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Do technical change and mechanisation negatively affect employment in the manufacturing sectors? An empirical assessment for the OECD countries

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ABSTRACT
The present study is aimed at assessing the impacts of technological change and mechanisation on employment in the manufacturing sectors of the OECD countries over the 1995-2018 period. To achieve this goal, the vertically integrated labour productivity and the vertically integrated capital-labour ratio were computed as measures of technological progress and capital intensity per unit of labour, whereas the CS-ARDL and CS-DL approaches were applied to obtain robust results in the presence of cross-sectional dependence and slope heterogeneity. The findings suggest that both technical change and mechanisation may lead to a relative decrease in employment in the short-run and long-run, though for skilled workers the effects appear to be positive. This increase in demand for skilled labour, however, may not be able to compensate for the decline in medium and lesser skilled labourers.

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1. Introduction

The relationship between technical change, mechanisation and employment has received a great deal of attention over the last decades. Although this controversial issue is not new in the economic literature, as will be shown later, some authors claim that technological innovations are inevitably destroying jobs in developed countries. Among these voices, Frey and Osborne (2017) are probably the authors whose work has most contributed to enlivening the discussion in recent years. Inspired by Keynes' (1930) classical piece entitled *Economic Possibilities for our Grandchildren*, Frey and Osborne (2017) contend that the impact of computerisation on the labour market may be negative in the United States (US) in the following decades.

Frey and Osborne sustain that at least 47% of US employment is vulnerable to computerisation, as well as to technological change and mechanisation. Moreover, Frey and Osborne (2017) state that many jobs will be automated within the next

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decade or two, hence increasing the risk of workers suffering from so-called technological unemployment. This pessimistic point of view, however, has been rejected by several researchers. For instance, Howcroft and Taylor (2022) reject the technological determinism expressed by Frey and Osborne and other authors (Makridakis, 2017).

Howcroft and Taylor (2022) reveal that Frey and Osborne's study is an exercise of speculative statistical predictions that neglects crucial variables such as the social and technical division of labour, the structure of the labour market, and the differences between skilled and unskilled labour, among other social-economic factors.

On the other hand, Howcroft and Taylor (2022) stress that there exist two predictions regarding technological change and its effects on employment, namely: utopian and dystopian. Utopian views are based on Marx's insight on the role of machinery as the material precondition for a socialist society (Rosdolsky, 1968, p. 425). Marx (1867) stated that automation, although it reduces workers to a mere moment in the labour process, in turn, would tend to reduce the expending of human energy in the production process to the lowest possible (Rosdolsky, 1968, p. 425).

Like Keynes (1930), Marx (1973) conceived that technological change and mechanisation would free humankind from the chains of work, thereby increasing disposable time for leisure.

In contrast, the dystopian standpoint suggests that technological change and mechanisation are not only removing jobs that require unskilled workers but also condemning skilled labourers to unemployment in developed countries (Makridakis, 2017). This catastrophic scenario would entail that any task could be done by machines and artificial intelligence, which means that unemployment and social inequalities would rise noticeably. Nonetheless, it is worth mentioning that the empirical evidence seems to be mixed, whereby it is not feasible to conclude whether technological change and mechanisation will displace human labour. In this regard, it suffices to note some recent relevant investigations[1].

By using microdata covering 677 European companies over the 1990–2008 period, Bogliacino *et al.* (2012) note that investments in research and development (R&D) may be labour-friendly, though the magnitude is not huge. Furthermore, Bogliacino *et al.* (2012) point out that positive and significant effects of R&D on employment are greater in innovation sectors than in manufacturing sectors with traditional technologies.

Acemoglu and Restrepo (2019) decompose the effect of automation on demand for labour into the productive effect and the displacement effect. While the productive effect expands the demand for labour through increasing value-added, the displacement effect arises when automation covers jobs that were previously carried out by human workers. According to their findings, a slowing of demand for labour may emerge from a poor increase in labour productivity and the failure to create new jobs compensating for the displacement effect. Nevertheless, Acemoglu and Restrepo (2019) underline that their results do not support the end of human work nor do they find that technological progress is always labour-friendly.

Acemoglu and Restrepo (2020) expand their study by assessing the effects of robotisation on employment and wages in the US. Applying the two-stage least-squares method (2SLS), the empirical evidence suggests that the effects of robotisation may be negative, though its impact appears to be low because an increase in one or more robots per thousand persons reduces the employment-population ratio by approximately 0.2% and wages by 0.42%.

Dosi *et al.* (2021), who analyse the impact of technological change on employment in 19 European countries over the 1998-2016 period, find that the labour-friendly effect of investment in R&D is minimal, whilst the replacement of obsolete fixed assets negatively affected the demand for labour, contravening the compensation mechanisms posited by nineteenth-century economists[2] (Marx, 1867, pp. 565–575). However, the authors highlight that their empirical assessment neglects potential demand creation channels because the period is characterised by an intense technological restructuring provoked by the 2007-08 crisis and the recession (2009-2014).

Lastly, Cords and Prettner (2022) analyse the automation impacts on the demand for labour in developed countries. The authors obtain empirical evidence supporting the hypothesis that technological change and mechanisation displace unskilled labour while improving both employment and wages for skilled labour. Furthermore, Cords and Prettner (2022) find that robotisation creates more jobs for skilled labour than those destroyed for unskilled labour in Austria and Germany. Conversely, this compensation mechanism appears not to hold in Australia and the US.

Thus, inspired by this lively discussion among scholars, this study is aimed at assessing whether technological change and mechanisation reduce manufacturing employment in the 38 OECD countries from 1998 to 2018. To the best of our knowledge, the novelty of our research is twofold. Following the notion of vertical integration of Pasinetti (1973) and the input-output approach of Leontief (1951), we compute the vertically integrated labour productivity and the vertically integrated capital-labour ratio to measure technological change and mechanisation.

Secondly, we apply for the first time the Cross-Sectional-Autoregressive-Distributed Lag (henceforth, CS-ARDL) method by Chudik and Pesaran (2015) and the Cross-Section Augmented Distributed Lag (henceforth, CS-DL) approach of Chudik *et al.* (2016) to estimate the long-run dynamic effects of technological change and mechanisation on manufacturing employment.

