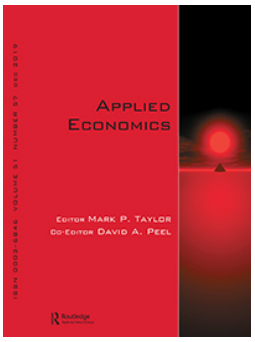

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Robotization and labour dislocation in the manufacturing sectors of OECD countries: a panel VAR approach

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ABSTRACT

Robots are the most important innovation which has affected the production process in the last three decades. Thanks to the latest advances in technology, they have been able to perform an ever-increasing number of tasks, eventually replacing human work within the whole production process. However, because of the scarcity of suitable data, the extent of this potentially disrupting process is not fully assessed. This paper makes up for the lack of empirical evidence on the effect of robotization on labour dislocation using data collected by the International Federation of Robotics (IFR) on the number of robots installed in the different manufacturing industries of 16 OECD countries over the period 2011–2016. We show that at the industry level a 1% growth in the number of robots reduces the growth rate of worked hours by 0.16, as well as the selling prices and the real values of the compensations of employees. Moreover, we show that a given sector is more likely to be robotized when it is expanding both in terms of relative prices and employee compensations. We conclude that, at least in the selected countries, the introduction of robots plays a key role in slowing down human labour and compensation growth.

KEYWORDS
Robotization; employment; wages; panel VAR models

JEL CLASSIFICATION
E24; J24; J31

I. Introduction

The introduction of new technologies in the production process have cyclically generated high hopes and fears: the potential improvements for the human being have always been compared with their eventual negative impact on employment and on human capital value. In the 19th century in England, the mechanization of the textile industry, while significantly increasing the productivity of the sector, led to the rising of the Luddites, a working-class protest movement. Luddites, who did not object *a priori* to innovation, fought specifically against textile machinery, which was presumed to make their skills and know-how unnecessary. In the 21st century, the anxiety and concern about the risks associated with automation and the disruptive role of robots in our society have grown in public and academic debate.[1] The rise of new Luddite movements, populist and antiscientific parties in many advanced countries is rooted in the dissatisfaction of the declining middle class, for which the introduction of new technologies is not reflected in a salary increase[2].

In the long-run process of productivity growth due to technological advances, robotization is the technology showing the largest potential impact on labour organization since the steam engine. Despite a substantial increase in the last two decades, robotization is far from reaching its full scale. Half of the jobs in many economic sectors are expected to disappear by 2060 because of automation, whereas some specific tasks will be entirely robotized long before[3]. While in the last 50 years economic growth was almost equally due to increasing productivity and increasing labour, in the next 50 years a similar growth (on average 3% per year) is expected to be the result only of increasing productivity[4]. The ever-increasing number of robots (over 2.5 million in 2019

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[1]Pew Research Center (2017).
[2]Brynjolfsson and McAfee (2014).
[3]OECD (2018).
[4]McKinsey & Company (2017).

according to IFR), and their expansion to the service sector, such as education, human health and care activities, can potentially worsen this situation, leading to the rise of a 'useless class'[5]: humans who cannot work, having been substituted by cheaper and better workers, the robots. In contrast with this negative vision, there is a large branch of economic literature showing that the expansion in machinery production in the last two centuries has been usually correlated with increasing productivity, salaries, and growth[6], and been beneficial to both capitalists and workers (albeit non-equally[7]). In other words, even if the short-term impact of human-robots replacement on jobs and compensations could be negative, the medium and long-run effect will be positive.

Both positive and negative vision about the ongoing process of robotization succeed in considering only partially its complex outcomes and generally, they lack empirical evidence, or they focus on historical events based on socioeconomic contexts often completely different from the present one. However, robots drastically differ from every other capital input known before. As defined by ISO 8373 a robot is 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications'[8]. It follows that robots are not single purpose or single-task machines since they can adapt to different tasks and different kinds of production. This characteristic makes robotized work a potential substitute for human work, much more than any other capital input[9].

Our contribution is aimed at filling the gap caused by the lack of empirical investigation about the effect of robotization on employment and wages at the macro level. Using the still largely unexplored database of the International Federation of Robotics (IFR), which, to our knowledge, is the most comprehensive data source on installed robots by country and by sector, we investigate the effect of robotization (measured as the number of robots' growth rate) on worked hours' and real wages' growth rates. The analysis focuses on 9 sectors and 16 OECD countries, namely Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom, and the United States[10].

The IFR database has been recently used in Graetz and Michaels (2017) and Acemoglu and Restrepo (2018). The former focuses on jobless recoveries affecting 28 industries in 17 leading (except for the US) economies over the period 1970–2011. Using both IFR and EU-KLEMS databases, the authors argue that there is no evidence that automation has caused jobless recoveries. The latter analyses the effect of industrial robots on US local labour markets between 1990 and 2007, arguing that increasing robotization had negative effects on employment-to-population ratio and wages.

Although differing in the methodology, time span, and countries, our work, is rooted in their line of thought.

By matching the IFR and the OECD STructural ANalysis database (STAN) and applying a Panel Vector Auto-Regression (PVAR) methodology, we investigate the effect of robotization on labour dislocation showing that a 1% increase in robots' growth rates reduces the total growth rate of hours worked by humans by 0.12 and has an ambiguous effect on real wages.

II. Literature review: technology in production

It is doubtless that automation can improve business performances by reducing costs, improving the quality of output and even allowing kinds of productions which would be impossible for human workers. Who would argue that it is not positive to produce more using fewer resources and reducing human effort and errors? A large body of macroeconomic literature supports this positive vision based on theoretical models in which advances in production technology, such

[5]Harari (2014).
[6]Graetz and Michaels (2017).
[7]Piketty and Saez (2014), Piketty and Zucman (2014).
[8]International Federation of Robotics (IFR) 2018, 1).
[9]DeCanio (2016).
[10]The choice is driven by IFR data availability and their possible match with STAN data. A detailed explanation is provided in Data section.

as automation, increase productivity thus generating benefits for the whole economy. In these models, an increase in productivity is generally reflected in an increase in labour demand (and, therefore, in salaries) through four main channels. First, at the intra-industry level, labour demand increases whenever the increased productivity is reflected in an overall sectoral growth requiring new workforce in non-automated tasks. Secondly, at a cross-industries level, sectors which are not affected by automation could benefit from decreasing real prices of automated sectors, and, accordingly, increase their labour demand too. Thirdly, being automation capital-augmenting, the accumulation of capital is itself an engine of growth and will increase labour demand. Fourthly, the creation of new tasks and jobs which cannot be automatized has a positive impact on employment, and consequently, on aggregate demand and growth[11]. In this regard, it can be observed that, from WWII and since the beginning of the 1980s, improvements in productivity have always been accompanied by increasing salaries and the rise of new sectors that, requiring new occupations, allowed workers substituted by machinery to find new jobs.

