of the first and third lag. In any case, the coefficient is always lower than one in absolute value. Conversely, the impact of GDP growth in terms of increasing returns to scale tends to be confirmed and the coefficient is positive and between zero and one when statistically significant. Nevertheless, most GMM estimates reveal a contemporaneous association between industrial productivity growth and changes in GDP. The correlation with GDP lags is envisaged by twostep system-GMM only.

To summarize, the preliminary evidence broadly suggest the existence of a Kaldor-Verdoorn's mechanism in the dynamics of labour productivity growth, despite results can change and become richer as we switch from a parsimonious to a complex functional form.

Then, what is the impact of robots on the Kaldor-Verdoorn's law, if any? We present the results out of Eq. (5) in Tab. 9 through Tab. 12. As a first step, we shall begin with asking what is the impact of robotisation for industries with a robot density lower than cross-country sectoral average. This is tantamount of assuming the dummy is equal to zero and there are no interaction terms. In this case, a lower robot density than average does not invalidate the Kaldor-Verdoorn's law. For the sake of simplicity, we first check Tab. 9.

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.101	-0.145	−0.099***	−0.242***	0.397	−0.311*	0.388***	−0.189***
	(0.106)	(0.15)	(0.008)	(0.007)	(0.484)	(0.169)	(0.025)	(0.006)
$\dot{a}_{ijt-2}$		-0.076		−0.188***		-0.159		−0.141***
		(0.171)		(0.010)		(0.137)		(0.010)
$\dot{k}_{ijt}$	0.492*	0.302	0.382***	0.269***	0.484	0.166	0.404***	0.348***
	(0.292)	(0.421)	(0.073)	(0.064)	(0.344)	(0.461)	(0.067)	(0.056)
$\dot{k}_{ijt-1}$	-0.014	-0.247	0.016	0.058**	-0.253	-0.338	-0.098	0.059***
	(0.081)	(0.605)	(0.025)	(0.025)	(0.361)	(0.503)	(0.064)	(0.022)
$\dot{k}_{ijt-2}$		0.324		0.099***		0.443*		0.093***
		(0.274)		(0.0235)		(0.254)		(0.018)
$\dot{Y}_{jt}$	0.077	0.375	0.015	0.071	0.503	0.437*	0.184**	0.055
	(0.227)	(0.254)	(0.088)	(0.085)	(0.418)	(0.259)	(0.092)	(0.090)
$\dot{Y}_{jt-1}$	0.183	0.049	0.072	0.053	-0.207	0.062	-0.062	0.058
	(0.192)	(0.486)	(0.063)	(0.051)	(0.431)	(0.490)	(0.071)	(0.050)
$\dot{Y}_{jt-2}$		0.425		-0.006		0.395		-0.026
		(0.454)		(0.047)		(0.301)		(0.044)
Constant					-0.049	-0.016	−0.059***	0.011**
					(0.045)	(0.023)	(0.010)	(0.005)
Observations	4851	4617	4851	4617	5087	4851	5087	4851
Instruments	107	100	107	106	108	104	108	110
AB (1)	−2.607***	−2.432**	−3.203***	−3.17***	-1.479	−2.07**	−3.227***	−3.186***
AB (2)	-1.270	-0.425	-0.822	-0.132	0.937	-0.593	0.383	-0.247
Hansen	70.740	63.790	70.740	71.640	71.860	73.790	71.860	83.060

Note: standard errors in brackets. Star significance: * p-value< 0.10, ** p-value< 0.05, *** p-value< 0.01.

Table 7. Preliminary empirical evidence (1)

The relationship between changes in labour productivity and in the capital-labour ratio is positive and statistically significant in most specifications. Moreover, this linkage extends in time, at least until the second lag of $\dot{k}$. Precisely, its contemporaneous coefficient ranges from a minimum value 0.55 to a maximum 0.95. Conversely, the magnitude gradually reduces to about 0.6 when we consider previous lags. The macro-level channel of the law is in place too, at least when we consider the contemporaneous correlation. We observe indeed that a unit increase in the growth of aggregate output is associated with a change in labour productivity growth in between 0.26 and 0.87. Yet, the impact of precedent output growth is not clear: most of the time it is not significantly different from zero, whereas when it is, it could be either positive or negative.

The outcomes are strongly confirmed when we extend the regressions to the third and fourth lag of the covariates (Tab. 10). The positive industry-level route envisaged by the technical progress function is generally stronger in magnitude and extends back into the past, at least until the third year before. Moreover, most of the negative relations between productivity and past GDP turn to be positive and significantly different from zero, with some exception notwithstanding, e.g., D-GMM twostep Model (IV).[15]

The second step in the analysis consists of understanding what is, if any, the impact of

[15] The adjustment process of productivity growth toward a long-period average finds another evidence. It is interesting to notice that the adjustment takes about three years, since the correlation between contemporaneous and fourth lag is positive.

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.246	-0.162	-0.150^{***}	-0.151^{***}	-0.092	-0.196	-0.224^{***}	-0.185^{***}
	(0.185)	(0.307)	(0.037)	(0.043)	(0.206)	(0.317)	(0.037)	(0.045)
$\dot{a}_{ijt-2}$	-0.112	-0.136	0.094^{***}	-0.082^{*}	-0.009	-0.181	0.010	-0.187^{***}
	(0.113)	(0.193)	(0.033)	(0.045)	(0.182)	(0.146)	(0.030)	(0.046)
$\dot{a}_{ijt-3}$	-0.139	-0.105	-0.058^{*}	-0.126^{***}	0.068	0.040	-0.134^{***}	0.019
	(0.155)	(0.285)	(0.031)	(0.049)	(0.070)	(0.356)	(0.026)	(0.041)
$\dot{a}_{ijt-4}$		0.004		-0.068^{*}		0.050		0.052
		(0.158)		(0.036)		(0.292)		(0.033)
$\dot{k}_{ijt}$	0.518	0.533	0.537^{***}	0.649^{***}	0.266	0.637^{*}	0.493^{***}	0.730^{***}
	(0.470)	(0.335)	(0.099)	(0.108)	(0.391)	(0.381)	(0.103)	(0.095)
$\dot{k}_{ijt-1}$	-0.420	-0.411	-0.174^{**}	-0.322^{***}	-0.137	-0.226	-0.183^{**}	-0.282^{***}
	(0.696)	(0.512)	(0.089)	(0.097)	(0.582)	(0.448)	(0.083)	(0.091)
$\dot{k}_{ijt-2}$	0.391	0.277	0.208^{***}	0.216^{**}	0.412	0.186	0.292^{***}	0.223^{***}
	(0.407)	(0.495)	(0.080)	(0.090)	(0.382)	(0.339)	(0.077)	(0.080)
$\dot{k}_{ijt-3}$	-0.322	-0.362	-0.203^{***}	-0.264^{***}	-0.100	-0.488	0.053	-0.437^{***}
	(0.283)	(0.401)	(0.077)	(0.080)	(0.091)	(0.421)	(0.069)	(0.082)
$\dot{k}_{ijt-4}$		0.275^{**}		0.165^{*}		-0.011		0.081
		(0.128)		(0.091)		(0.280)		(0.078)
$\dot{Y}_{jt}$	0.430	0.396	0.075	0.028	0.534^{*}	0.639^{*}	0.204^{*}	0.112
	(0.275)	(0.338)	(0.110)	(0.109)	(0.321)	(0.341)	(0.109)	(0.114)
$\dot{Y}_{jt-1}$	0.047	-0.037	0.031	0.015	0.046	0.243	0.074	0.024
	(0.466)	(0.581)	(0.102)	(0.123)	(0.543)	(0.733)	(0.108)	(0.120)
$\dot{Y}_{jt-2}$	0.369	0.497	0.031	0.133	0.390	0.660	0.171^{*}	0.286^{**}
	(0.326)	(0.369)	(0.102)	(0.114)	(0.370)	(0.414)	(0.103)	(0.117)
$\dot{Y}_{jt-3}$	0.081	0.067	0.025	-0.143	-0.084	0.188	0.115	0.015
	(0.285)	(0.331)	(0.109)	(0.112)	(0.134)	(0.340)	(0.100)	(0.116)
$\dot{Y}_{jt-4}$		-0.138		-0.063		-0.344		-0.129
		(0.202)		(0.116)		(0.417)		(0.105)
Constant					-0.013	-0.036	0.001	-0.011
					(0.028)	(0.031)	(0.010)	(0.010)
Observations	4383	4150	4383	4150	4617	4383	4617	4383
Instruments	93	95	96	92	103	96	100	96
AB (1)	-2.471^{**}	-1.995^{**}	-3.191^{***}	-3.237^{***}	-2.327^{**}	-1.771^{*}	-3.211^{***}	-3.411^{***}
AB (2)	-0.726	-0.177	-1.222	-0.619	-0.494	0.337	-1.182	0.570
Hansen	54.280	61.860	60.120	58.970	70.790	57.800	66.030	57.800