The study is organised as follows. In Section 2, the theoretical framework is briefly developed. In Section 3, the data and methods are presented, while a preliminary analysis is conducted. In sector 4, the empirical results are critically discussed. Section 5 summarises the concluding remarks.

2. Theoretical framework

In a commendable exercise of intellectual honesty, in the third edition of his masterpiece *Principles of Political Economy and Taxation*, Ricardo (1821, Chapter 31) admitted the need to revise his prior belief that technological change and the introduction of machinery benefited all social classes to the same degree.

In this vein, Ricardo abandoned the so-called compensation theory to explain why the substitution of machinery for human labour may be harmful to workers. According to Ricardo, his initial mistake stemmed from the incorrect assumption that an increase in the net income (*i.e.*, profits plus rents) entails an increase in the gross income (*i.e.*, wages, profits and rents). Contrary to this, Ricardo posited that technical progress and mechanisation could lead to creating a redundant population if the gross income decreases while net income is rising.

Thus, technological unemployment can arise in the extremely restrictive scenario[3] where machinery reduces the national income. Nevertheless, Ricardo preferred to draw attention to the fact that the expansion of capital may not be accompanied by a proportional increase in the demand for labour.

As pointed out by Ricardo, both technical change and mechanisation increase the proportion between fixed assets and labour compensation[4] (*i.e.*, the capital-labour ratio in modern terms), thereby moderating the increase in demand for labour regarding the expansion of capital. In such a framework, therefore, technological change and mechanisation may reduce relatively the demand for labour.

Marx (1867, Chapter 25) takes up Ricardo's standpoint by enunciating *the general law of capitalist accumulation*. According to Marx (1867, p. 782), accelerated capital accumulation and centralisation lead towards strong changes in the capital-labour ratio (organic composition of capital in the Marxian sense), reflected in the diminishing labour compensation relative to fixed and circulating capital (*i.e.*, constant capital). Since capital expansion enhances labour productivity, raises the scale of production, reduces the price of wage-goods, and enlarge markets, a relatively redundant working population—or relative surplus population—arises as a necessary product of accumulation.

By changing the capital-labour ratio, technological innovations and mechanisation attract and replace labourers, creating an unlimited labour supply to maintain the real wage rate below the maximum rate of profit[5] (upper limit). Therefore, Marx (1867, p. 788) concludes that the redundant population is a necessity to assure the capital accumulation process in the long-run.

Interestingly, Marx (1867, Chapters 791–792) contends that capital accumulation progressively displaces skilled workers by less skilled, disclosing a deskilling bias of technical progress. In this regard, it is worth mentioning that, as noted by Roll (1939, p. 14), economic theories are influenced by the "economic structure of any given epoch".

In the nineteenth century, the competition between machines and human labour displaced highly qualified artisans in favour of operatives doing the same tasks more easily. Goldin and Katz (1998, p. 699) highlight that the transition from artisanal shops to factory production not only increased the capital-output ratio but also reduced the demand for skilled labourers regarding unskilled labour in manufacturing sectors.

Katz and Margo (2013) validate this tendency by finding empirical evidence of the deskilling bias of technical progress in the nineteenth century. Moreover, as stated by Brugger and Gehrke (2018), Marx's position may lie in the assumption that capitalists introduced unskilled-biased innovations to reduce the bargaining power of workers. Along these lines, Acemoglu (2002) asserts that English firms preferred to employ unskilled labourers because in that way they made more profit from the technological innovations that arose in the nineteenth century. Although Marx's insight on the deskilling bias of technical progress appears to be consistent with the circumstances of his epoch, modern literature points out that in the twentieth century the tendency changed

Goldin and Katz (1998) emphasise that technical progress has spurred the demand for skilled labour over the last seven decades. Given that the demand for skilled labour grew at the expense of unskilled labour, Goldin and Katz contend that the technologies developed during the twentieth century are technologies-skill complementarities. In addition, Acemoglu (1998) argues that technologies have complemented skills in the twentieth century due to technological progress being driven by the size of the market for different inventions. Specifically, a greater supply of skilled labour stimulates the rise of technologies-skill complementarities. On the other hand, Stiglitz (2014) points out that the rigidities in the labour market caused by efficiency wages do not allow the rise in the demand for skilled labour to compensate for the decline in the demand for unskilled labour.

There could be excessively skill-biased innovation and high unemployment if the elasticity of substitution between skilled and unskilled labour were less than unity, whereby the classical compensation theory does not hold in a context where technologies are skilled complementarities. Thus, based on the above, the following mechanisms may be theorised:

1. Technological change and mechanisation, both spurred by capital accumulation, tend to change the relationship between capital and labour, thereby reducing the relative demand for labour and creating a redundant workers population. This mechanism is called the Barton-Ricardo-Marx effect.
2. Given the structure of the labour market in the twentieth and twenty-first centuries, technological change and mechanisation tend to displace unskilled workers in favour of those workers whose abilities and training are above average. This mechanism is known as the technologies-skill complementarity effect.
3. Because of the redundant population and the substitution elasticities between skilled and unskilled labour, both mechanisms eliminate the compensation effect.

3. Data, methods and preliminary analysis

The previous section disclosed those mechanisms which constitute the theoretical basis that gives grounds for an appraisal of whether technological change and mechanisation might reduce employment in the manufacturing sectors of the OECD countries. To conduct the empirical assessment, statistical information was gathered from the national input-output tables (IOTs 2021 edition) and the Database for Structural Analysis (ISIC 4 SNA 08) included in the OECD statistics.

It is worth mentioning that the OECD statistics data covers the 38 member countries (see Table 1), whereas the national IOTs encompass 17 manufacturing sectors classified in accordance with International Standard Industrial Classification Revision 4 (henceforth, ISIC 4) (see Table 2). Given that the national IOTs span from 1995 to 2018, all the

Table 1. OECD countries.

Australia	Denmark	Ireland	Mexico	Spain
Austria	Estonia	Israel	Netherlands	Sweden
Belgium	Finland	Italy	New Zealand	Switzerland
Canada	France	Japan	Norway	Turkey
Chile	Germany	Korea	Poland	United Kingdom
Colombia	Greece	Latvia	Portugal	United States
Costa Rica	Hungary	Lithuania	Slovak Republic	
Czech Republic	Iceland	Luxembourg	Slovenia	

Source: own elaboration based on OECD statistics.