However, automation has a potential drawback for labour demand. Automation and, generalizing, productivity growth, could lead to the displacement of labour. Caused by constraints to aggregate demand or to labour mobility[12], this dislocation can take the form of an aggregate employment decrease and/or of a decrease of labour share on total value-added[13]. Furthermore, this displacement depends on the level of substitution and complementarity between hi-tech and low-tech industries: technological bias, in fact, could cause dislocation whenever there is a mismatch between skills needed to perform new tasks and those owned by workers replaced by robots[14]. While the dislocation in terms of labour demand seems to be counterbalanced by the increasing demand for labour in other industries, the labour share dislocation seems to have been worsened by automation[15], making robots one of the main potential causes of the emerging 'great decoupling' between salaries and productivity[16]. Workers ousted by robots, in fact, migrate to non-automatized, low-skilled-low-paid occupations, finally reducing the aggregate income from labour (thus the labour share) in the economy. Moreover, whenever this effect is large enough to reduce aggregate demand, it could cause a long-lasting crisis[17].

Finally, it must be observed that this dichotomic interpretation of the effect of robotization on labour results from different theoretical and empirical approaches based on colliding hypotheses, applied to different national contexts and periods. Whereas it is generally agreed that, in the long run, advances in technology positively affect salaries and employment, ensuring growth and wealth, a radical change in technology generally causes a structural break which could lead to dramatic socio-economic consequences. The enclosures in 18th century Britain created the perfect conditions for industrialization to occur, but, at the same time, they represent one of the most dramatic examples of worker dislocation. The automatization of agriculture in the US in the 1920s, while freeing humans from the risk of starvation, caused an uneven increase in agricultural production followed by a dramatic fall in the relative prices of the sector, which directly led to the 1929 crisis and, indirectly, to WWII. Do robots represent such a disruptive turning point in technology? If robots are better and cheaper than human workers, why are there still so many jobs?[18]

III. Data

To evaluate the effect of robotization on labour dislocation we use data on robots and data on sectoral employment and wages from IFR and

[11]Acemoglu and Restepro (2018).
[12]Delli Gatti et al. (2012).
[13]Autor and Salomons (2018).
[14]Vivarelli (2014).
[15]Autor and Salomons (2018).
[16]Brynjolfsson and McAfee (2014).
[17]Valentini et al. (2017).
[18]David (2015).

STAN database respectively. We identify in growth rates, instead of levels, the most appropriate way to capture the effect of increasing robotization in labour dislocation. While levels are generally affected by the size of countries and sectors under investigation, institutional factors and historical trends, growth rates are less exposed to these biases. Specifically, we consider as dependent variables the growth rates of the number of hours worked in a sector and the related real hourly wage, while our explanatory variable is the Operational Stock of Robot (OSR) growth rate, namely the yearly growth rate of the absolute number of operating robots.

Unlike Graetz and Michaels (2017) and Acemoglu and Restrepo (2018), who focus on the period before the 2006 financial crisis, we analyse the period 2011–2016. Our choice is mainly driven by the lack of cross-country comparable data for the US before 2011[19] and by the fact that STAN data are available only until 2016[20]. This choice accidentally leads to three main pros[21]. First, it allows avoiding the negative effect of the business cycle of the 2007 financial crisis and the 2010 sovereign debt crisis, both ended by 2011. Secondly, it allows focusing on a post-crisis period which is still largely understudied. Thirdly, it allows avoiding substantial data variations due to their eventual collection in different historical moments. Since we focus on the growth rates of robots, their fluctuations in the 1980s and 1990s in many sectors are often dramatically large in many sectors, mainly because the initial stocks were close to or equal to 0. Focusing on recent years should mitigate this effect, reducing the need for restrictive hypotheses.

A second choice regards the countries to be included in the analysis. Given the goal of the paper, the OECD-STAN is the only database able to provide comparable data about worked hours and wages at the sectoral level for the largest group of countries. As a result, we could not analyse China, which is not an OECD member, as well as Australia, Canada, Chile, Ireland, Mexico and South Korea (which, on the contrary, are OECD members) since some of the sectors of these countries are affected by missing data. This means that only considering China and South Korea, we lose two of the most 'robotized' countries, where about half of all the industrial robots installed worldwide in 2018 are located. China *per se* experienced a growth of 20% of robotization in the last year – 2 out of 5 robots installed in the word in the last year were installed in China (IFR, 2018). Unfortunately, to the best of our knowledge, there is no reliable database covering Chinese data on hours worked and wages at ISIC rev. 4 disaggregation, which is the classification we use in the Panel VAR analysis.

We further dropped Luxembourg (which is not covered by IFR data), Iceland (whose economy is too small) and Eastern European countries. These latter are so different in terms of structure and dynamics of their labour markets and compensations from the other OECD countries as to negatively affect the analysis. Including or not these countries in the econometric analysis provides similar results, with the important difference that the former is not significant.

The breakdowns provided in the Operational Stock of Robots (OSR) from IFR do not match with sectors of the ISIC rev.4 used in STAN. For instance, in IFR all industries of the Services sector are grouped in only two categories: 'all other non-manufacturing' and 'education/research'. The former, which includes all services (except for education and research), is excessively aggregated to be appealing for our analysis. The latter shows extremely large variations in growth rates mainly because robotization only recently affected the sector. A similar issue involves 'Mining and quarrying', 'Electricity, gas, water supply' and 'Agriculture, Forestry and Fishing', all sectors that have very little room for robotization nowadays. Therefore, to avoid bias resulting from the poor quality of data, we exclude those sectors.

[19]In IFR, US, Canada and Mexico are merged in 'North America' until 2010. Hence, for US there are data on the stock of robots only from 2011 onwards (growth rates from 2012).
[20]STAN updates are available at http://stats.oecd.org/wbos/fileview2.aspx?IDFile=3f0cc18c-076e-4dbe-ad7e-a6ecd2efcd3c accessed on 13 July 2019.
[21]The cons stands in the relatively limited number of observations in time (6), which does not allow for more time lagged regressors as discussed later on.