Note: standard errors in brackets. Star significance: * p-value< 0.10, ** p-value< 0.05, *** p-value< 0.01.

Table 8. Preliminary empirical evidence (2)

a higher-than-average robot density. Inspecting the coefficients of the several interaction terms in Tab. 9 and Tab. 10 is not sufficient to grasp the overall effect. This belief is reinforced also by the fact that the coefficients of the interaction terms can be either positive or negative, significant or not significant. To overcome this limitation, we compute the combined effects as reported in Tab. 11 and Tab. 12.[16] In particular, we define η_z and γ_z as follows:

$$\eta_z = \beta_z + \varepsilon_z$$

$$\gamma_z = \delta_z + \vartheta_z$$

in which η_z is the combined effect of robotisation on the relationship between the growth in productivity and changes in the capital-labour ratio, while γ is about the impact of the increasing returns to scale component on the growth in productivity. The empirical evidence is contrasting and somewhat puzzling. Let us focus first on difference-GMM estimates as in Tab. 11. When analysing onestep results, we grasp that η_z is mostly never statistically significant, with the exception of the third lag, while γ_z is generally significantly positive when we refer to the contemporaneous correlation. On the one hand, the overall non-significance of η_z means that a higher-than-average robot density removes and cancels the positive channel between $\dot{k}$ and $\dot{a}$, which is at work when dealing with less-than-average robotised industries. On the other hand, the higher-than-average robot density strengthens the contemporaneous association between changes in sectoral productivity and GDP growth. With an average coefficient greater than one, the impact of higher robot density on the macro-level relationship that links GDP to industry productivity growth entails a form of technological unemployment, since a unit increase in the GDP growth is associated with more that a unit change in sectoral productivity, with no benefits in terms of employment.
In contrast, the results differ when we switch to the twostep difference-GMM, that account for heteroskedasticity in the computation of the coefficients. Firstly, the robot density does not nullify the mechanisms underlying the technical progress function but keeps them at work. The coefficients of both the contemporaneous and lagged $\dot{k}$ are positive, statistically significant, and between 0.1 and 0.3, somehow smaller than for lower-than-average robotised industries. This implies that an increased robotisation weakens but does not remove the positive relationship between $\dot{a}$ and $\dot{k}$ through time. The mechanisms behind the technical progress component of the Kaldor-Verdoorn's law seem less powerful. Though the impact on the macro-level channel is similar as above, we nonetheless point to the uncertain and negative impact of previous lags in GDP growth that emerges in the three-lags twostep specification. These contrasting results are generally matched by system-GMM es-

[16]Tab. 11 and Tab. 12 are organised by GMM estimator.

timates in Tab. 12.

This puzzling picture agrees with the empirical literature. A weakened relationship between labour productivity growth and changes in the capital-labour ratio entails an increase in the employment growth at the micro and meso-economic level. Empirical studies reveal indeed a positive correlation between employment and increased robotisation at firm and industry level (Domini et al. 2021, Graetz and Michaels 2018, Klenert et al. 2020). Yet, industries with a higher-than-average degree of robotisation experience a reinforcing effect that operates through the macro-level extension of the idea of division of labour as argued long ago by Young (1928), among the others. In this case, the average magnitude of the effect is above unity, and it denotes a form of technological unemployment. The contrasting and puzzling dynamics at work at different levels of the economic activity is in agreement with Acemoglu, Autor, Hazell and Restrepo (2020) and Bordot (2022), among the others.
We further elaborate on the robustness of these results in the following subsection.[17]

3.4 Robustness check

We carry out a battery of robustness checks by modifying the definition of some variables of interest. Precisely, the main empirical findings above were based on a measure of net capital stock, the ratio between operational stock of robots and net capital, and a computation of GDP from the expenditure side. We now operate a substitution of gross capital for net capital stock and of output-side GDP for the expenditure-side computation. For what concerns to the measure of robotisation, the dummy variable is now based on the ratio between the operational stock of robots and employment levels by total engaged in ten thousand units, to comply with other works in the literature (Graetz and Michaels 2018, Klenert et al. 2020) and with IFR definition of robot density.
Tab. 13 and Tab. 14 are about preliminary empirical evidence of the Kaldor-Verdoorn's law as previously showed in Tab. 7 and Tab. 8. The existence of mechanisms *à la* Kaldor-Verdoorn is confirmed and a little strengthened in Tab. 13. The channel linking the growth in the capital-labour ratio to productivity improvements is at work and, if the magnitude of the coefficients is very similar to what reported in Tab. 7, the same magnitude looks a little larger when observing the effect of the first and second lag in $\dot{k}$ on $\dot{a}$. Moreover, the significant and positive influence of the macro-level dynamics on labour productivity growth

[17]Regressions in Tab. 9 and Tab. 10 are equipped with Arellano and Bond (1991) autocorrelation tests ($AB(1)$ and $AB(2)$) and the Hansen test for over-identifying restrictions. The overall reliability of our estimates is witnessed by the fact that there is no serial correlation of second order and the pool of instruments is exogenous. These assertions come out from the non-rejection of the null hypothesis of both the $AB(2)$ and the Hansen tests. Furthermore, we have reported the instrument count, whose value is always well below the number of cross-sectional units. We use this rule of thumb to deal with the well-known problem of "too many instruments" in GMM estimations (Roodman 2009a,b).