Table 2. Manufacturing sectors.

ISIC 4	Sector	ISIC 4	Sector
10, 11, 12	Food products, beverages and tobacco	25	Fabricated metal products
13, 14, 15,	Textiles, textile products, leather and footwear	26	Computer, electronic and optical equipment
16	Wood and products of wood and cork	27	Electrical equipment
17, 18	Paper products and printing	28	Machinery and equipment
19	Coke and refined petroleum products	29	Motor vehicles, trailers, and semi-trailers
20	Chemical and chemical products	30	Other transport equipment
21	Pharmaceuticals, medicinal chemical and botanical products	31, 32, 33	Manufacturing; repair and installation of machinery and equipment
22	Rubber and plastics products		
23	Other non-metallic mineral products		
24	Basic metals		

Source: own elaboration based on OECD statistics.

statistical information required to perform the empirical analysis corresponds to this period. Likewise, the Database for Structural Analysis contains sectoral information regarding the numbers of employees, number of hours worked by employees, labour compensation, stock of capital, gross output and gross value added. Lastly, excepting the variables related to employment, the data are measured in United States dollars (USD).

The statistical method applied to achieve the aim of this study consists in panel data cointegration analysis due to its numerous advantages over time series and cross-sectional data. As Hsiao (2007) highlights, the panel data analysis has a more accurate inference of model parameters since it contains more freedom degrees and more sample variability than times series and cross-sectional data.

Furthermore, the panel data analysis uncovers the dynamic relationships and is more suitable than cross-sectional and time-series data in the presence of nonstationary variables. Last but not least, the impacts derived from omitted variables are better controlled by using panel data than by applying time series or cross-sectional data.

To measure the technological progress and the mechanisation, this research computes the vertically integrated labour productivity and the vertically integrated capital-labour ratio, respectively.

Following Pasinetti (1973), the vertically integrated labour productivity can be derived from the so-called vertically integrated labour coefficients, which represent the amount of direct and indirect labour time embodied in each i-th final commodity produced by each i-th industry from a national economy for a certain period. To obtain the vertically integrated labour coefficients, a row vector of direct labour coefficients was calculated as follows:

$$e = \left(\frac{l_1}{x_1} \quad \frac{l_2}{x_2} \ldots \frac{l_i}{x_i} \right) \tag{1}$$

Where e stands for the row vector of the direct labour coefficients, l_i represents the number of hours worked in each i-th sector from each n-th OECD country member, while x_i is the gross output at current prices of each i-th sector from each n-th OECD country member.

To obtain the vertically integrated labour coefficients vector, the row vector of direct labour coefficients was multiplied by the Leontief inverse matrix, whose columns reflect the direct and indirect inputs requirements to produce each i-th final commodity:

$$v = e(I - A)^{-1} = (v_1 \ v_2 \ldots v_i) \tag{2}$$

Where v_i denotes each i-th vertically integrated labour coefficient in each n-th OECD country member, $(I - A)^{-1}$ is the Leontief inverse matrix of each n-th OECD country, while the rest was previously defined. Hence, if the vertically integrated labour coefficients are inverted, we may obtain the vertically integrated labour productivity:

$$vyl = v^{-1} = \left(v_1^{-1} \ v_2^{-1} \ldots v_i^{-1}\right) = \left(vyl_1 \ vyl_2 \ldots vyl_i\right) \tag{3}$$

Note that the vertically integrated labour productivity (vyl) captures both direct and indirect labour productivity, which means that it considers all those inputs involved in the process of commodities production. In this regard, De Juan and Febrero (2000) highlight that fixed capital and intermediate inputs are integrated as indirect labour, thereby reflecting that human labour is the only factor implicated in the production process of commodities.

De Juan and Febrero (2000) also point out that vertically integrated labour productivity takes into account both the structural relationships among sectors and productivity transfers from innovative sectors to those industries which need—directly and indirectly—their inputs. Lastly, vertically integrated labour productivity is a pure technological index, since it is not affected by changes in distribution, output composition and other factors which are not linked to technological progress (De Juan & Febrero, 2000, p. 69).

To calculate the vertically integrated capital-labour ratio, a diagonal matrix with direct capital-labour ratios on the main diagonal and zeros elsewhere was computed:

$$\widehat{kl} = \begin{pmatrix} \frac{k_1}{l_1} & 0 & \ldots & 0 \\ 0 & \frac{k_1}{l_1} & \ldots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \ldots & \frac{k_i}{l_i} \end{pmatrix} \tag{4}$$

In equation (4), $\widehat{kl}$ denotes the diagonal matrix of direct capital-labour ratios, k_i reflects the gross capital stock at replacement cost of the i-th sector from the n-th OECD country, whilst l_i is the number of workers employed in the i-th sector from the n-th OECD country. Multiplying the diagonal matrix by the Leontief inverse gives the matrix of vertically integrated capital-labour ratios:

$$vkl = \widehat{kl}(I - A)^{-1} \tag{5}$$

By summing each i-th column of vkl, the vertically integrated capital-labour ratio of each i-th manufacturing sector from each n-th OECD country may be obtained. It should be noted that the vertically integrated capital-labour ratio captures the direct and indirect amount of capital employed to every unit of labour employed. Therefore, by means of the vertically integrated capital-labour ratio, we may analyse the effects of a general mechanisation process on manufacturing employment.

Given that manufacturing employment is not only affected by technical progress and mechanisation but also by the bargaining power of workers, the industrial business cycle dynamics and the rise of the global value chains, we control these variables by using the following proxies: real average wages[6] ($rw_{i,t}$), gross value added at constant prices ($gva_{i,t}$) and the share of domestic employment embodied in foreign final demand ($lxfd_{i,t}$).