OSR data must be aggregated according to the ISIC rev.4 classifications before being merged with STAN data. From the latter we select the following variables: HRSE ('Hours worked, employee'); VALK ('Value added, volumes'); WAGE ('Wages and Salaries')[22] and VALP ('Value added deflator').[23] Hourly productivity is derived from VALK and HRSE. Real wages are computed deflating sectoral wages using the sectoral deflator (VALP is also used to calculate VALK, and hence productivity) and, as an alternative measure, using the GDP deflator of the whole economy. The former is the real wage from the employer perspective and embeds the effect of increases in productivity on labour costs. The latter is the real wage from the employee perspective and defines his purchasing power. Hourly wage is, then, computed using real wages and HRSE.

Even so, several outliers (extremely positive and extremely negative values in yearly growth rates of robots, rapidly switching signs of values) still affect the remaining sectors with a possible negative impact on the quality of the panel analysis. Dropping outliers is generally not a good practice whenever there is no clear evidence of measurement errors. To avoid arbitrariness in the selection of reliable values, we adopt the following procedure: we compute the standard deviation of robot growth rates for each sector/country between 2011 and 2016. Then, since a very high standard deviation value could be a signal of the bad quality of data for the concerned sector, we apply the Blocked Adaptive Computationally efficient Outlier Nominators (BACON) algorithm proposed by Billor, Hadi, and Velleman (2000) on those standard deviations, using a 10% cut-off parameter to identify outliers[24]. We, therefore, drop 20 sector/country combinations out of a total of 139[25]. Summary statistics are provided in Appendix Tables A1-A4.

IV. Empirical specification and discussion

In macroeconomic literature, the PVAR methodology is often used to capture the dynamic interdependencies among variables using a minimal set of restrictions while studying interdependent economies[26]. In a VAR system, all variables are processed as endogenous variables. Panel VAR models (Holtz-Eakin, Newey, and Rosen 1988), which apply VAR to panel data settings, can be used in several contexts. For example, Head, Lloyd-Ellis, and Sun (2014) apply PVAR to study house prices and incomes; Mora and Logan (2012) to stress how shocks to the capital of a bank may influence its portfolio; Carpenter and Demiralp (2012) to identify the transmission of monetary policies; Neumann, Fishback, and Kantor (2010) to examine the dynamic relationships between relief spending and local private labour markets during the New Deal; finally, Caballero, Fernández, and Park (2018), to deal with the relation between economic activity and external financial indicators.

A VAR model is a system of simultaneously estimated equations in which each variable is explained by its own lags and the lagged values of the other variables. Following the methodology proposed by Abrigo and Love (2016), a k-variate panel VAR of order p, with panel-specific fixed effects and without exogenous covariate, can be represented by the following system of linear equations:

$$\boldsymbol{Y}_{i,t} = \boldsymbol{A}_1 \boldsymbol{Y}_{i,t-1} + \boldsymbol{A}_2 \boldsymbol{Y}_{i,t-2} + \ldots + \boldsymbol{A}_{p-1} \boldsymbol{Y}_{i,t-p} + \boldsymbol{u}_{i,t} + \boldsymbol{e}_{i,t}$$

[22]Except for Japan that has data only on LABR ('Labour cost') which includes contributions to social security, private pensions, health insurance, life insurance and similar schemes.

[23]Three sectors (ISIC codes 24–25-28) had to be grouped to match IFR data. The aggregation of HRSE, VALK and WAGE is made summing values while VALP is aggregated by means of weighted average, using the values of VALU ('Value added, current prices') as weights.

[24]See Weber (2010) for further details. The procedure was applied using the STATA bacon.ado.

[25]Namely, dropped combinations are: 'Austria – Textiles, etc … ', 'Belgium – Textiles, etc … ', 'Denmark – Construction' 'Denmark – Furniture and other manufacturing, etc.', 'Finland – Transport Equipment, etc … ', "Greece – Basic metals and fabricated metal products", 'Greece – Electrical Equipment', 'Greece – Chemical, rubber, plastics, fuel products … ', 'Greece – Transport equipment', 'Netherlands – Construction', 'Netherlands – Electrical equipment', 'Netherlands – Furniture and other manufacturing, etc … ', 'Netherlands – Textiles, etc … ', 'Norway – Furniture and other manufacturing, etc … ', 'Portugal – Furniture and other manufacturing, etc … ', 'Portugal – Textiles, etc … ', 'Portugal – Wood and paper products, etc.', 'Sweden – Furniture and other manufacturing, etc … ', 'Sweden – Textiles, etc … ', 'UK – Wood and paper products, etc.'. The descriptive statistics of the final dataset are presented in (Tables A1, B1, C1 and D1).

[26]Canova and Ciccarelli (2013).

$$i \in 1, \ldots, N; t \in 1, \ldots, T_i;$$

where $\boldsymbol{Y_{i,t}}$ is a vector of dependent variables, while $u_{i,t}$ and $e_{i,t}$ are vectors of dependent variable-specific fixed effects and idiosyncratic errors, respectively. The matrices $\boldsymbol{A}_1$, $\boldsymbol{A}_2$ …, $\boldsymbol{A_p}$ are the parameters to be estimated.

We control for individual fixed effects by forward-mean-differencing (Helmert transformation), thus removing the mean of all future observations available for each sector/country 'i' at the time 't'. The Helmert transformation preserves the orthogonality between the variables and their lags. This allows to abstract from individual heterogeneity and follows the standard procedure of using lagged regressors as instruments in a system GMM estimation (Arellano and Bover 1995; Love and Zicchino 2006). Equation-by-equation GMM estimation yields consistent estimates of PVAR and fitting the model as a system of equations may result in efficiency gains being appropriate for a dataset with small T and large N (Abrigo and Love, 2016).

The use of the lagged values and of the Helmert transformation implies that we need 5 observations for every 3 observations to be used in the estimation. This explains why we could only consider those countries whose sectors have at least 5 observations.

We compute 6 different PVARs. In each of them, the vector $Y_{i,t}$ includes two variables: robot growth rates and the growth rates of one among hours, wages and sector deflator[27]. The small T of our dataset does not offer many options in terms of lags selection. Nevertheless, comparing the Coefficient of Determination of models with one or two lags always supports the one lag period estimates[28]. The stability condition of the six panel var is verified by computing the modulus of each eigenvalue of the estimated model. Hamilton (1994) and Lütkepohl (2005) show that a VAR model is stable if all moduli of the companion matrix are strictly less than one[29]. This condition is verified in all our six specifications. Time series are composed by the growth rates of each variable, which are all stationary.