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.273^{***}	-0.0515	-0.264^{***}	-0.120^{***}	-0.166^{**}	-0.0879	-0.156^{***}	-0.0629^{***}
	(0.0791)	(0.113)	(0.00402)	(0.00626)	(0.0684)	(0.0915)	(0.0126)	(0.00488)
$\dot{a}_{ijt-2}$		-0.0649		-0.0919^{***}		-0.100^{*}		-0.0556^{***}
		(0.0559)		(0.00693)		(0.0523)		(0.00395)
$\dot{k}_{ijt}$	0.954^{**}	0.833^{**}	0.810^{***}	0.783^{***}	-0.227	0.546^{*}	-0.134	0.539^{***}
	(0.386)	(0.341)	(0.0661)	(0.0643)	(0.788)	(0.305)	(0.103)	(0.0665)
$\dot{k}_{ijt-1}$	-0.028	0.178	-0.0143	0.0227	0.584^{**}	-0.0984	0.590^{***}	0.0134
	(0.118)	(0.279)	(0.0298)	(0.0332)	(0.27)	(0.306)	(0.0653)	(0.0232)
$\dot{k}_{ijt-2}$		0.28		0.186^{***}		0.649^{**}		0.134^{***}
		(0.232)		(0.0309)		(0.294)		(0.027)
$\dot{Y}_{jt}$	0.871^{**}	0.351	0.796^{***}	0.262^{***}	-0.0607	0.559^{*}	-0.0233	0.452^{***}
	(0.416)	(0.323)	(0.0699)	(0.0778)	(0.573)	(0.294)	(0.0965)	(0.0893)
$\dot{Y}_{jt-1}$	-0.0614	0.627	-0.126^{***}	0.031	0.461^{*}	0.255	0.286^{***}	-0.141^{***}
	(0.16)	(0.385)	(0.0475)	(0.0498)	(0.236)	(0.35)	(0.0782)	(0.0495)
$\dot{Y}_{jt-2}$		-0.0487		0.0487		0.097		0.0565
		(0.318)		(0.038)		(0.238)		(0.0363)
$d_{ijt} \cdot \dot{k}_{ijt}$	-0.562	-0.573	-0.516^{***}	-0.578^{***}	0.654	-0.354	0.493^{***}	-0.309^{***}
	(0.342)	(0.367)	(0.0714)	(0.0818)	(0.869)	(0.374)	(0.113)	(0.0888)
$d_{ijt-1} \cdot \dot{k}_{ijt-1}$	0.098	-0.263	0.122^{***}	0.139^{***}	-0.612^{*}	0.0788	-0.630^{***}	0.0978^{***}
	(0.146)	(0.462)	(0.0359)	(0.039)	(0.37)	(0.479)	(0.0788)	(0.0311)
$d_{ijt-2} \cdot \dot{k}_{ijt-2}$		-0.239		-0.179^{***}		-0.600^{**}		-0.139^{***}
		(0.26)		(0.0316)		(0.282)		(0.031)
$d_{ijt} \cdot \dot{Y}_{jt}$	0.45	1.006	0.287^{**}	0.785^{***}	1.975	0.699	1.669^{***}	0.465^{***}
	(0.623)	(0.871)	(0.117)	(0.125)	(1.219)	(0.768)	(0.131)	(0.123)
$d_{ijt-1} \cdot \dot{Y}_{jt-1}$	-0.0215	-1.098	0.0334	0.045	-1.179^{**}	-0.395	-1.034^{***}	0.0331
	(0.255)	(0.713)	(0.0732)	(0.0916)	(0.599)	(0.688)	(0.124)	(0.0734)
$d_{ijt-2} \cdot \dot{Y}_{jt-2}$		0.478		0.0388		0.118		-0.0917^{*}
		(0.521)		(0.0527)		(0.446)		(0.0502)
Constant					-0.00843	-0.0146	-0.00156	0.00208
					(0.0183)	(0.0161)	(0.0037)	(0.00289)
Observations	2828	2610	2828	2610	3048	2828	3048	2828
Instruments	153	142	153	152	154	148	154	158
AB (1)	-1.891^{*}	-2.63^{***}	-3.217^{***}	-4.009^{***}	-4.215^{***}	-2.721^{***}	-4.103^{***}	-3.94^{***}
AB (2)	-2.276^{**}	0.784	-3.512^{***}	1.284	-1.132	0.887	-1.3	0.99
Hansen	131.2	107.7	131.2	115.7	127.7	113.6	127.7	111.8

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 9. Empirical findings (1)