Taking the Napierian logarithm, the multiple linear regression estimated by ordinary least-squares (OLS) is denoted as:

$$\begin{aligned} \mathrm{LOG}(emp_{i,t}) = \beta_0 + \beta_1 \mathrm{LOG}(vyl_{i,t}) + \beta_2 \log(vkl_{i,t}) + \beta_3 \mathrm{LOG}(rw_{i,t}) \\ + \beta_4 \log(gva_{i,t}) + \beta_5 \log(lxfd_{i,t}) + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Where LOG means the Napierian logarithm, β_0 is the constant, β_n stands for the coefficients of the regressors ($n = 2, 3, 4, 5$), $\varepsilon_{i,t}$ is the error term, the subscript i corresponds to the i-th sector ($n = 1, 2, \ldots, 17$) of the n-th OECD country ($n = 1, 2, \ldots, 38$), while t is the period ($t = 1995 \ldots 2018$).

Since the database does not distinguish between skilled and unskilled workers employed in each manufacturing sector, the sample was divided following the OECD sectoral classification based on the technological intensity (see Table 3). Thus, we consider that high and medium-high tech intensity manufacturing sectors employ skilled workers, medium tech intensity manufacturing sectors demand medium skilled labour, whereas medium-low- and low-tech intensity manufacturing sectors are those whose employees are less skilled workers.

Table 3. OECD activities classification based on tech intensity.

ISIC rev. 4	High and medium-high tech intensity	ISIC rev. 4	Medium tech intensity	ISIC rev. 4	Medium-low- and low-tech intensity
20	Chemical and chemical products	22	Rubber and plastics products	10, 11, 12	Food products, beverages and tobacco
21	Pharmaceuticals, medicinal chemical and botanical products	23	Other non-metallic mineral products	13, 14, 15	Textiles, textile products, leather and footwear
26	Computer, electronic and optical equipment	24	Basic metals	16	Wood and products of wood and cork
27	Electrical equipment	31, 32, 33	Manufacturing; repair and installation of machinery and equipment	17, 18	Paper products and printing
28	Machinery and equipment,			19	Coke and refined petroleum products
29	Motor vehicles, trailers and semi-trailers			25	Fabricated metal products
30	Other transport equipment				

Source: own elaboration based on OECD.

The data was organised into four balanced panels that comprise (1) all manufacturing sectors, (2) the high and medium-high tech intensity manufacturing sectors, (3) the medium tech intensity manufacturing sectors, and (4) the medium-low- and low-tech intensity manufacturing sectors.

The preliminary analysis starts by evaluating whether the regressors are correlated by employing the multicollinearity test based on the variance inflation factor (henceforth, VIF). As shown in Table 4, the statistical evidence suggests that the explanatory variables may not be correlated because the results obtained are below the VIF threshold value set at 5. Therefore, the choice of regressors appears to be appropriate to perform the econometric assessment.

Given that cross-sectional dependence arises when assessing macroeconomics and financial data (Banerjee & Carrion-i-Silvestre, 2017), the standard panel cointegration techniques may lead to a misleading inference and over-rejecting the null hypothesis because they often incur in the so-called size distortion problem (Chudik *et al.*, 2016; Pesaran, 2006, 2007). Hence, it is essential to examine cross-sectional dependence while working with panel data comprising numerous countries or sectors over relatively extended periods.

According to Table 5, the cross-sectional dependence (CD) test developed by Pesaran (2021) discloses that the null hypothesis of cross-sectional independence should be rejected as the *p*-values are much smaller than the usual levels of significa-tion. Therefore, the statistical evidence indicates that the cross-sectional dependence should be considered in the empirical assessment.

It should be highlighted that the slope heterogeneity across the panel might occur in the presence of cross-sectional dependence. Therefore, the further step consists of testing the null hypothesis of slope homogeneity by using the Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013) tests. The results outlined in Table 6

Table 4. VIF test.

Variable	(1) VIF	(2) VIF	(3) VIF	(4) VIF
$LOG(vyl_{i,t})$	2.65	1.82	1.88	3.08
$LOG(vkl_{i,t})$	1.90	2.96	2.23	2.73
$LOG(rw_{i,t})$	1.84	1.82	1.75	1.39
$LOG(gva_{i,t})$	1.27	1.23	1.52	1.56
$LOG(lxfd_{i,t})$	1.17	1.14	1.85	3.96

Note: the *regress* and *vif* commands were applied.
Source: own elaboration based on Stata 17.

Table 5. Pesaran (2021) CD test.

	1		2		3		4	
Variable	CD-test	*p*-value	CD-test	*p*-value	CD-test	*p*-value	CD-test	*p*-value
$LOG(emp_{i,t})$	3.78	0.000***	3.91	0.000***	3.11	0.000***	7.28	0.000***
$LOG(vyl_{i,t})$	111.19	0.000***	44.68	0.000***	24.69	0.000***	38.27	0.000***
$LOG(vkl_{i,t})$	50.76	0.000***	20.48	0.000***	9.79	0.000***	15.33	0.000***
$LOG(rw_{i,t})$	22.75	0.000***	15.71	0.000***	1.71	0.000***	3.47	0.000***
$LOG(gva_{i,t})$	21.53	0.000***	8.57	0.000***	6.04	0.000***	8.77	0.000***
$LOG(lxfd_{i,t})$	29.02	0.000***	8.95	0.000***	5.42	0.000***	12.78	0.000***

Note:.
*** Denotes rejection at 1%. The *xtcd* command by Eberhardt (2011b) was used.
Source: own elaboration based on Stata 17.

Table 6. Slope heterogeneity tests.

Pesaran and Yamagata (2008)								
	(1)		(2)		(3)		(4)	
Variable	Delta	*p*-value	Delta	*p*-value	Delta	*p*-value	Delta	*p*-value
	1.998	0.000***	−1.810	0.067*	1.817	0.064*	1.904	0.051*
adj.	2.253	0.000***	−1.731	0.083*	1.979	0.057*	1.784	0.078*
Blomquist and Westerlund (2013)								
Variable	Delta	*p*-value	Delta	*p*-value	Delta	*p*-value	Delta	*p*-value
	1.983	0.047**	−1.750	0.080*	−1.842	0.060*	1.920	0.044**
adj.	2.377	0.017**	−2.098	0.036**	−1.999	0.049**	1.924	0.041**

Note: *** Denotes rejection at 1%. ** Denotes rejection at 5%. The *xthst* command by Bersvendsen and Ditzen (2020) was employed.
Source: own elaboration based on Stata 17.

suggest the existence of slope heterogeneity across the four panels data, insofar as the null hypothesis may be rejected at least at the 10% level of significance.