Standard errors are clustered by the panel variable (sector/country). Table 1 shows the results of the PVAR analysis which, it is worth remembering, has been performed in the manufacturing sectors of the above mentioned 16 OECD countries.

Results suggest that an increase in robots' growth rates leads to (first part of Table 1):

(i) a significant decrease (−0.16) in growth rates of hours worked[30] (column 1);
(ii) an increase in real hourly wage growth rates, which is significant when deflated using GDP deflator (columns 2 and 3);
(iii) a significant (negative) effect on total wages growth rates, which is significant when deflated using both the industry-level deflator and GDP deflator (column 4 and 5);
(iv) a significant decrease in industry sectoral deflator, hence for industry price growth rates (column 6).

Moreover, looking at the effect of these variables on robot growth rates (the second part of Table 1):

(i) hours worked to have a non-significant effect on robotization (column 1);
(ii) hourly wage growth has a non-significant effect on robotization when deflated using both industry-level deflator and GDP deflator (columns 2 and 3);
(iii) the growth rate of total compensations of employees has a positive effect on robot growth rates, and this effect is significant when wages are deflated by GDP deflator (columns 4 and 5);
(iv) the growth rates of sectoral prices significantly and positively affect robot growth rates (column 6), meaning that employers invest in new technologies (namely robots) when expecting a given return on investment.

[27]We also computed the effect for employment rate and hours per employee with compatible results in terms of signs and significance.
[28]This applies to all our six specifications with different variables associated to robot growth rates (PVARSOC in Stata).
[29]PVARSTABLE in Stata.
[30]Similar results can be obtained while focusing on employment rates.

Table 1. Panel VAR results

	panel var (1)	panel var (2)	panel var (3)	panel var (4)	panel var (5)	panel var (6)
	dep var: Hours	dep var: Real Hourly Wage (sec. deflator)	dep var: Real Wages (sec. deflator)	dep var: Real Hourly Wage (GDP deflator)	dep var: Real Wages (GDP deflator)	dep var: Sectoral deflator
Robot (t-1)	**−0.163*****	**0.0487**	**−0.105***	**0.063****	**−0.090***	**−0.176***
	[0.046]	**[0.038]**	**[0.063]**	**[0.028]**	**[0.047]**	**[0.094]**
Hours (t-1)	0.664***					
	[0.046]					
Real Hourly Wage (sec. deflator) (t-1)		0.332***				
		[0.058]				
Real Wages (sec. deflator) (t-1)			0.376***			
			[0.092]			
Real Hourly Wage (GDP deflator) (t-1)				0.311***		
				[0.081]		
Real Wages (GDP deflator) (t-1)					0.418***	
					[0.115]	
Sectoral deflator (t-1)						0.184
						[0.114]
	dep var: Robot	**dep var: Robot**	**dep var: Robot**	**dep var: Robot**	**dep var: Robot**	**dep var: Robot**
Robot (t-1)	0.228***	0.341***	0.337***	0.337***	0.326***	0.363***
	[0.046]	[0.096]	[0.096]	[0.096]	[0.096]	[0.104]
Hours (t-1)	**0.118**					
	[0.129]					
Real Hourly Wage (sec. deflator) (t-1)		**0.022**				
		[0.144]				
Real Wages (sec. deflator) (t-1)			**0.062**			
			[0.111]			
Real Hourly Wage (GDP deflator) (t-1)				**0.178**		
				[0.142]		
Real Wages (GDP deflator) (t-1)					**0.261****	
					[0.131]	
Sectoral deflator (t-1)						**0.216*****
						[0.080]
GMM criterion Q(b)	5.89e-34	1.59e-34	2.16e-35	7.76e-35	3.44e-34	1.81e-34
CD	0.91	0.86	0.87	0.90	0.88	0.86
N sector/country (cluster)	118	118	118	118	118	118
t mean	3.5	3.5	3.5	3.5	3.5	3.5
N	413	413	413	413	413	413

All variables: growth rates. Standard errors in brackets. Standard errors are clustered on Sector i - country j.
Panel-specific fixed effects removed using forward orthogonal deviation or Helmert transformation.
Optimal lag selection (options: one or two) through Overall Coefficient of Determination (pvarsoc in Stata).
All the panel satisfy stability condition (all the eigenvalues lie inside the unit circle) (pvarstable in Stata).
Sources: STAN OECD (Hours, Total Wages, Prices/value-added deflator); International Federation of Robotics (Robot).
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

V. Concluding remarks

By performing the p-var methodology, we analysed the effect of an increase in robotization in labour and wages dislocation in the manufacturing sectors of 16 OECD countries. Despite the limits due to data availability, we were able to identify some important casual relations.[31]

First, robotization growth reduces the growth of hours worked while increasing hourly wages.

Secondly, in the sectors where robotization is growing at a faster pace, total real wages increase at a slower rate. These results suggest that the substitution effect is larger than the complementarity effect between robots and humans in these sectors, finally causing a reduction in workers' purchasing power.

Thirdly, the prices of sectors where robots grow at a faster pace increase at a slower pace than those where robots grow at a slower pace. This evidence is consistent with a sluggish demand curve. Robots, indeed, increase workers' productivity (that is highlighted by the increase of hourly wage) and output as well. To increase sales, however, prices must be lowered, which is a feasible strategy since robots allow to reduce the costs of labour.

[31] According to Abrigo and Love (2016), the PVAR specification used in this paper allows us to consider the significance of the coefficients of the lagged regressors as evidence of 'granger causality'.

Fourth, a given sector is more likely to be robotized when it performs better in terms of price growth. Finally, the growth rate of robots increases significantly as total wages grow.

All these pieces of evidence support the idea that, while other capital goods have been complementary to human labour in the production process, robots are behaving as substitutes for workers. Their use is more likely to increase as much as prices and payrolls of a given sector follow a growth path, allowing employers to substantially reduce labour costs.

Disclosure statement

No potential conflict of interest was reported by the authors.