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.354^{***}	-0.295^{**}	-0.329^{***}	-0.210^{***}	-0.327^{***}	-0.202	-0.317^{***}	-0.263^{***}
	(0.121)	(0.14)	(0.0175)	(0.0523)	(0.11)	(0.191)	(0.0238)	(0.0584)
$\dot{a}_{ijt-2}$	-0.309^{**}	-0.00641	-0.337^{***}	-0.0208	-0.137	0.118	-0.171^{***}	0.0693
	(0.146)	(0.124)	(0.0229)	(0.0459)	(0.163)	(0.145)	(0.0224)	(0.0536)
$\dot{a}_{ijt-3}$	-0.151	-0.301^{***}	-0.170^{***}	-0.130^{***}	-0.0409	0.132	-0.0488^{**}	0.148^{***}
	(0.122)	(0.111)	(0.0167)	(0.0379)	(0.153)	(0.118)	(0.019)	(0.0526)
$\dot{a}_{ijt-4}$		0.0405		0.286^{***}		0.322^{*}		0.275^{***}
		(0.0798)		(0.0393)		(0.177)		(0.0483)
$\dot{k}_{ijt}$	0.915^{**}	0.396	0.799^{***}	0.729^{***}	1.003^{**}	1.103^{**}	0.813^{***}	1.257^{***}
	(0.426)	(0.41)	(0.10)	(0.138)	(0.51)	(0.54)	(0.095)	(0.202)
$\dot{k}_{ijt-1}$	0.3	0.316	0.220^{***}	0.529^{***}	0.16	0.803^{*}	0.147^{**}	0.769^{***}
	(0.32)	(0.358)	(0.0695)	(0.147)	(0.241)	(0.473)	(0.061)	(0.199)
$\dot{k}_{ijt-2}$	0.396	0.241	0.287^{***}	0.576^{***}	0.415	0.168	0.380^{***}	0.607^{***}
	(0.329)	(0.267)	(0.101)	(0.115)	(0.352)	(0.295)	(0.0884)	(0.201)
$\dot{k}_{ijt-3}$	0.0756	0.127	0.162^{**}	0.238^{**}	-0.0195	0.128	0.00887	0.187
	(0.103)	(0.25)	(0.0781)	(0.119)	(0.379)	(0.33)	(0.0964)	(0.174)
$\dot{k}_{ijt-4}$		-0.0319		-0.247^{*}		-0.747		-0.126
		(0.125)		(0.14)		(0.569)		(0.207)
$\dot{Y}_{jt}$	0.528	-0.31	0.597^{***}	-0.600^{***}	0.518^{*}	-0.172	0.468^{***}	0.515^{**}
	(0.338)	(0.463)	(0.125)	(0.172)	(0.272)	(0.497)	(0.0909)	(0.234)
$\dot{Y}_{jt-1}$	0.505	-0.191	0.286^{***}	-0.251	0.444	0.741^{*}	0.221^{**}	0.591^{***}
	(0.373)	(0.513)	(0.105)	(0.17)	(0.361)	(0.417)	(0.102)	(0.193)
$\dot{Y}_{jt-2}$	0.15	0.141	0.167^{*}	-0.172	0.22	0.0689	0.303^{***}	-0.0208
	(0.264)	(0.31)	(0.0908)	(0.138)	(0.302)	(0.373)	(0.0883)	(0.185)
$\dot{Y}_{jt-3}$	-0.168	-0.488	-0.112	-0.553^{***}	-0.102	-0.275	-0.0135	0.323^{*}
	(0.192)	(0.507)	(0.094)	(0.139)	(0.294)	(0.418)	(0.0954)	(0.192)
$\dot{Y}_{jt-4}$		0.0393		-0.461^{***}		-0.694^{*}		0.289
		(0.176)		(0.136)		(0.368)		(0.293)
$d_{ijt} \cdot \dot{k}_{ijt}$	-0.887^{**}	-0.528	-0.814^{***}	-1.073^{***}	-0.772	-1.144^{**}	-0.626^{***}	-1.122^{***}
	(0.419)	(0.437)	(0.131)	(0.182)	(0.481)	(0.577)	(0.129)	(0.247)
$d_{ijt-1} \cdot \dot{k}_{ijt-1}$	-0.498	-0.0602	-0.309^{***}	-0.494^{***}	-0.00564	-0.423	0.0631	-0.261
	(0.417)	(0.417)	(0.0819)	(0.156)	(0.30)	(0.482)	(0.0755)	(0.263)
$d_{ijt-2} \cdot \dot{k}_{ijt-2}$	-0.496	-0.30	-0.407^{***}	-0.600^{***}	-0.386	-0.24	-0.315^{***}	-0.394
	(0.333)	(0.3)	(0.0906)	(0.135)	(0.371)	(0.435)	(0.0907)	(0.249)
$d_{ijt-3} \cdot \dot{k}_{ijt-3}$	0.147	0.412	0.0864	0.091	0.179	0.129	0.145	0.0108
	(0.126)	(0.53)	(0.082)	(0.154)	(0.381)	(0.495)	(0.0998)	(0.236)
$d_{ijt-4} \cdot \dot{k}_{ijt-4}$		0.194		0.542^{***}		0.714		0.156
		(0.166)		(0.149)		(0.543)		(0.213)
$d_{ijt} \cdot \dot{Y}_{jt}$	0.388	1.071	0.058	1.396^{***}	0.865	1.660^{*}	0.782^{***}	1.064^{***}
	(0.645)	(0.782)	(0.192)	(0.29)	(0.618)	(0.946)	(0.136)	(0.352)
$d_{ijt-1} \cdot \dot{Y}_{jt-1}$	-0.698	-0.0341	-0.505^{***}	0.123	-0.376	-0.761	-0.0876	-0.101
	(0.553)	(0.657)	(0.156)	(0.244)	(0.634)	(0.616)	(0.172)	(0.336)
$d_{ijt-2} \cdot \dot{Y}_{jt-2}$	-0.0035	-0.676	0.0235	0.17	0.0369	-0.0994	0.158	1.085^{***}
	(0.478)	(0.546)	(0.127)	(0.194)	(0.496)	(0.506)	(0.14)	(0.244)
$d_{ijt-3} \cdot \dot{Y}_{jt-3}$	0.383^{*}	0.701	0.116	0.718^{***}	0.0733	0.212	-0.0343	-0.357
	(0.211)	(0.95)	(0.103)	(0.196)	(0.45)	(0.69)	(0.118)	(0.24)
$d_{ijt-4} \cdot \dot{Y}_{jt-4}$		-0.0763		0.520^{***}		0.573		-0.174
		(0.315)		(0.162)		(0.488)		(0.303)
Constant					-0.0209	-0.00906	-0.0223^{***}	-0.0533^{***}
					(0.0169)	(0.0211)	(0.00587)	(0.0131)
Observations	2394	2182	2394	2182	2610	2394	2610	2394
Instruments	141	135	136	130	142	136	142	116
AB (1)	-3.956^{***}	-2.433^{**}	-3.998^{***}	-3.619^{***}	-3.815^{***}	-2.37^{**}	-3.927^{***}	-3.093^{***}
AB (2)	0.419	-1.473	1.64	-1.333	-0.253	-0.538	0.0664	-0.441
Hansen	96.77	93.54	94.84	83.47	113.20	88.29	113.20	53.42

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 10. Empirical findings (2)

Dep. Var. : $\dot{a}_{ijt}$	D-GMM							
	onestep				twostep			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
η_t	0.392	0.260	0.028	-0.132	0.293***	0.205***	-0.014	−0.343***
	(0.252)	(0.289)	(0.022)	(0.232)	(0.036)	(0.036)	(0.075)	(0.010)
η_{t-1}	0.070	-0.085	-0.198	0.256	0.107***	0.162***	-0.089	0.035
	(0.098)	(0.301)	(0.219)	(0.344)	(0.022)	(0.022)	(0.055)	(0.080)
η_{t-2}		0.041	-0.100	-0.059		0.007	−0.121**	-0.024
		(0.223)	(0.244)	(0.270)		(0.021)	(0.056)	(0.074)
η_{t-3}			0.222**	0.539			0.248***	0.329***
			(0.105)	(0.422)			(0.039)	(0.077)
η_{t-4}				0.162				0.295***
				(0.127)				(0.065)
γ_t	1.320**	1.350*	0.915*	0.760	1.082***	1.047***	0.655***	0.796***
	(0.624)	(0.724)	(0.489)	(0.542)	(0.085)	(0.085)	(0.121)	(0.193)
γ_{t-1}	-0.083	-0.470	-0.193	-0.225	-0.093	0.076	−0.219**	−0.128
	(0.206)	(0.425)	(0.349)	(0.348)	(0.057)	(0.064)	(0.103)	(0.156)
γ_{t-2}		0.429	0.147	-0.534		0.087*	0.191	-0.001
		(0.433)	(0.431)	(0.418)		(0.049)	(0.121)	(0.145)
γ_{t-3}			0.215	0.214			0.004	0.164
			(0.216)	(0.548)			(0.077)	(0.125)
γ_{t-4}				-0.037				0.059
				(0.271)				(0.112)

Note: $\eta_z = \beta_z + \varepsilon_z$; $\gamma_z = \delta_z + \vartheta_z$. Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 11. Combined effects from difference-GMM estimates

Dep. Var. : $\dot{a}_{ijt}$	S-GMM							
	onestep				twostep			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
η_t	0.427*	0.192	0.231	-0.041	0.360***	0.230***	0.187**	0.136
	(0.236)	(0.264)	(0.219)	(0.274)	(0.051)	(0.043)	(0.078)	(0.124)
η_{t-1}	-0.029	-0.020	0.154	0.380	-0.040	0.111***	0.210***	0.508***
	(0.204)	(0.313)	(0.234)	(0.406)	(0.044)	(0.021)	(0.063)	(0.151)
η_{t-2}		0.049	0.029	-0.072		-0.005	0.065	0.213
		(0.193)	(0.256)	(0.319)		(0.021)	(0.062)	(0.158)
η_{t-3}			0.160	0.258			0.154***	0.197
			(0.158)	(0.325)			(0.052)	(0.132)
η_{t-4}				-0.033				0.030
				(0.301)				(0.106)
γ_t	1.914**	1.258*	1.383***	1.488***	1.645***	0.917***	1.250***	1.589***
	(0.859)	(0.647)	(0.482)	(0.608)	(0.095)	(0.077)	(0.106)	(0.244)
γ_{t-1}	-0.717	-0.140	0.068	-0.020	−0.748***	−0.108**	0.134	0.490**
	(0.446)	(0.404)	(0.374)	(0.357)	(0.090)	(0.051)	(0.121)	(0.246)
γ_{t-2}		0.215	0.257	-0.030		-0.035	0.461***	1.065***
		(0.370)	(0.426)	(0.364)		(0.044)	(0.103)	(0.190)
γ_{t-3}			-0.029	-0.064			-0.048	-0.035
			(0.305)	(0.408)			(0.076)	(0.179)
γ_{t-4}				-0.121				0.115
				(0.412)				(0.158)