Because the first generation of panel unit root tests are not suitable in the presence of neglected cross-section dependence, we apply the cross-sectional augmented Im, Pesaran and Shin (CIPS) and the cross-section augmented Dickey–Fuller (CADF) tests developed by Pesaran (2007) to check whether the variables are nonstationary in level and integrated of order I(1).

According to the findings reported in Table 7, the variables seem to be nonstationary and integrated of order I(1) insofar as it is not feasible to reject the null hypothesis of unit root. Furthermore, if the variables are transformed into their first difference, they become stationary and integrated of order I(0). Hence, the statistical evidence suggests that the variables are nonstationary and integrated of order I(1). Nevertheless, to be economically meaningful, nonstationary variables should be cointegrated.

The last step of the preliminary data analysis involves determining whether the variables are cointegrated computing the panel cointegration and the error correction model (ECM) cointegration tests by Westerlund (2007), which are adequate in the presence of both cross-sectional dependence and slope heterogeneity. According to Table 8, the panel cointegration test rejects the null hypothesis of no cointegration for the four panels, suggesting that the variables are cointegrated.

Following Persyn and Westerlund (2008), the ECM cointegration test is performed by setting the Bartlett kernel window ≈ 3 and including robust *p*-values with 800 bootstrap replications, while the Akaike information criterion (AIC) is used to choose the optimal lag and lead lengths. The results from Table 9 reveal that the four statistics can reject the null hypothesis of no cointegration for all panels data as the *p*-values are less than 5%. The findings support the hypothesis of a stable long-term relationship between the six variables, whereby they may share a common trend in the long-run. It having been established that the variables are cointegrated, we proceed to examine the short and long-run equations by using the CS-ARDL and CS-DL.

4. Results and discussion

In this section, we estimate the short-run and the long-run equations of the variables by employing techniques that control cross-sectional dependence and slope heterogeneity,

Table 7. Panel unit root tests.

CIPS

Variable	(1) Without trend	(1) With trend	(2) Without trend	(2) With trend	(3) Without trend	(3) With trend	(4) Without trend	(4) With trend
$LOG(emp_{i,t})$	−0.968 (0.167)	3.467 (1.000)	1.937 (0.974)	0.326 (0.628)	2.063 (0.980)	0.720 (0.764)	1.012 (0.844)	3.248 (0.999)
$LOG(vyl_{i,t})$	−1.542 (0.061)	2.522 (0.994)	−0.207 (0.418)	0.910 (0.819)	−0.077 (0.469)	1.730 (0.958)	−1.537 (0.062)	1.652 (0.951)
$LOG(vkl_{i,t})$	2.922 (0.998)	5.484 (1.000)	5.550 (1.000)	6.582 (1.000)	−1.093 (0.137)	−0.475 (0.317)	3.160 (0.999)	4.168 (1.000)
$LOG(rw_{i,t})$	0.823 (0.795)	−1.299 (0.097)	1.825 (0.966)	−0.353 (0.362)	1.343 (0.910)	−0.651 (0.258)	4.057 (1.000)	2.156 (0.984)
$LOG(gva_{i,t})$	3.797 (1.000)	0.939 (0.826)	1.598 (0.945)	1.858 (0.968)	1.944 (0.974)	−0.275 (0.392)	2.617 (0.996)	0.903 (0.817)
$LOG(lxfd_{i,t})$	1.707 (0.956)	0.839 (0.799)	−1.164 (0.122)	0.218 (0.586)	3.071 (0.999)	0.614 (0.731)	0.065 (0.526)	−0.471 (0.319)
First difference								
$\Delta LOG(emp_{i,t})$	−4.656 (0.000***)	−2.538 (0.006***)	−3.597 (0.000***)	−3.837 (0.000***)	−4.329 (0.000***)	−3.258 (0.001***)	−2.507 (0.006***)	−2.296 (0.011**)
$\Delta LOG(vyl_{i,t})$	−3.812 (0.000***)	−11.842 (0.000***)	−2.758 (0.003***)	−8.850 (0.000***)	−7.913 (0.000***)	−4.118 (0.000***)	−2.240 (0.013**)	−6.013 (0.000***)
$\Delta LOG(vkl_{i,t})$	−3.009 (0.001***)	−4.733 (0.000***)	−3.162 (0.001***)	−7.684 (0.000***)	−8.538 (0.000***)	−4.115 (0.000***)	−5.594 (0.000***)	−3.617 (0.000***)
$\Delta LOG(rw_{i,t})$	−11.481 (0.000***)	−8.028 (0.000***)	−3.571 (0.000***)	−5.829 (0.000***)	−11.746 (0.000***)	−5.195 (0.000***)	−4.944 (0.000***)	−2.659 (0.004***)
$\Delta LOG(gva_{i,t})$	−5.116 (0.000***)	−2.457 (0.007***)	−4.017 (0.000***)	−8.540 (0.000***)	−9.065 (0.000***)	−3.904 (0.000***)	−3.480 (0.000***)	−2.383 (0.009***)
$\Delta LOG(lxfd_{i,t})$	−5.197 (0.000***)	−2.170 (0.015**)	−3.540 (0.000***)	−4.998 (0.000***)	−9.611 (0.000***)	−2.276 (0.011**)	−3.084 (0.001***)	−1.487 (0.068*)
CADF								
Variable	**(1) Without trend**	**(1) With trend**	**(2) Without trend**	**(2) With trend**	**(3) Without trend**	**(3) With trend**	**(4) Without trend**	**(4) With trend**
$LOG(emp_{i,t})$	0.302 (0.619)	4.412 (1.000)	3.037 (0.999)	3.013 (0.999)	1.683 (0.954)	1.585 (0.944)	1.062 (0.856)	3.420 (1.000)
$LOG(vyl_{i,t})$	−1.719 (0.043**)	2.252 (0.988)	−1.506 (0.066*)	0.045 (0.518)	−1.995 (0.023**)	0.716 (0.763)	−0.714 (0.237)	2.195 (0.986)
$LOG(vkl_{i,t})$	3.788 (1.000)	7.724 (1.000)	4.999 (1.000)	6.503 (1.000)	−0.096 (0.462)	−0.056 (0.478)	3.277 (0.999)	4.722 (1.000)
$LOG(rw_{i,t})$	0.114 (0.545)	2.247 (0.988)	1.460 (0.928)	0.192 (0.576)	1.546 (0.939)	−0.558 (0.289)	3.962 (1.000)	2.708 (0.997)
$LOG(gva_{i,t})$	3.558 (1.000)	−0.865 (0.193)	1.495 (0.933)	0.291 (0.614)	3.124 (0.999)	1.575 (0.942)	3.710 (1.000)	0.678 (0.751)
$LOG(lxfd_{i,t})$	2.756 (0.997)	1.162 (0.877)	−0.925 (0.177)	0.946 (0.828)	3.993 (1.000)	2.200 (0.986)	−0.064 (0.474)	−0.158 (0.437)
First difference								
$\Delta LOG(emp_{i,t})$	−4.656 (0.000***)	−2.538 (0.006***)	−11.929 (0.000***)	−10.645 (0.000***)	−10.474 (0.000***)	−9.308 (0.000***)	−10.567 (0.000***)	−10.063 (0.000***)
$\Delta LOG(vyl_{i,t})$	−4.412 (0.000***)	−19.263 (0.000***)	−14.877 (0.000***)	−13.600 (0.000***)	−7.913 (0.000***)	−6.319 (0.000***)	−12.352 (0.000***)	−11.398 (0.000***)
$\Delta LOG(vkl_{i,t})$	−16.971 (0.000***)	−14.911 (0.000***	−9.053 (0.000***)	−7.684 (0.000***)	−8.538 (0.000***)	−7.699 (0.000***)	−11.741 (0.000***)	−10.404 (0.000***)
$\Delta LOG(rw_{i,t})$	−6.472 (0.000***)	−3.722 (0.000***)	−13.670 (0.000***)	−11.876 (0.000***)	−10.614 (0.000***)	−11.746 (0.000***)	−11.949 (0.000***)	−10.528 (0.000***)
$\Delta LOG(gva_{i,t})$	−5.553 (0.000***)	−4.935 (0.000***)	−13.162 (0.000***)	−11.927 (0.000***)	−9.065 (0.000***)	−7.894 (0.000***)	−9.795 (0.000***)	−8.574 (0.000***)
$\Delta LOG(fxd_{i,t})$	−19.887 (0.000***)	−17.572 (0.000***)	−12.655 (0.000***)	−10.736 (0.000***)	−9.611 (0.000***)	−8.476 (0.000***)	−12.238 (0.000***)	−11.385 (0.000***)