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APPENDIX: DESCRIPTIVE STATISTICS

ISIC rev. 4 code: Industry

F: Construction
10–11-12: Food products, beverages and tobacco
13–14-15: Textiles, wearing apparel, leather and related products
16–17-18: Wood and paper products; printing and reproduction of recorded media
19–20-21–22-23: Chemical, rubber, plastics, fuel products and other non-metallic mineral products

Table A1. Descriptive statistics (Austria, Belgium, Denmark, Finland).

codes		Robot		Hours		Real Hourly Wage (sector deflator)		Real Wages (sector deflator)		Real Hourly Wage (GDP deflator)		Real Wages (GDP deflator)		Sectoral deflator	
(ISIC rev. 4)	N	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
							AUSTRIA								
F	6	14.36	8.72	0.04	1.15	−0.44	0.47	−0.40	0.88	−1.59	1.51	−1.55	1.41	6.44	1.21
10–11-12	6	16.78	5.43	0.35	0.95	2.21	2.05	2.56	1.75	−1.59	1.84	−1.25	2.00	3.73	5.68
13–14-15	0														
16–17-18	6	12.72	8.35	−1.18	1.27	4.03	3.18	2.82	4.06	−1.60	1.52	−2.77	1.56	0.29	4.66
19–20-21–22-23	6	10.52	6.29	0.25	0.84	4.38	3.25	4.65	3.95	−1.22	1.83	−0.97	2.25	2.16	5.11
24–25-28	6	12.80	2.16	1.49	0.92	2.56	2.70	4.11	3.56	−1.60	1.53	−0.12	2.26	0.69	1.84
26–27	6	20.38	9.05	0.33	1.41	1.72	2.59	2.06	3.23	−2.54	1.74	−2.22	1.74	3.67	5.52
29–30	6	15.64	7.30	1.39	2.60	1.92	4.16	3.41	6.37	−2.10	2.43	−0.70	4.78	4.53	3.11
31–32-33	6	18.70	16.14	−0.78	1.11	1.51	3.04	0.70	2.48	−1.32	2.94	−2.11	2.41	3.99	4.40
							BELGIUM								
F	6	6.01	3.70	−0.03	3.53	1.47	1.63	1.42	2.84	−1.89	1.88	−1.96	2.16	2.17	3.70
10–11-12	6	15.35	9.66	0.33	0.82	2.68	6.77	3.02	6.72	−1.05	1.85	−0.73	1.53	3.23	7.42
13–14-15	0														
16–17-18	6	24.44	19.26	−2.45	1.47	1.34	1.87	−1.13	2.96	−2.02	1.63	−4.43	1.50	0.00	3.15
19–20-21–22-23	6	13.26	3.85	−0.31	1.28	2.04	4.62	1.74	5.10	−1.16	1.04	−1.47	0.87	3.73	8.81
24–25-28	6	15.87	5.61	−1.87	3.34	7.36	5.34	5.24	3.73	−1.76	2.41	−3.64	2.77	−2.46	3.07
26–27	6	9.42	15.42	−2.00	2.27	−1.36	3.05	−3.34	3.09	−1.54	2.33	−3.52	2.33	3.43	4.56
29–30	6	17.37	16.00	−2.52	5.63	1.46	5.30	−1.12	7.32	−1.07	3.11	−3.49	7.31	2.22	11.94
31–32-33	6	9.60	9.65	−0.05	0.96	1.65	1.78	1.59	1.64	−0.88	1.60	−0.94	1.12	4.19	3.75
							DENMARK								
F	0														
10–11-12	5	10.25	4.39	−3.19	1.11	6.07	7.77	2.69	7.80	−1.41	1.31	−4.56	2.02	−9.03	14.61
13–14-15	5	6.13	9.96	−1.62	7.35	0.51	3.56	−1.14	7.89	−1.58	1.12	−3.12	8.05	3.27	13.42
16–17-18	5	−6.37	4.75	−3.06	2.75	0.28	3.80	−2.80	4.43	−2.35	1.30	−5.35	2.63	2.11	8.40
19–20-21–22-23	5	10.11	2.19	2.14	2.06	−0.28	7.49	1.83	7.62	−0.64	1.27	1.48	2.40	14.83	15.26
24–25-28	5	−1.23	2.65	0.40	2.45	0.50	3.51	0.89	3.97	−1.57	1.16	−1.19	2.05	1.61	3.27
26–27	5	−1.13	3.25	−1.01	3.12	0.91	4.47	−0.17	3.88	−0.68	1.12	−1.68	3.34	5.75	14.63
29–30	5	9.79	10.11	−2.11	11.14	0.41	7.15	−1.44	15.53	−2.24	1.26	−4.20	11.94	3.23	21.49
31–32-33	0														
							FINLAND								
F	6	7.53	7.69	1.02	2.84	−1.54	2.57	−0.54	3.69	−2.36	1.27	−1.38	2.19	6.82	6.45
10–11-12	6	−4.16	1.81	0.01	1.39	−0.62	4.95	−0.65	4.15	−2.28	0.69	−2.27	1.68	2.72	6.18
13–14-15	6	−15.91	12.42	−4.59	3.31	1.49	1.73	−3.13	4.80	−1.36	1.28	−5.90	3.13	−1.25	4.98
16–17-18	6	−1.85	5.32	−3.49	3.06	1.55	6.53	−2.06	5.74	−1.99	1.54	−5.44	1.85	0.59	10.30
19–20-21–22-23	6	−7.82	8.27	−1.64	2.59	0.07	6.06	−1.51	7.55	−1.72	1.62	−3.37	1.46	6.81	10.57
24–25-28	6	−1.14	0.95	0.10	3.06	0.42	1.60	0.54	3.72	−2.42	0.94	−2.33	2.64	1.35	1.71
26–27	6	−13.72	4.31	−4.38	4.35	1.47	3.79	−2.89	7.01	−1.57	2.86	−5.84	5.91	−3.11	22.07
29–30	0														
31–32-33	6	12.27	15.56	−10.2	3.71	−1.27	2.31	−2.24	5.22	−2.36	1.46	−3.39	2.37	3.41	2.80

All variables: growth rates. N = number of observations between 2011 and 2016. Sources: STAN OECD (Hours, Total Wages, Prices/deflator); International Federation of Robotics (Robot)

Table A2. Descriptive statistics (France, Germany, Greece, Italy).