Note: $\eta_z = \beta_z + \varepsilon_z$; $\gamma_z = \delta_z + \vartheta_z$. Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 12. Combined effects from system-GMM estimates

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.095	-0.134	-0.099^{***}	-0.142^{***}	-0.172^{***}	-0.304^{**}	-0.359^{***}	-0.307^{***}
	(0.116)	(0.131)	(0.006)	(0.014)	(0.063)	(0.153)	(0.014)	(0.014)
$\dot{a}_{ijt-2}$		-0.228^{**}		-0.231^{***}		-0.18		-0.218^{***}
		(0.093)		(0.008)		(0.123)		(0.008)
$\dot{k}_{ijt}$	0.395^{*}	0.259	0.432^{***}	0.264^{***}	0.749^{**}	0.093	0.356^{***}	0.179^{***}
	(0.215)	(0.281)	(0.041)	(0.039)	(0.333)	(0.365)	(0.034)	(0.038)
$\dot{k}_{ijt-1}$	0.034	-0.034	0.010	-0.060	-0.060	-0.182	0.130^{***}	-0.044
	(0.081)	(0.345)	(0.022)	(0.043)	(0.089)	(0.353)	(0.048)	(0.043)
$\dot{k}_{ijt-2}$		0.068		0.056^{**}		0.308		0.110^{***}
		(0.081)		(0.025)		(0.226)		(0.018)
$\dot{Y}_{jt}$	0.199	0.414	0.169^{**}	0.206^{**}	0.451	0.307	0.381^{***}	0.033
	(0.527)	(0.407)	(0.073)	(0.081)	(0.447)	(0.412)	(0.081)	(0.072)
$\dot{Y}_{jt-1}$	-0.040	-0.566	-0.023	-0.276^{***}	0.039	-0.39	0.116	-0.163^{**}
	(0.158)	(0.382)	(0.046)	(0.083)	(0.147)	(0.387)	(0.072)	(0.073)
$\dot{Y}_{jt-2}$		0.315^{*}		0.159^{***}		0.711^{**}		0.103^{***}
		(0.166)		(0.046)		(0.354)		(0.040)
Constant					-0.001	-0.035	-0.006	0.005
					(0.039)	(0.040)	(0.009)	(0.009)
Observations	3609	3430	3609	3430	3790	3609	3790	3609
Instruments	107	103	107	103	111	104	105	107
AB (1)	-2.319^{**}	-2.291^{**}	-2.777^{***}	-2.719^{***}	-2.835^{***}	-2.104^{**}	-2.638^{***}	-2.605^{***}
AB (2)	-1.208	1.144	-0.81	0.56	-1.159	-0.592	-1.375	-0.314
Hansen	83.05	80.75	83.05	80.75	87.53	82.32	88.7	85.9

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 13. Preliminary empirical evidence: robustness check (1)

now is not limited to contemporaneous lag of $\dot{Y}$, but involves also its second lag. However, the association between productivity growth and the first lag in $\dot{Y}$ is negative when statistically significant. Therefore, the relationship displays a cyclical pattern.
When switching to less parsimonious specifications as in Tab. 14, again we find results very close to Tab. 8. For what regards the technical progress component of the Kaldor-Verdoorn's law, we observe that a unit increase in the contemporaneous growth rate of the capital-labour ratio is associated with a rise of about 0.33 to 0.73 in the growth rate of labour productivity, when the coefficient is statistically significant. Nevertheless, the extension to the third and fourth lag in $\dot{k}$ in the regression raises concerns on the cyclicality of such relationship. A similar issue seems at work when we deal with the impact of GDP growth. The relation is generally positive and significant, also when accounting for subsequent lags, but we point to the negative and statistically significant coefficients corresponding the first and third lag. Overall, the Verdoorn's law is confirmed by this robustness check with yet some care about the interpretation of the results.

Let us turn to the impact of robotisation. With respect to less-than-average robotised industries, the evidence of Kaldor-Verdoorn's mechanisms is somehow stronger than in previous scenarios. Most GMM specifications in Tab. 15 tend to identify a significant and positive relationship between $\dot{a}$ and $\dot{k}$ that extends to the second lag. It is important to remember that in Tab. 9 we sometimes found a negative impact of past GDP growth upon

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.263	-0.290^{*}	-0.251^{***}	-0.285^{***}	-0.283	-0.354^{*}	-0.183^{***}	-0.256^{***}
	(0.160)	(0.174)	(0.022)	(0.033)	(0.200)	(0.203)	(0.007)	(0.023)
$\dot{a}_{ijt-2}$	-0.025	-0.210^{*}	-0.053^{***}	-0.241^{***}	-0.162^{*}	-0.256^{**}	-0.192^{***}	-0.209^{***}
	(0.122)	(0.112)	(0.020)	(0.033)	(0.096)	(0.102)	(0.006)	(0.013)
$\dot{a}_{ijt-3}$	0.002	-0.280^{**}	-0.007	-0.282^{***}	0.029	-0.266^{*}	0.018^{***}	-0.021^{***}
	(0.079)	(0.131)	(0.010)	(0.038)	(0.278)	(0.139)	(0.006)	(0.008)
$\dot{a}_{ijt-4}$		-0.176^{**}		-0.188^{***}		-0.200^{**}		-0.042^{***}
		(0.088)		(0.026)		(0.088)		(0.008)
$\dot{k}_{ijt}$	0.325	0.52	0.328^{***}	0.585^{***}	0.491	0.727^{*}	0.120^{***}	0.627^{***}
	(0.501)	(0.421)	(0.054)	(0.069)	(0.585)	(0.441)	(0.042)	(0.044)
$\dot{k}_{ijt-1}$	-0.264	-0.108	-0.201^{***}	-0.129^{*}	-0.045	-0.211	0.089^{***}	-0.200^{***}
	(0.596)	(0.645)	(0.057)	(0.072)	(0.496)	(0.549)	(0.020)	(0.046)
$\dot{k}_{ijt-2}$	0.257	-0.082	0.212^{***}	-0.138^{*}	-0.122	-0.304	0.085^{***}	0.109^{***}
	(0.297)	(0.331)	(0.057)	(0.077)	(0.292)	(0.320)	(0.019)	(0.022)
$\dot{k}_{ijt-3}$	-0.137	0.081	-0.109^{***}	0.107	-0.258	-0.199	-0.019	-0.022
	(0.135)	(0.234)	(0.030)	(0.067)	(0.248)	(0.282)	(0.018)	(0.021)
$\dot{k}_{ijt-4}$		-0.143		-0.084		-0.352		0.092^{***}
		(0.240)		(0.067)		(0.328)		(0.024)
$\dot{Y}_{jt}$	0.738	0.601	0.424^{***}	0.387^{***}	0.57	0.877^{**}	0.317^{***}	0.436^{***}
	(0.528)	(0.375)	(0.113)	(0.133)	(0.374)	(0.426)	(0.086)	(0.093)
$\dot{Y}_{jt-1}$	-0.406	-0.191	-0.173^{**}	-0.002	-0.165	-0.255	0.055	-0.081
	(0.551)	(0.557)	(0.083)	(0.100)	(0.467)	(0.582)	(0.042)	(0.087)
$\dot{Y}_{jt-2}$	0.176	0.258	0.045	0.224^{**}	0.429	0.461^{*}	0.046	0.162^{***}
	(0.318)	(0.269)	(0.078)	(0.092)	(0.375)	(0.242)	(0.043)	(0.048)
$\dot{Y}_{jt-3}$	0.241	0.473	0.139^{**}	0.121	0.476	0.492	0.051	0.092^{**}
	(0.159)	(0.455)	(0.060)	(0.120)	(0.308)	(0.421)	(0.044)	(0.041)
$\dot{Y}_{jt-4}$		-0.248		-0.134		0.003		-0.092^{**}
		(0.272)		(0.103)		(0.298)		(0.042)
Constant					0.042	0.0003	0.051^{***}	-0.025^{***}
					(0.061)	(0.037)	(0.010)	(0.005)
Observations	3251	3073	3251	3073	3430	3251	3430	3251
Instruments	99	86	99	86	97	93	109	105
AB (1)	-2.086^{**}	-2.074^{**}	-2.745^{***}	-2.693^{***}	-1.777^{*}	-2.114^{**}	-2.846^{***}	-2.738^{***}
AB (2)	-1.525	-0.801	-0.897	-0.742	-0.429	-0.755	0.215	-0.052
Hansen	78.86	61.54	78.86	61.54	69.82	66.68	82.24	82.42