Note: *** Denotes rejection at 1%. ** Denotes rejection at 5%. * Denotes rejection at 10%. The symbol Δ stands for the first difference. To perform the CIPS and the CADF test, the *multipurt* routine by Eberhardt (2011a) and the command *pescadf* by Lewandowski (2007) were employed.
Source: own elaboration based on Stata 17.

Table 8. Westerlund (2007) cointegration test.

	(1)	(2)	(3)	(4)
Variance ratio (statistic)	64.077	36.688	44.875	31.589
p-value	0.000***	0.000***	0.000***	0.000***
Panels	646	266	152	228
Avg. Number of periods	23	23	23	23

Note: *** Denotes rejection at 1%. The *xtcointtest westerlund* command was used.
Source: own elaboration based on Stata 17.

Table 9. Westerlund (2007) ECM panel cointegration test.

	(1)		(2)		(3)		(4)	
Statistics	z value	robust *p*-value	z value	robust *p*-value	z value	robust *p*-value	z value	robust *p*-value
G_t	12.473	0.052*	11.173	0.078*	12.770	0.039**	12.222	0.045**
G_a	13.736	0.007***	12.031	0.067*	12.502	0.042**	12.997	0.022**
P_t	12.974	0.024**	11.004	0.088*	11.888	0.074*	12.794	0.028**
P_a	12.497	0.044**	12.001	0.069*	12.111	0.058*	12.097	0.062*

Note: *** Denotes rejection at 1%. ** Denotes rejection at 5%. * Denotes rejection at 10%. The *xtwest* command by Persyn and Westerlund (2008) was applied.
Source: own elaboration based on Stata 17.

namely: the CS-ARDL and CS-DL. As noted by Chudik and Pesaran (2015), the CS-ARDL has some advantages over other methods that also control for cross-sectional dependence and slope heterogeneity. For instance, like the traditional ARDL, the CS-ARDL can obtain robust estimations with the combination of I(0) and I(1) variables. Given that the CS-ARDL is based on the mean group estimators, it is much more suitable in the presence of slope heterogeneity than those methods based on pooled or weighted estimators.

Furthermore, the CS-ARDL controls the presence of weak exogeneity and endogeneity by lagging the dependent variable and by including lagged cross-sectional averages in the regression (Chudik & Pesaran, 2015). Lastly, the CS-ARDL is able to control both unobserved common factors and structural breaks.

The results derived from the CS-ARDL are outlined in Table 10. Starting with the panel data that include all manufacturing sectors, both the vertically integrated labour productivity and vertically integrated capital-labour ratio are statistically significant, and their coefficients are negative both in the short-run and long-run. *Ceteris paribus*, a 1% increase in vertically integrated labour productivity reduces manufacturing employment by approximately 0.116% and 0.065% in the short-run and long-run, respectively. Similarly, if the vertically integrated capital-labour ratio rises 1%, the manufacturing employment decreases by approximately 0.345% (short-run) and 0.169% (long-run).

These results seem to be in line with the mechanism disclosed by Ricardo (1821) and Marx (1867), which states that technological progress and mechanisation reduce the relative demand for labour, generating, in turn, a permanent redundant worker population to guarantee capital accumulation in the long-term. Regarding the control variables, it is noteworthy to mention that only the real gross value added is statistically significant both in the short-run and long-run. This result is reasonable due to the demand for labour depending on the business cycle.

On the other hand, it should be stressed that the effect of an increase in the real wage on manufacturing sectors is not statistically significant, which suggests that the

Table 10. CS-ARDL (1).