codes		Robot		Hours		Real Hourly Wage (sector deflator)		Real Wages (sector deflator)		Real Hourly Wage (GDP deflator)		Real Wages (GDP deflator)		Sectoral deflator	
(ISIC rev. 4)	N	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
FRANCE															
F	**6**	**23.04**	12.69	**−1.57**	0.98	**−0.36**	1.93	**−1.93**	1.08	**−0.74**	1.29	**−2.29**	1.60	**2.12**	4.38
10–11-12	**6**	**7.16**	2.61	**1.05**	1.64	**0.20**	3.16	**1.24**	3.10	**−0.65**	1.94	**0.38**	1.42	**4.06**	5.13
13–14-15	**5**	**−1.68**	9.90	**−2.48**	1.15	**0.91**	4.33	**−1.57**	4.82	**−0.71**	1.40	**−3.19**	0.70	**1.82**	3.24
16–17-18	**5**	**9.42**	2.70	**−3.09**	0.86	**2.95**	3.18	**−0.25**	2.54	**−0.50**	1.49	**−3.59**	0.75	**0.21**	5.67
19–20-21–22-23	**5**	**−0.06**	2.60	**−1.28**	1.11	**2.91**	3.67	**1.59**	3.28	**−0.91**	1.49	**−2.18**	1.33	**0.77**	4.91
24–25-28	**5**	**0.73**	2.96	**−0.94**	1.05	**0.83**	3.34	**−0.13**	2.87	**−1.23**	1.19	**−2.17**	0.85	**0.46**	2.87
26–27	**5**	**−0.40**	4.53	**−1.97**	2.20	**3.48**	2.90	**1.41**	2.51	**−1.23**	0.80	**−3.18**	1.91	**−2.50**	3.24
29–30	**6**	**−6.04**	2.85	**−1.53**	0.65	**−1.62**	4.94	**−3.14**	4.58	**−0.36**	2.29	**−1.89**	1.87	**9.08**	13.07
31–32-33	**5**	**9.37**	12.45	**−1.55**	1.29	**−0.69**	1.67	**−2.23**	2.12	**−0.11**	1.77	**−1.67**	1.24	**5.72**	1.24
GERMANY															
F	**6**	**10.68**	18.50	**0.44**	1.28	**−1.42**	1.35	**−0.98**	2.16	**−2.15**	1.44	**−1.73**	1.53	**9.71**	2.73
10–11-12	**5**	**3.50**	1.84	**0.13**	1.51	**4.07**	8.06	**4.30**	9.55	**−2.64**	2.07	**−2.54**	0.70	**2.19**	9.02
13–14-15	**5**	**7.14**	10.59	**−0.18**	2.00	**−0.12**	2.15	**−0.28**	4.01	**−2.63**	1.38	**−2.82**	1.98	**3.81**	4.73
16–17-18	**5**	**−10.82**	15.20	**−0.63**	1.38	**0.68**	2.04	**0.02**	0.86	**−3.60**	1.94	**−4.23**	1.07	**2.14**	2.22
19–20-21–22-23	**5**	**2.43**	3.13	**1.94**	1.55	**0.18**	2.42	**2.14**	3.62	**−2.87**	1.95	**−1.01**	1.55	**5.02**	4.36
24–25-28	**5**	**5.03**	1.39	**2.18**	2.33	**0.18**	1.21	**2.38**	3.44	**−2.72**	1.66	**−0.60**	2.56	**2.16**	1.43
26–27	**5**	**2.27**	2.33	**1.39**	2.14	**2.18**	2.15	**3.63**	4.20	**−2.58**	1.55	**−1.24**	1.64	**3.19**	3.09
29–30	**5**	**3.29**	2.16	**2.82**	1.14	**2.54**	2.04	**5.44**	2.97	**−1.09**	2.05	**1.69**	2.05	**9.23**	4.86
31–32-33	**5**	**−10.90**	13.62	**0.72**	1.01	**−0.73**	1.04	**−0.01**	1.74	**−3.11**	1.60	**−2.42**	1.32	**6.08**	3.09
GREECE															
F	**6**	**2.46**	**4.23**	**−10.29**	**15.32**	**1.36**	**12.31**	**−10.11**	**12.22**	**2.82**	**16.16**	**−9.41**	**10.00**	**−16.79**	**14.51**
10–11-12	**6**	**16.53**	**15.10**	**−0.89**	**1.83**	**−7.24**	**6.16**	**−8.06**	**6.42**	**2.46**	**3.58**	**1.51**	**2.89**	**7.75**	**5.71**
13–14-15	**0**														
16–17-18	**6**	**0.00**	**0.00**	**−6.32**	**3.47**	**−5.57**	**10.09**	**−11.42**	**11.02**	**−0.41**	**11.00**	**−6.62**	**11.45**	**−12.15**	**13.64**
19–20-21–22-23	**0**														
24–25-28	**0**														
26–27	**0**														
29–30	**0**														
31–32-33	**6**	**12.09**	**16.16**	**−7.74**	**3.76**	**−2.87**	**9.48**	**−10.33**	**9.86**	**3.71**	**8.12**	**−4.24**	**9.16**	**−5.52**	**9.60**
ITALY															
F	**6**	**12.28**	**13.72**	**−4.68**	**5.27**	**−0.04**	**1.85**	**−4.77**	**4.46**	**0.32**	**2.20**	**−4.45**	**3.86**	**0.18**	**5.05**
10–11-12	**6**	**20.00**	**5.10**	**−0.37**	**1.73**	**2.38**	**3.02**	**2.00**	**3.46**	**0.63**	**2.41**	**0.23**	**1.20**	**2.13**	**6.42**
13–14-15	**6**	**0.52**	**8.64**	**−0.58**	**2.93**	**0.85**	**3.25**	**0.22**	**2.96**	**−0.12**	**2.48**	**−0.75**	**1.15**	**2.16**	**4.52**
16–17-18	**6**	**8.73**	**2.32**	**−4.29**	**2.78**	**2.68**	**2.44**	**−1.77**	**1.66**	**1.06**	**2.31**	**−3.33**	**1.25**	**−1.27**	**4.39**
19–20-21–22-23	**6**	**−7.63**	**8.13**	**−1.77**	**2.74**	**0.73**	**4.18**	**−1.12**	**2.83**	**0.36**	**2.29**	**−1.46**	**1.69**	**2.94**	**11.43**
24–25-28	**6**	**3.35**	**2.65**	**0.26**	**3.00**	**1.01**	**2.80**	**1.21**	**2.20**	**0.03**	**2.50**	**0.23**	**1.05**	**0.95**	**1.48**
26–27	**6**	**2.39**	**6.27**	**−2.02**	**2.57**	**0.67**	**3.26**	**−1.42**	**1.56**	**0.70**	**2.52**	**−1.38**	**1.36**	**2.17**	**5.22**
29–30	**6**	**−6.66**	**4.71**	**0.49**	**4.52**	**1.93**	**3.69**	**2.39**	**4.66**	**0.40**	**3.22**	**0.80**	**2.85**	**2.08**	**8.84**
31–32-33	**6**	**2.93**	**9.68**	**−0.57**	**2.93**	**−1.43**	**2.31**	**−2.00**	**3.30**	**−0.05**	**1.90**	**−0.66**	**1.69**	**4.80**	**2.75**