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 14. Preliminary empirical evidence: robustness check (2)

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.306^{***}	-0.0257	-0.301^{***}	-0.0220^{***}	-0.458^{***}	-0.0656	-0.461^{***}	0.0482^{***}
	(0.0915)	(0.110)	(0.00172)	(0.00637)	(0.0924)	(0.0615)	(0.00646)	(0.00583)
$\dot{a}_{ijt-2}$		-0.0768^{**}		-0.0747^{***}		-0.121		-0.0313^{***}
		(0.033)		(0.00309)		(0.0904)		(0.00278)
$\dot{k}_{ijt}$	0.821^{***}	0.931^{***}	0.809^{***}	0.884^{***}	0.342	0.662^{**}	0.375^{***}	0.785^{***}
	(0.309)	(0.337)	(0.0306)	(0.0335)	(0.501)	(0.323)	(0.0478)	(0.0386)
$\dot{k}_{ijt-1}$	-0.0368	0.146	0.00777	0.104^{***}	0.178	0.0961	0.143^{**}	-0.0631
	(0.112)	(0.411)	(0.0278)	(0.0386)	(0.587)	(0.446)	(0.059)	(0.0488)
$\dot{k}_{ijt-2}$		0.13		0.167^{***}		0.0505		0.0847^{***}
		(0.115)		(0.0388)		(0.306)		(0.0255)
$\dot{Y}_{jt}$	0.857^{**}	0.573^{*}	0.856^{***}	0.381^{***}	0.239	0.568^{*}	0.238^{***}	0.384^{***}
	(0.359)	(0.346)	(0.0373)	(0.0723)	(0.444)	(0.327)	(0.0656)	(0.0606)
$\dot{Y}_{jt-1}$	0.25	0.319	0.262^{***}	0.180^{***}	1.234	0.356	1.070^{***}	0.0142
	(0.21)	(0.253)	(0.0309)	(0.0566)	(0.782)	(0.24)	(0.0635)	(0.0525)
$\dot{Y}_{jt-2}$		0.129		0.133^{***}		0.285		0.025
		(0.138)		(0.0444)		(0.238)		(0.0365)
$d_{ijt} \cdot \dot{k}_{ijt}$	-0.222	-0.353	-0.200^{***}	-0.318^{***}	0.349	-0.0108	0.312^{***}	-0.229^{***}
	(0.325)	(0.451)	(0.0354)	(0.0335)	(0.574)	(0.586)	(0.0542)	(0.0379)
$d_{ijt-1} \cdot \dot{k}_{ijt-1}$	0.0419	-0.058	0.00379	-0.0123	0.081	0.197	0.11	0.226^{***}
	(0.187)	(0.595)	(0.0291)	(0.0352)	(0.658)	(0.489)	(0.0691)	(0.0556)
$d_{ijt-2} \cdot \dot{k}_{ijt-2}$		-0.0364		-0.0707^{**}		0.231		-0.0242
		(0.142)		(0.0347)		(0.251)		(0.0241)
$d_{ijt} \cdot \dot{Y}_{jt}$	-0.029	0.356	-0.0395	0.494^{***}	0.808	0.371	0.801^{***}	0.329^{***}
	(0.512)	(0.729)	(0.0386)	(0.0767)	(0.813)	(0.568)	(0.063)	(0.0731)
$d_{ijt-1} \cdot \dot{Y}_{jt-1}$	-0.0928	-0.13	-0.120^{***}	-0.0118	-0.656	-0.033	-0.519^{***}	0.215^{***}
	(0.179)	(0.432)	(0.0394)	(0.0629)	(0.472)	(0.375)	(0.0655)	(0.0703)
$d_{ijt-2} \cdot \dot{Y}_{jt-2}$		0.246		0.214^{***}		0.219		0.182^{***}
		(0.171)		(0.0377)		(0.371)		(0.0385)
Constant					-0.0111	-0.0064	-0.0125^{***}	-0.00094
					(0.0261)	(0.0188)	(0.00241)	(0.00208)
Observations	2027	1866	2027	1866	2190	2027	2190	2027
Instruments	153	147	153	147	149	148	149	153
AB (1)	-0.972	-2.335^{**}	-2.046^{**}	-3.559^{***}	-1.27	-2.193^{**}	-2.621^{***}	-3.615^{***}
AB (2)	-2.35^{**}	0.742	-3.049^{***}	0.898	-2.581^{***}	0.433	-2.551^{**}	0.42
Hansen	133.4	118.2	133.4	118.2	129.9	114.1	129.9	112.3

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 15. Robustness check (1)

current productivity changes. The results in the robustness check present no evidence of that. Conversely, the coefficient is usually positive and different from zero.[18] The inclusion of further lags in the functional form tends to corroborate what previously showed (Tab. 16). Albeit Verdoorn's mechanisms keep on affecting the attainments in productivity, a form of ciclicality in the overall relationship is again a possibility not to discard and consider for further research.

Finally, Tab. 17 and Tab. 18 show the incidence of a robotisation higher than sector average. The outcomes are here somewhat different from the analysis of the previous subsection. On the one hand, we find once more the evidence that increasing robotisation weakens the technical progress channel with a positive effect in terms of employment growth. In this way, investments in new capital stock have greater benefits in terms of employment than productivity if compared to less-robotised industries. On the other hand, however, even if it is true that the macro-level route is strengthened, the results do not lead to arguments

[18] Though the magnitude is generally between zero and one, the twostep GMM specification in Tab. 15 point to a unitary coefficient with respect to $\dot{Y}_{jt-1}$. This value envisages an effect that leads to technological unemployment. It is then important to compare it to what reported for highly-robotised industries.