	(1)			(2)			(3)			(4)		
Dep.: $\Delta LOG(emp_{i,t})$	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)
Short-Run Estimates												
ECT(-1)	−0.751	0.074	−10.18 (0.000***)	−0.934	0.095	−9.85(0.000***)	−0.565	0.146	−3.88(0.000***)	−0.646	0.120	−5.38 (0.000***)
$\Delta LOG(vyl_{i,t})$	−0.116	0.046	−2.55 (0.011**)	0.045	0.053	1.86 (0.089*)	−0.290	0.089	−3.25 (0.001***)	−0.311	0.133	−2.33 (0.020**)
$\Delta LOG(vkl_{i,t})$	−0.345	0.084	−4.09 (0.000***)	−0.243	0.067	−3.64 (0.000***)	−0.184	0.100	−1.83 (0.067*)	−0.547	0.186	−2.94 (0.003***)
$\Delta LOG(rw_{i,t})$	−0.022	0.031	−0.71 (0.479)	−0.036	0.056	−0.64 (0.524)	0.005	0.078	0.06 (0.951)	0.127	0.079	1.61 (0.107)
$\Delta LOG(gva_{i,t})$	0.096	0.040	2.40 (0.017**)	0.031	0.062	0.50 (0.614)	0.214	0.051	4.20 (0.000***)	0.083	0.077	1.08 (0.281)
$\Delta LOG(fxd_{i,t})$	−0.103	0.063	−1.64 (0.100*)	−0.067	0.076	−0.88 (0.377)	−0.337	0.154	−2.19 (0.029**)	−0.008	0.117	−0.06 (0.949)
Long-Run Estimates												
$LOG(vyl_{i,t})$	−0.065	0.026	−2.47 (0.014**)	0.021	0.030	1.92 (0.072*)	−0.171	0.048	−3.56 (0.000***)	−0.169	0.074	−2.29 (0.022**)
$LOG(vkl_{i,t})$	−0.169	0.043	−3.91 (0.000***)	−0.124	0.035	−3.58 (0.000***)	−0.086	0.057	−1.50 (0.133)	−0.287	0.095	−3.01 (0.003***)
$LOG(rw_{i,t})$	−0.023	0.021	−1.08 (0.280)	−0.016	0.033	−0.49 (0.624)	0.007	0.047	0.15 (0.877)	0.076	0.045	1.70 (0.089*)
$LOG(gva_{i,t})$	0.070	0.027	2.64 (0.008***)	0.019	0.031	0.60 (0.550)	0.128	0.026	4.98 (0.000***)	0.055	0.042	1.33 (0.183)
$LOG(fxd_{i,t})$	−0.039	0.040	−0.98 (0.329)	−0.043	0.037	−1.17 (0.241)	−0.188	0.086	−2.18 (0.029**)	0.016	0.076	0.21 (0.832)
R-squared (MG)	0.81			0.76			0.80			0.89		
CD-statistic (p-value)	2.89 (0.004***)			−1.19 (0.234)			−1.32 (0.186)			1.94 (0.052*)		
Obs.	14,858			6,118			3,496			5,244		

Note: *** Denotes rejection at 1%. ** Denotes rejection at 5%. * Denotes rejection at 10%. The symbol Δ stands for the first difference. The *xtdcce2* command by Ditzen (2018) was employed.
Source: own elaboration based on Stata 17.

labour market adjustment policies implemented over the last three decades may have contained wage growth to maintain the firms' profitability.

Another explanation could rest in Ricardo's and Marx's theories of the real value of wages and the relative wage. In such a framework, wages are conceived as a proportion of the total output rather than an absolute quantity of money received by the workers for their labour. Therefore, an increase in real wages might not affect profitability and employment if its share in total output decreases with the expansion of labour productivity.

We now turn to analyse the results for the panel data corresponding to the high and medium-high-tech intensity manufacturing sector. Table 10 reports that the increase in vertically integrated labour productivity improves manufacturing employment both in the short-run and the long-run.

Prima facie, the findings suggest that technological progress is skilled-labour friendly, which is consistent with other investigations (Bogliacino *et al.*, 2012). However, as we can see in Table 10, the increase in the vertically integrated capital-labour ratio may hurt manufacturing employment in these manufacturing sectors, showing that even skilled labourers could be substituted by machinery in the short-run and the long-run.

Even though the econometrical evidence appears to support that technological progress spurs the demand for skilled labour in those innovative manufacturing sectors, this increase in employment is unable to compensate for the decline in the rest of the manufacturing sectors. In this vein, the results indicate that the reduction in employment in the medium tech intensity and the medium-low- and low-tech intensity manufacturing sectors is larger than the positive effect of technological progress reported for high and medium-high tech intensity manufacturing sectors.

As the results show, the error correction terms (ECTs) are statistically significant and their values are between 0 and 1, suggesting the presence of a long-run causal relationship between the regressors and the dependent variable (see Table 10). However, employment in manufacturing sectors that demands skilled labour (model 2) converges towards its long-run equilibrium by 93.4%, while the speed of adjustment towards a long-run equilibrium state in the medium-tech intensity and the medium-low- and low-tech intensity manufacturing sectors is lower: 56.5% and 64.6% respectively. In other words, the disequilibrium in skilled worker employment is adjusted in the long-run faster than mid-skilled and low-skilled labour employment.

Therefore, the ECTs support that technological change and mechanisation may affect the demand for skilled labour to a lesser extent than the demand for mid-skilled and low-skilled labour, which is consistent with prior investigations that applied distinct empirical strategies (Cords & Prettner, 2022).

We proceed to interpret the outcomes found by using the CS-DL estimator. As noted by Chudik *et al.* (2016), despite the CS-DL having several advantages over the CS-ARDL, this estimator should not be deemed superior but as complementary. Therefore, the results obtained using the CS-DL approach are considered a robustness check. According to Table 11, the long-run relationships reported by the CS-DL are consistent with those found by the CS-ARDL. For instance, the increase both in the vertically integrated labour productivity and the vertically integrated capital-labour ratio appear to have a negative effect on manufacturing employment when all sectors are included in the sample.

Table 11. CS-DL ($\rho = 1$).

