UNINT
Università
degli Studi Internazionali di Roma

UNINT.EU

AISSEC 2020

LABOR MARKET OUTCOMES IN THE GLOBAL ECONOMY:
PATTERNS OF STRUCTURAL TRANSFORMATION, EDUCATION AND INEQUALITY

Are machines stealing your salary? Productivity increase and jobless growth.

Andrea Gentili (Unint) – presenting
Fabiano Compagnucci (GSSI)
Enzo valentine (UNIMC)
Mauro Gallegati (UNIVPM)
Paper published at Structural Change and Economic Dynamics (2018) + Paper Published at Applied Economics (2020)

Robotization (and automation)

Anxiety and concern about the risks associated with automation (Pew Research Centre, 2017)

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" IFR (2017, pp 1)

Ever-increasing number of robots (over 2.5 million in 2019 according to IFR)

Robotization expansion to service sector, such as education, human health and care activities

Half of the jobs in many economic sectors are expected to disappear by 2060 because of automation (OECD, 2012)

For the next 50 years economic growth (on average 3% per year) is expected to be the result only of increasing productivity (McKinsey Global Institute, 2017)

Literature - pro

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?

In “theory” an increase in productivity is generally reflected in an increase in labor demand (and, therefore, in salaries):

- intra-industry level, labor demand increases whenever the increased productivity is reflected in an overall sectoral growth requiring new workforce in non-automated tasks;
- cross-industries level, sectors which are not affected by automation could benefit from decreasing real prices of automated sectors, and, accordingly, increasing their labor demand too;
- being automation capital-augmenting, the accumulation of capital is itself an engine of growth and labor demand increasing;
- the creation of new tasks and jobs which cannot be automatized has a positive impact on employment;