Dep. Var. : $\dot{a}_{ijt}$	D-GMM				S-GMM			
	onestep		twostep		onestep		twostep	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$\dot{a}_{ijt-1}$	-0.344^{**}	-0.332^{**}	-0.342^{***}	-0.241^{***}	-0.345^{**}	-0.286^{***}	-0.0474^{***}	-0.115^{***}
	(0.172)	(0.147)	(0.0122)	(0.0144)	(0.152)	(0.108)	(0.00677)	(0.0127)
$\dot{a}_{ijt-2}$	-0.357^{***}	-0.235^{*}	-0.366^{***}	-0.189^{***}	-0.104	-0.10	-0.0798^{***}	-0.0257^{***}
	(0.127)	(0.129)	(0.0103)	(0.016)	(0.15)	(0.114)	(0.00481)	(0.00606)
$\dot{a}_{ijt-3}$	-0.179	-0.434^{***}	-0.170^{***}	-0.0604^{***}	-0.0409	-0.0611	-0.0440^{***}	0.0278^{***}
	(0.119)	(0.0917)	(0.00632)	(0.00811)	(0.144)	(0.161)	(0.00471)	(0.00583)
$\dot{a}_{ijt-4}$		0.0129		0.0679^{***}		0.0609		0.134^{***}
		(0.10)		(0.00806)		(0.0929)		(0.00656)
$\dot{k}_{ijt}$	1.094^{***}	0.393	1.072^{***}	0.239^{***}	1.294^{***}	0.779^{**}	1.156^{***}	0.551^{***}
	(0.387)	(0.365)	(0.0691)	(0.0799)	(0.501)	(0.381)	(0.0466)	(0.0604)
$\dot{k}_{ijt-1}$	-0.062	-0.166	-0.0043	0.223^{***}	0.192	0.25	-0.117^{***}	0.00989
	(0.384)	(0.473)	(0.0557)	(0.0766)	(0.347)	(0.376)	(0.0402)	(0.0675)
$\dot{k}_{ijt-2}$	-0.127	0.0465	-0.125^{**}	0.174^{***}	0.00712	0.265	0.0681^{**}	0.0273
	(0.365)	(0.384)	(0.0546)	(0.0592)	(0.452)	(0.451)	(0.0271)	(0.0279)
$\dot{k}_{ijt-3}$	0.0734	0.705^{*}	0.0612^{*}	0.119^{***}	-0.171	0.51	-0.0531^{*}	-0.110^{***}
	(0.116)	(0.366)	(0.0358)	(0.0278)	(0.406)	(0.384)	(0.0273)	(0.0284)
$\dot{k}_{ijt-4}$		-0.0504		0.146^{***}		-0.146		-0.0782^{**}
		(0.125)		(0.0384)		(0.158)		(0.0307)
$\dot{Y}_{jt}$	0.715^{*}	0.0174	0.692^{***}	-0.0477	0.619^{*}	0.262	0.321^{***}	0.0694
	(0.428)	(0.430)	(0.0708)	(0.103)	(0.324)	(0.362)	(0.0618)	(0.0903)
$\dot{Y}_{jt-1}$	0.726^{*}	0.0372	0.621^{***}	-0.423^{***}	0.453	-0.0579	0.128^{**}	-0.249^{***}
	(0.399)	(0.553)	(0.0979)	(0.0868)	(0.344)	(0.533)	(0.0505)	(0.0687)
$\dot{Y}_{jt-2}$	0.422	0.115	0.323^{***}	0.0386	0.339	0.103	0.0225	0.0712^{**}
	(0.383)	(0.307)	(0.066)	(0.0606)	(0.41)	(0.273)	(0.0298)	(0.0359)
$\dot{Y}_{jt-3}$	0.0181	0.397	-0.0513	-0.00809	-0.0643	0.193	-0.118^{***}	-0.174^{***}
	(0.188)	(0.30)	(0.0599)	(0.0602)	(0.272)	(0.341)	(0.0382)	(0.0468)
$\dot{Y}_{jt-4}$		0.166		0.280^{***}		0.321^{**}		0.201^{***}
		(0.158)		(0.0467)		(0.149)		(0.045)
$d_{ijt} \cdot \dot{k}_{ijt}$	-0.685^{*}	-0.258	-0.689^{***}	-0.138^{*}	-0.800^{**}	-0.118	-0.646^{***}	-0.104^{*}
	(0.365)	(0.444)	(0.0726)	(0.0795)	(0.387)	(0.485)	(0.0522)	(0.0618)
$d_{ijt-1} \cdot \dot{k}_{ijt-1}$	0.188	0.929	0.134^{**}	0.618^{***}	0.0796	0.708	0.108^{**}	0.661^{***}
	(0.369)	(0.594)	(0.0541)	(0.0704)	(0.379)	(0.618)	(0.0425)	(0.0701)
$d_{ijt-2} \cdot \dot{k}_{ijt-2}$	0.407	0.238	0.407^{***}	-0.0333	0.113	0.202	-0.0107	0.0331
	(0.351)	(0.399)	(0.0576)	(0.0622)	(0.382)	(0.373)	(0.0332)	(0.0312)
$d_{ijt-3} \cdot \dot{k}_{ijt-3}$	0.0874	-0.15	0.122^{***}	0.164^{***}	0.321	-0.0814	0.168^{***}	0.305^{***}
	(0.141)	(0.310)	(0.0355)	(0.0335)	(0.429)	(0.248)	(0.0289)	(0.0365)
$d_{ijt-4} \cdot \dot{k}_{ijt-4}$		0.0579		-0.188^{***}		0.0595		0.0158
		(0.144)		(0.0389)		(0.171)		(0.0316)
$d_{ijt} \cdot \dot{Y}_{jt}$	-0.0639	0.115	-0.0437	0.273^{***}	0.255	0.706	0.347^{***}	0.619^{***}
	(0.463)	(0.565)	(0.0611)	(0.103)	(0.592)	(0.655)	(0.0584)	(0.088)
$d_{ijt-1} \cdot \dot{Y}_{jt-1}$	-0.229	0.326	-0.178^{*}	0.774^{***}	0.0428	0.704	-0.107^{**}	0.810^{***}
	(0.447)	(0.562)	(0.0964)	(0.107)	(0.635)	(0.857)	(0.0506)	(0.0827)
$d_{ijt-2} \cdot \dot{Y}_{jt-2}$	0.162	0.439	0.271^{***}	0.465^{***}	0.0698	0.396	0.0497	0.202^{***}
	(0.324)	(0.358)	(0.0617)	(0.0527)	(0.354)	(0.413)	(0.0341)	(0.0378)
$d_{ijt-3} \cdot \dot{Y}_{jt-3}$	0.223	-0.289	0.231^{***}	0.054	0.680^{*}	0.115	0.196^{***}	0.132^{**}
	(0.182)	(0.46)	(0.0536)	(0.0574)	(0.378)	(0.466)	(0.034)	(0.0551)
$d_{ijt-4} \cdot \dot{Y}_{jt-4}$		-0.146		-0.254^{***}		-0.377^{*}		-0.296^{***}
		(0.198)		(0.051)		(0.213)		(0.0535)
Constant					0.00746	-0.00818	0.00332	-0.00021
					(0.0111)	(0.0166)	(0.00223)	(0.003)
Observations	1706	1549	1706	1549	1866	1706	1866	1706
Instruments	141	135	141	140	142	141	157	151
AB (1)	-2.936^{***}	-2.18^{**}	-3.896^{***}	-5.065^{***}	-2.734^{***}	-2.022^{**}	-3.587^{***}	-4.563^{***}
AB (2)	0.0464	-0.712	0.44	0.745	-1.338	-0.585	-0.387	-0.776
Hansen	106.5	87.24	106.5	97.31	117.9	104.9	131.2	117.2