	(1)			(2)			(3)			(4)		
Dep.: $\Delta LOG(emp_{i,t})$	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)	Coef.	Std. Error	z (*p*-value)
$\Delta LOG(vyl_{i,t})$	−0.093	0.128	−1.72 (0.068*)	0.012	0.083	1.64 (0.089*)	−0.073	0.077	−1.95 (0.042**)	−0.232	0.344	−2.13 (0.033**)
$\Delta LOG(vkl_{i,t})$	−0.339	0.112	−3.02 (0.003***)	−0.347	0.074	−4.70 (0.000***)	−0.349	0.149	−2.34 (0.019**)	−0,432	0,183	−2.36 (0.018**)
$\Delta LOG(rw_{i,t})$	−0.003	0.058	−0.04 (0.964)	−0.002	0.058	−0.03 (0.973)	0.009	0.075	0.12 (0.902)	0,102	0,118	0.86 (0.389)
$\Delta LOG(gva_{i,t})$	0.050	0.052	1.91 (0.056**)	0.076	0.061	1.24 (0.214)	0.114	0.042	2.73 (0.006***)	−0,186	0,205	−0.91 (0.364)
$\Delta LOG(fxdi,t)$	−0.103	0.136	0.37 (0.712)	−0.117	0.073	−1.61 (0.108)	0.094	0.112	0.84 (0.399)	−1,080	0,512	−2.11 (0.035**)
R-squared (MG)	0.68			0.67			0.69			0.88		
CD-statistic (p-value)	−0.780			−0.76			−0.22			−1.91		
	(0.438)			(0.448)			(0.824)					
Obs.	14,858			6,118			3,496			5,244		

Note: *** Denotes rejection at 1%. ** Denotes rejection at 5%. *** Denotes rejection at 10%. The symbol Δ stands for the first difference. The *xtdcce2* command by Ditzen (2018) was employed.
Source: own elaboration based on Stata 17.

The CS-DL also supports that the growth in vertically integrated labour productivity improves employment in high and medium-high tech intensity manufacturing sectors, but it is not enough to compensate for the decrease in the demand for medium and lesser skilled workers in the rest of the manufacturing industries. Moreover, like the CS-ARDL, the CS-DL estimator shows that the actual gross value added is the only control variable that is statistically significant. Overall, the empirical evidence appears to be supportive of the theoretical mechanisms on which this research rests.

5. Concluding remarks

This study attempted to assess the potential impacts of technological progress and mechanisation on manufacturing employment by means of a combination of the input-output approach and the second generation of panel cointegration techniques. By computing the vertically integrated labour productivity and the vertically integrated capital-labour ratio, two theoretical mechanisms were tested. The first of them, is the so-called Barton-Ricardo-Marx effect, which states that technological change and mechanisation reduce the relative demand for labour. The second one is known in the literature as the technologies-skill complementarity effect, which discloses that innovations displace unskilled labourers in favour of skilled workers.

Given that these findings suggest that both mechanisms appear to hold in the OECD over the 1995–2018 period, the chief conclusion that can be inferred is that technological change and mechanisation contribute to maintaining a redundant workers population to guarantee capital accumulation in the long-run.

Nevertheless, this long-term trend should not be interpreted as the end of human labour and the full replacement of workers by machinery, insofar as the value of coefficients reported by the CS-ARDL and CS-DL estimators are relatively small, showing that the potential repulsion effect provoked by the increase in labour productivity, the introduction of machinery and the automation of tasks is not strong enough to conclude that technological progress and mechanisation are detrimental for workers employed in manufacturing sectors from the OECD countries.

Because the present empirical assessment adopted a supply-side approach, it neglected the importance of the extent of the market, the demand for those final goods produced by the manufacturing sectors included in the sample, or the process of product innovation. It should be noted that these variables could smooth the Barton-Ricardo-Marx effect in the long-run. Further research including these factors is needed to evaluate more accurately the influence of technological progress and mechanisation on employment.

Hence, if policymakers are looking for improving employment in the OECD countries, they should lighten the potential negative effects of technological progress and mechanisation by developing and applying measures focused on increasing research and development expenditure to spur product innovations, by enlarging markets through growing national income, and enhancing workers' skills by means of training and education spending.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. Given the vast number of studies on the subject, we cannot offer a comprehensive survey of the empirical literature.
2. Marx, who coined the term compensation theory, along with Mill, MacCulloch, Torrens and Senior, excluding Ricardo from its supporters.
3. Despite criticism from Wicksell (1981) and Schumpeter (1954), Samuelson (1989) sustains that Ricardo was right in this sense. Mathematically, Samuelson (1989, pp. 50–54) shows that the introduction of machinery may reduce national output, contravening Ricardo's critics. Like Ricardo, Samuelson states that this result is in concordance with the principles of the political economy and is not a vulgar prejudice.
4. Following Barton, Ricardo had made the blunder of confusing labour compensation with all circulating capital. In the Ricardian model, the capital-labour ratio corresponds to the fixed capital-circulating capital ratio. Even with this confusion, Marx (1867) praises both Barton and Ricardo because they disclosed that the process of capital accumulation creates a relative superfluous workers population.
5. It must be stressed that Marx denies the so-called iron law of wages by Malthus and Lasalle. As Marx (1867, p. 275) states, "the determination of the value of labour-power contains a historical and moral element". Therefore, the basket of goods consumed by the workers does not allow only physiological reproduction since the necessary requirements and the way of satisfying them are historical products that depend on the level of economic development. That is, the basket of goods tends to be greater with the expansion of capital, contravening the iron law of wages based on physiological subsistence. Moreover, Marx extended the category of the real value of wages by Ricardo (1821, Chapter 1), renaming it the relative wages (*i.e.*, the proportion of wages of total output). According to Marx, although capital accumulation, technical progress and mechanisation may raise both nominal and real wages, this increase can be lower than the enlargement of labour productivity, provoking the tendency for relative wages to fall. In such a framework, wages should be considered regarding total output rather than an absolute amount, which means that in Marx's theory it is not decisive if nominal and real wages rise or fall (Rosdolsky, 1968, p. 296).
6. Real average wages were calculated by dividing total labour compensation at current prices between the hours worked. Later, nominal average wages were indexed by the consumer price index (cpi) of each sample country, whose information is available in the OECD statistics.

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