All variables: growth rates. N = number of observations between 2011 and 2016. Sources: STAN OECD (Hours, Total Wages, Prices/deflator); International Federation of Robotics (Robot)

24–25-28: Basic metals and fabricated metal products; machinery and equipment
26–27: Electrical/electronic and optical equipment
29–30: Transport equipment
31–32-33: Furniture; other manufacturing; repair/installation of machinery and equipment

Table A3. Descriptive statistics (Japan, Netherlands, Norway, Portugal).

codes		Robot		Hours		Real Hourly Wage (sector deflator)		Real Wages (sector deflator)		Real Hourly Wage (GDP deflator)		Real Wages (GDP deflator)		Sectoral deflator	
(ISIC rev. 4)	N	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
							JAPAN								
F	**6**	**−1.57**	11.80	**−0.44**	1.15	**−0.06**	1.62	**−0.51**	0.98	**−0.68**	2.39	**−1.13**	2.14	**4.50**	4.00
10–11-12	**6**	**8.98**	2.04	**−1.18**	2.80	**0.06**	2.44	**−1.11**	4.05	**−0.59**	3.82	**−1.80**	3.61	**2.30**	5.55
13–14-15	**0**														
16–17-18	**0**														
19–20-21–22-23	**0**														
24–25-28	**6**	**−0.95**	5.96	**−0.14**	1.79	**−1.15**	3.01	**−1.27**	4.04	**−0.74**	3.25	**−0.85**	4.47	**1.86**	2.63
26–27	**6**	**3.23**	4.73	**−2.47**	4.01	**5.50**	5.99	**2.92**	7.71	**−0.06**	3.78	**−2.53**	5.44	**−4.45**	10.59
29–30	**6**	**−3.86**	2.56	**0.97**	2.75	**−0.77**	6.30	**0.23**	7.46	**−0.15**	3.89	**0.80**	4.38	**6.44**	14.45
31–32-33	**0**														
							NETHERLANDS								
F	**0**														
10–11-12	**6**	**26.82**	8.43	**0.28**	1.24	**−0.27**	3.33	**−0.00**	3.25	**−0.72**	1.21	**−0.44**	2.02	**7.79**	7.45
13–14-15	**0**														
16–17-18	**6**	**26.89**	8.15	**−3.58**	2.63	**1.12**	2.72	**−2.52**	2.89	**−1.45**	1.41	**−4.99**	2.33	**−2.11**	6.26
19–20-21–22-23	**6**	**10.83**	3.01	**−0.84**	1.65	**−0.04**	10.84	**−0.95**	10.15	**−0.62**	2.23	**−1.48**	1.73	**6.86**	27.02
24–25-28	**6**	**15.58**	4.44	**1.06**	1.31	**0.40**	1.95	**1.47**	2.30	**−0.65**	0.66	**0.40**	1.33	**1.34**	1.26
26–27	**0**														
29–30	**6**	**27.60**	9.49	**0.84**	2.48	**1.47**	2.03	**2.32**	2.91	**−0.38**	1.19	**0.44**	1.50	**5.10**	9.13
31–32-33	**0**														
							NORWAY								
F	**0**														
10–11-12	**6**	**4.91**	4.35	**0.26**	1.07	**−0.02**	4.53	**0.23**	4.35	**−0.92**	6.62	**−0.66**	6.75	**8.25**	6.69
13–14-15	**6**	**0.00**	0.00	**−0.84**	3.16	**2.43**	8.73	**1.47**	7.86	**−1.28**	5.68	**−2.05**	7.58	**5.03**	11.01
16–17-18	**6**	**1.85**	7.10	**−3.09**	2.41	**0.26**	2.30	**−2.84**	3.52	**−1.42**	6.81	**−4.40**	8.23	**3.87**	7.43
19–20-21–22-23	**6**	**2.59**	12.41	**−0.72**	1.38	**1.69**	7.96	**0.96**	8.18	**−0.87**	6.66	**−1.57**	7.15	**7.29**	14.64
24–25-28	**5**	**−1.51**	2.04	**1.59**	2.94	**2.31**	3.77	**3.96**	5.42	**−1.32**	7.31	**0.17**	6.52	**2.08**	3.66
26–27	**5**	**−7.24**	3.92	**−1.65**	3.41	**2.55**	3.45	**0.92**	6.15	**−1.60**	6.54	**−3.35**	4.82	**5.07**	4.79
29–30	**6**	**1.11**	14.09	**−3.92**	9.38	**3.38**	3.23	**−0.47**	12.22	**−0.88**	6.66	**−5.15**	6.41	**−0.64**	6.93
31–32-33	**0**														
							PORTUGAL								
F	**6**	**4.58**	5.24	**−7.32**	8.26	**0.62**	2.25	**−6.83**	7.37	**0.28**	5.61	**−7.39**	4.87	**−5.53**	6.56
10–11-12	**5**	**17.03**	9.39	**−1.09**	2.56	**0.74**	4.72	**−0.42**	3.53	**0.74**	4.89	**−0.45**	2.78	**2.18**	9.69
13–14-15	**0**														
16–17-18	**0**														
19–20-21–22-23	**5**	**21.37**	10.47	**−1.88**	3.23	**−2.58**	6.43	**−4.52**	5.27	**0.34**	4.37	**−1.63**	3.23	**6.10**	20.51
24–25-28	**5**	**9.88**	2.58	**−0.70**	3.04	**1.23**	2.90	**0.50**	3.71	**1.00**	4.70	**0.21**	3.25	**0.14**	2.37
26–27	**5**	**8.14**	2.49	**1.21**	3.00	**4.21**	7.13	**5.40**	6.60	**−0.11**	7.00	**0.96**	5.00	**−7.31**	10.73
29–30	**5**	**15.18**	4.74	**1.27**	3.89	**2.50**	4.76	**3.73**	4.64	**−0.08**	6.24	**1.03**	4.00	**−0.28**	6.13
31–32-33	**0**														