Note: Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 16. Robustness check (2)

Dep. Var. : $\dot{a}_{ijt}$	D-GMM							
	onestep				twostep			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
η_t	0.590*	0.578	0.409	0.135	0.609***	0.566***	0.393***	0.101***
	(0.347)	(0.489)	(0.271)	(0.270)	(0.013)	(0.011)	(0.018)	(0.024)
η_{t-1}	0.005	0.088	0.126	0.763**	0.012	0.092***	0.130***	0.841***
	(0.146)	(0.275)	(0.202)	(0.367)	(0.012)	(0.017)	(0.020)	(0.021)
η_{t-2}		0.094	0.279	0.284		0.097***	0.281***	0.141***
		(0.096)	(0.224)	(0.217)		(0.014)	(0.017)	(0.019)
η_{t-3}			0.161	0.554*			0.183***	0.283***
			(0.115)	(0.321)			(0.015)	(0.014)
η_{t-4}				0.008				−0.043***
				(0.111)				(0.015)
γ_t	0.828	0.929	0.651	0.132	0.816***	0.875***	0.649***	0.225***
	(0.700)	(0.690)	(0.421)	(0.382)	(0.037)	(0.056)	(0.056)	(0.047)
γ_{t-1}	0.157	0.189	0.496	0.364	0.142***	0.168***	0.443***	0.351***
	(0.134)	(0.362)	(0.385)	(0.328)	(0.023)	(0.045)	(0.051)	(0.056)
γ_{t-2}		0.375**	0.583	0.554*		0.347***	0.594***	0.504***
		(0.176)	(0.441)	(0.327)		(0.032)	(0.038)	(0.042)
γ_{t-3}			0.241	0.108			0.180***	0.046
			(0.196)	(0.362)			(0.039)	0.037)
γ_{t-4}				0.020				0.027
				(0.214)				(0.045)

Note: $\eta_z = \beta_z + \varepsilon_z$; $\gamma_z = \delta_z + \vartheta_z$. Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 17. Combined effects from difference-GMM estimates: robustness check

about technological unemployment. Despite a single exception, the coefficient is always in the range [0;1].

To summarize, the battery of robustness checks do confirm the previous results, in which highly-robotised industries experience a weakening, at least, of the linkage between capital-labour ratio and productivity. In contrast, we claim that, even if robotisation enhances the macro-level channel through GDP growth, the effect is not sufficient to engender a technological unemployment dynamics as noticed prior. The somewhat puzzling results are in a way coherent with the empirical literature on the effects of robotisation on productivity and employment.

4 Conclusion

Even since Kaldor (1966), the Kaldor-Verdoorn's law has fuelled an intense debate among scholars interested in economic growth, catching-up and development issues, productivity growth and the role exerted by aggregate demand in shaping productivity dynamics. If this law has become widely accepted and embodied in most Post-Keynesian growth models, the relentless structural changes undergone by major developed and developing capitalist economies have always prompted researchers to detect empirical evidence of the mechanisms behind the law. Its validity, despite the many alternative and sometimes contrasting

Dep. Var. : $\dot{a}_{ijt}$	S-GMM							
	onestep				twostep			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
η_t	0.690*	0.652	0.494	0.661*	0.686***	0.556***	0.510***	0.447***
	(0.368)	(0.413)	(0.339)	(0.351)	(0.021)	(0.013)	(0.022)	(0.021)
η_{t-1}	0.259	0.293	0.271	0.959*	0.253***	0.163***	-0.010	0.671***
	(0.201)	(0.120)	(0.395)	(0.568)	(0.029)	(0.019)	(0.015)	(0.027)
η_{t-2}		0.282	0.120	0.467		0.061***	0.057***	0.060***
		(0.249)	(0.230)	(0.302)		(0.011)	(0.012)	(0.015)
η_{t-3}			0.150	0.428			0.115***	0.194***
			(0.162)	(0.329)			(0.010)	(0.014)
γ_t	1.047	0.938	0.874*	0.968**	1.039***	0.712***	0.668***	0.688***
	(0.699)	(0.677)	(0.484)	(0.490)	(0.043)	(0.050)	(0.039)	(0.039)
γ_{t-1}	0.578	0.323	0.496	0.646	0.553***	0.229***	0.021	0.561***
	(0.571)	(0.322)	(0.407)	(0.425)	(0.046)	(0.053)	(0.026)	(0.047)
γ_{t-2}		0.504	0.409	0.499		0.207***	0.072***	0.274***
		(0.346)	(0.283)	(0.342)		(0.029)	(0.025)	(0.032)
$\gamma t-3$			0.616**	0.308			0.078***	-0.043
			(0.272)	(0.283)			(0.025)	(0.037)
γ_{t-4}				-0.056				-0.095^{**}
				(0.207)				(0.038)

Note: $\eta_z = \beta_z + \varepsilon_z$; $\gamma_z = \delta_z + \vartheta_z$. Standard errors in brackets. Star significance: * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 18. Combined effects from system-GMM estimates: robustness check

specifications, has generally been confirmed as a stylized fact by the majority of the literature (McCombie et al. 2002, McCombie and Spreafico 2015). However, the research on the topic overlooks to a large extent the arrival of new breakthrough technologies that belong to the Fourth Industrial Revolution (Schwab 2016). The rising robotisation experienced by many industries in most countries led us to wonder in which way this process affects the route with which the Kaldor-Verdoorn's law shapes labour-productivity dynamics, if any.

To fill this gap in the literature, we applied the GMM estimator to a panel of 17 industries in 25 OECD countries from 1990 to 2018. The outcomes suggest that the industries with a high and increasing robotisation are impacted differently according to the level of economic activity we consider. On the one hand, the channel often labelled as "technical-progress function" (Kaldor 1957, 1961) seems weakened, if not removed, by the rising robotisation. This result envisages benefits in terms of employment growth that are in agreement with the empirical literature on the topic. On the other hand, a higher-than-average degree of robotisation strengthens the macroeconomic route that relates productivity growth at the industry-level to the increasing returns to scale that manifest as a general expansion of economic activities through the many interactions between sectors.
Conversely, the cumulative-causation mechanisms are not invalidated and are still at work for those industries with a level of robotisation lower than the corresponding average. Yet, it is important to notice that, although our results are "robust" from an econometric point of view, the outcomes are sometimes of difficult interpretation and may depend on the specific

econometric structure underlying the model. Moreover, we based our analysis on industry-level data that do not allow us to properly disentangle the dynamics at firm level. We will deal with these and further issues in future research.

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