All variables: growth rates. N = number of observations between 2011 and 2016. Sources: STAN OECD (Hours, Total Wages, Prices/deflator); International Federation of Robotics (Robot)

Table A4. Descriptive statistics (Spain, Sweden, United Kingdom, United States).

codes (ISIC rev. 4)	N	Robot		Hours		Real Hourly Wage (sector deflator)		Real Wages (sector deflator)		Real Hourly Wage (GDP deflator)		Real Wages (GDP deflator)		Sectoral deflator	
		mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
SPAIN															
F	6	−5.22	10.95	−6.92	11.28	1.29	4.66	−6.11	7.84	−1.05	4.44	−8.27	7.68	−7.94	12.19
10–11-12	5	9.14	1.75	−1.06	2.30	−1.87	6.75	−2.84	8.36	1.92	3.22	0.79	2.29	4.91	7.65
13–14-15	5	−13.85	10.29	−1.59	6.70	0.47	2.98	−1.20	6.39	1.94	3.39	0.15	4.28	0.70	8.03
16–17-18	5	0.13	3.26	−5.05	6.04	−0.58	4.63	−5.79	3.16	0.57	4.74	−4.73	1.64	−3.13	7.77
19–20-21–22-23	5	−0.04	3.05	−3.14	3.87	1.98	2.45	−1.19	5.30	1.73	3.11	−1.55	1.38	1.33	6.76
24–25-28	5	5.65	3.96	−3.02	4.71	4.17	2.52	0.95	3.13	1.53	3.68	−1.65	2.77	−2.00	1.89
26–27	5	1.81	8.11	−5.07	3.53	1.91	2.06	−3.25	4.38	2.17	3.19	−3.09	1.68	−1.83	5.98
29–30	5	−1.90	5.77	0.37	4.30	1.57	5.31	1.86	5.08	2.31	4.41	2.56	2.55	7.54	11.25
31–32-33	5	−13.39	16.87	−4.22	6.39	0.87	2.35	−3.32	7.93	2.51	2.45	−1.93	4.42	1.48	4.58
SWEDEN															
F	6	2.62	12.21	3.13	1.40	−1.64	0.62	1.44	1.69	−2.93	1.66	0.11	2.20	8.51	5.57
10–11-12	5	3.98	5.51	−1.56	1.90	−1.10	2.55	−2.63	3.52	−1.79	3.40	−3.37	1.68	6.75	5.93
13–14-15															
16–17-18	5	6.28	4.21	−2.67	2.43	0.99	6.58	−1.75	6.05	−2.07	2.96	−4.72	2.09	4.46	13.21
19–20-21–22-23	5	1.86	6.40	−1.39	2.66	0.97	8.19	−0.41	9.11	−2.00	3.54	−3.39	3.28	2.55	11.56
24–25-28	5	4.53	5.00	−1.12	2.98	1.11	2.06	0.02	4.98	−2.14	3.32	−3.25	3.95	1.92	2.02
26–27	5	−12.31	12.95	−7.69	14.35	1.91	6.93	−5.18	19.55	−3.55	6.15	−10.35	18.00	−9.82	21.93
29–30	5	6.90	7.78	−0.01	5.04	0.94	3.93	0.86	5.10	−1.31	5.32	−1.53	2.01	10.79	19.36
31–32-33															
UNITED KINGDOM															
F	5	−11.58	6.74	1.06	2.90	−1.03	3.08	0.03	4.19	−2.96	3.58	−2.00	1.30	7.82	3.05
10–11-12	5	8.42	2.09	0.24	1.33	−0.73	5.63	−0.46	6.50	−3.27	1.94	−3.03	2.90	6.38	9.73
13–14-15	5	1.79	6.74	−0.85	6.98	−1.51	11.20	−2.95	5.14	1.93	10.38	0.55	5.17	16.82	18.69
16–17-18															
19–20-21–22-23	5	6.38	9.36	−0.61	1.34	−0.73	2.69	−1.34	2.87	−3.13	4.26	−3.76	3.00	3.62	10.01
24–25-28	5	11.08	3.12	0.90	1.94	−2.86	3.03	−2.00	2.86	−2.62	2.31	−1.72	3.80	5.29	5.15
26–27	5	0.71	7.05	−1.09	3.63	0.54	3.82	−0.67	0.90	−2.84	3.01	−3.98	1.07	2.73	4.31
29–30	5	5.06	6.87	1.88	2.65	−0.15	4.02	1.73	4.89	−1.72	6.48	0.04	5.31	14.35	19.19
31–32-33	5	6.84	11.03	0.55	3.88	1.77	5.98	2.19	3.94	−0.47	4.69	−0.06	1.30	7.19	6.11
UNITED STATES															
F		9.07	5.57	4.43	1.04	−1.61	1.13	2.75	1.20	−2.75	1.16	1.56	1.76	12.24	2.70
10–11-12	5	11.96	4.34	2.19	0.92	−3.85	1.95	−1.75	1.73	−3.44	1.28	−1.33	1.63	12.66	4.08
13–14-15	5	47.19	15.17	−2.02	1.13	2.09	2.74	0.03	2.52	−2.08	1.43	−4.06	1.08	3.01	1.56
16–17-18	5	26.26	7.78	0.46	0.70	−1.32	2.15	−0.88	1.51	−3.59	1.18	−3.15	1.30	5.67	4.71
19–20-21–22-23	5	12.92	4.73	1.24	0.60	2.39	3.27	3.65	3.15	−3.05	0.69	−1.85	1.08	1.29	6.32
24–25-28	5	12.95	6.15	0.26	2.79	0.15	0.85	0.42	3.06	−3.50	0.68	−3.25	2.79	1.72	1.01
26–27	5	15.65	2.31	−0.24	1.31	2.28	1.82	2.04	2.24	−2.77	1.26	−3.00	1.78	3.14	1.63
29–30	5	13.62	4.36	3.77	2.20	−3.22	2.37	0.41	2.03	−4.81	1.85	−1.26	0.87	9.48	5.33
31–32-33	5	32.35	16.30	1.56	0.82	0.12	0.69	1.68	1.22	−3.00	1.51	−1.49	0.93	4.38	3.54

All variables: growth rates. N = number of observations between 2011 and 2016. Sources: STAN OECD (Hours, Total Wages, Prices/deflator); International Federation of Robotics (Robot)