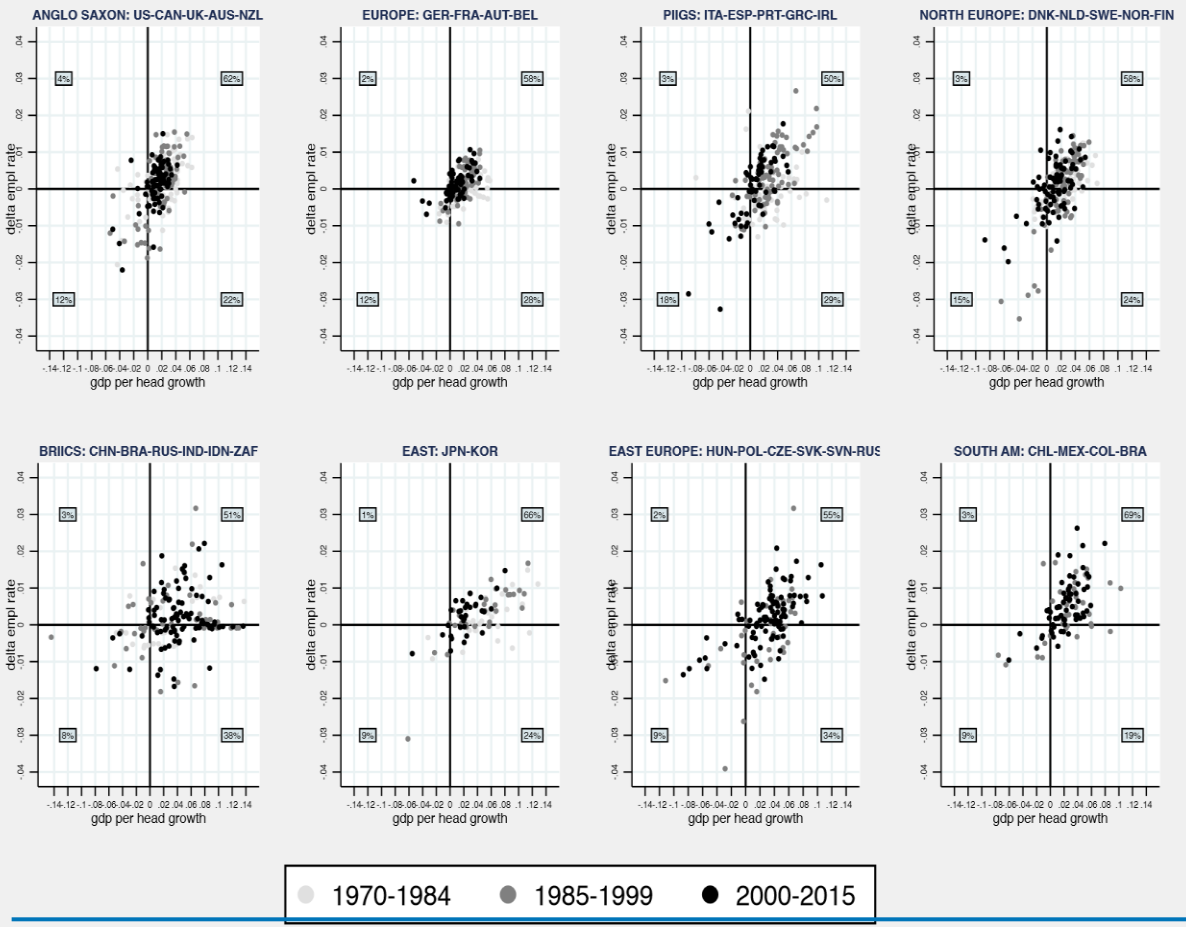
Literature - cons

Automation and, generalizing, productivity growth, could lead to the displacement of labor because of:

- constraints to aggregate demand (Vivarelli and Pianta, 2000; Bessen 2018);
- constraints to labour mobility:
  - Impossibility to migrate (Delli Gatti et al. 2012 – on 1929 crisis)
  - Technological bias (Vivarelli, 2010; Acemoglu, 2002; Acemoglu and Restepro, 2018)
- Capital “rent seeking” (Stiglitz, 2018)

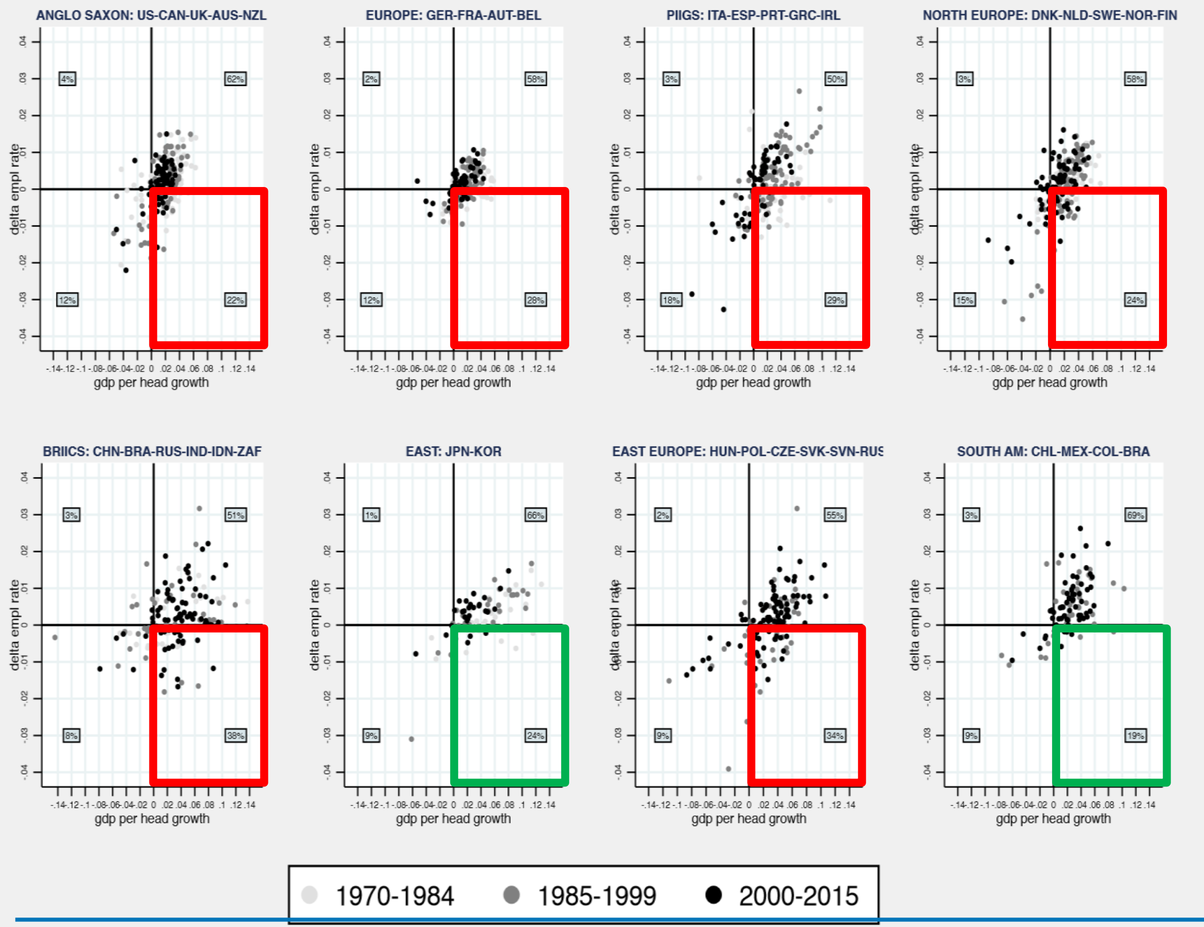
Leading to:

- Distribution of wages (Piketty and Zucman, 2014)
- Great decoupling (Brynjolfsson and McAfee, 2014)



Empirical evidence: Jobless Growth

All data from OECD STAN database.
All computation and graph are authors' elaborations



Empirical evidence: Jobless Growth

Only far-east and latin america follows the theory or the Okun’s law

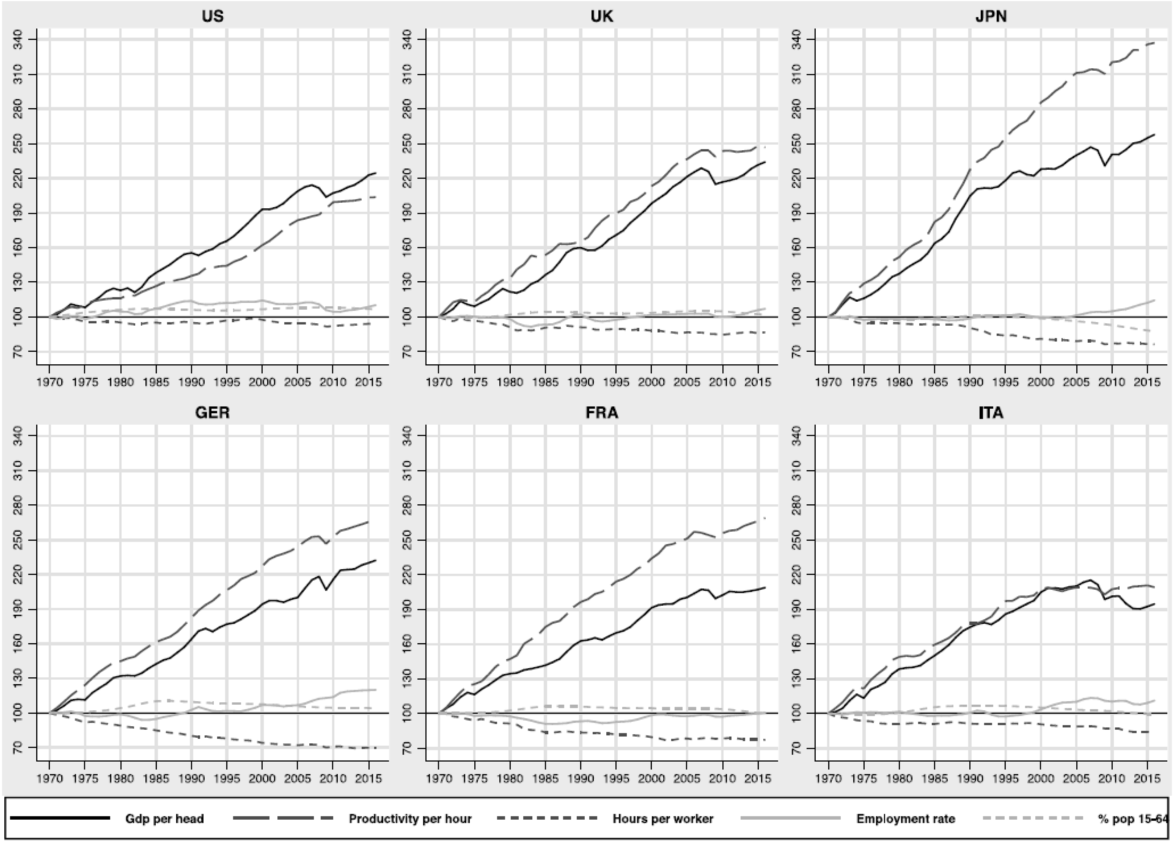
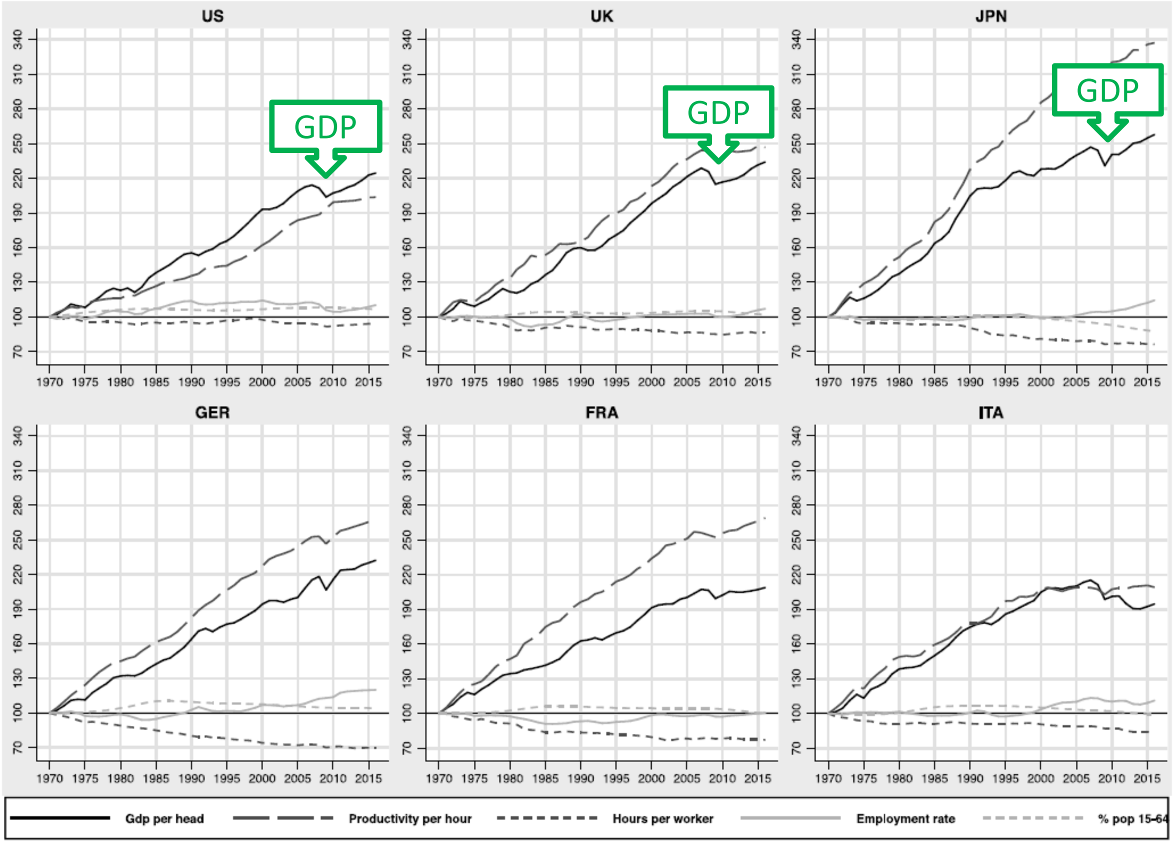


Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.

Empirical evidence: Jobless Growth

$$\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{N_a}\frac{N_a}{N}$$



Empirical evidence: Jobless Growth

Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N}=\frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.

Empirical evidence: Jobless Growth

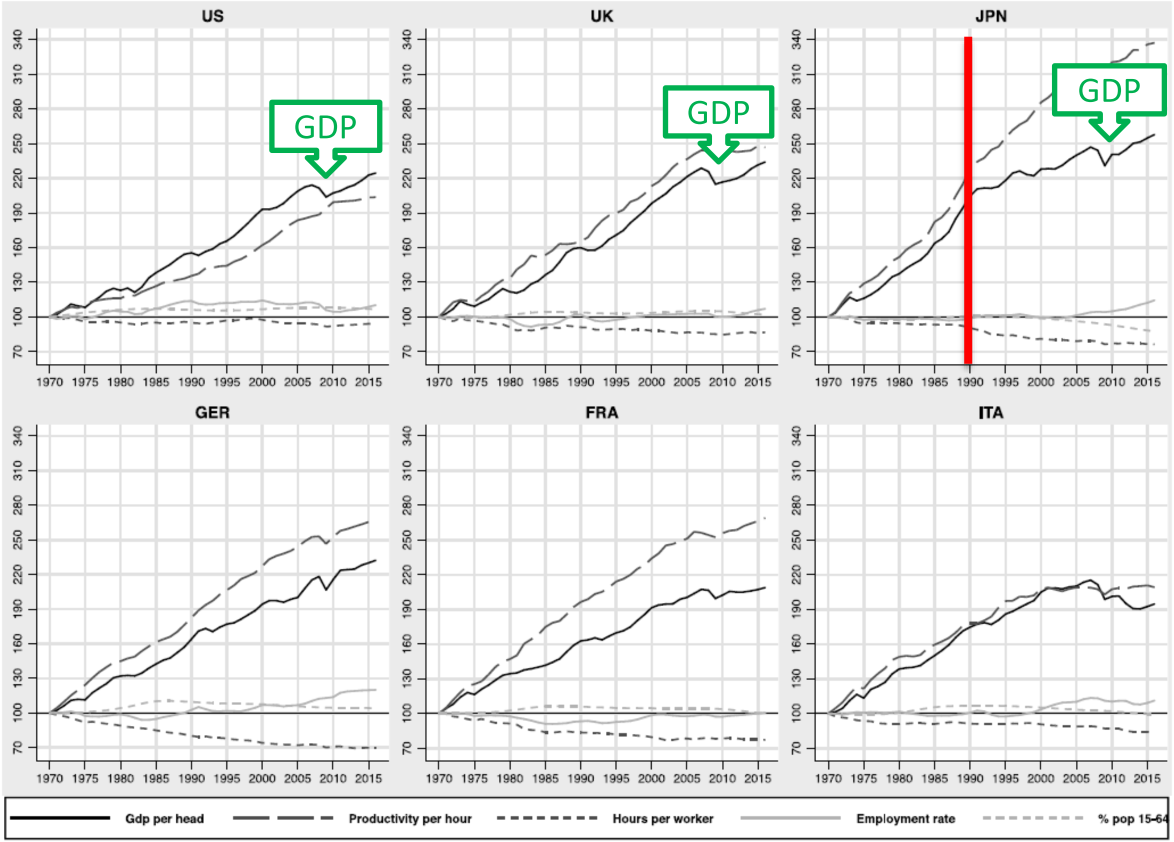
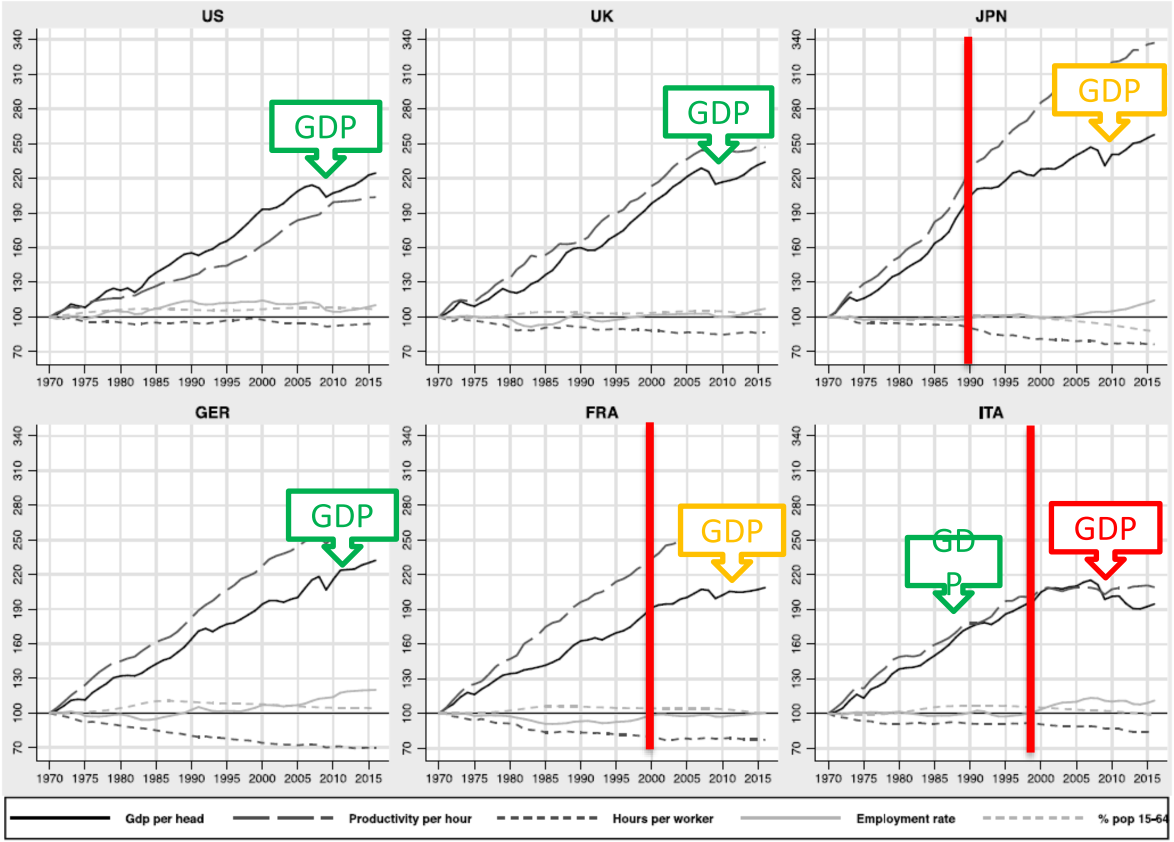
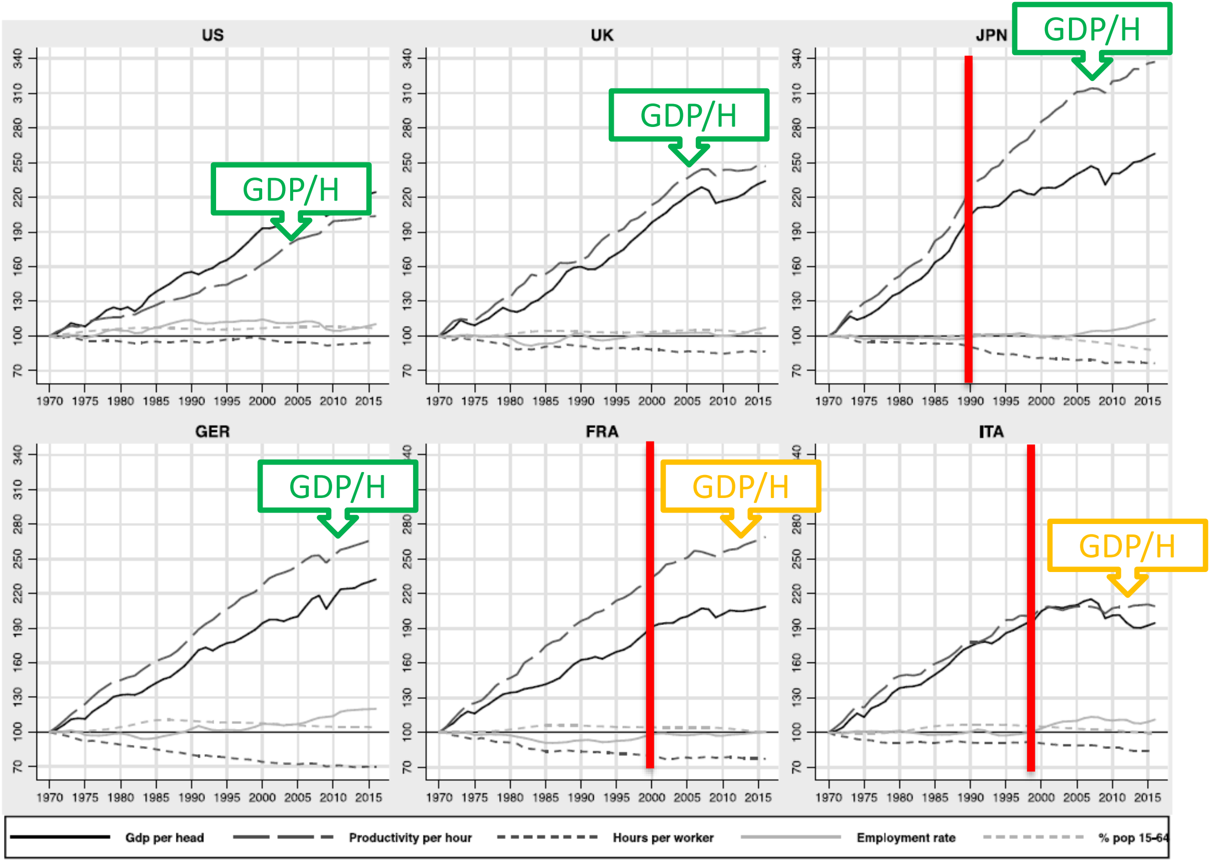


Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.



Empirical evidence: Jobless Growth

Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.



Empirical evidence: Jobless Growth

Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.

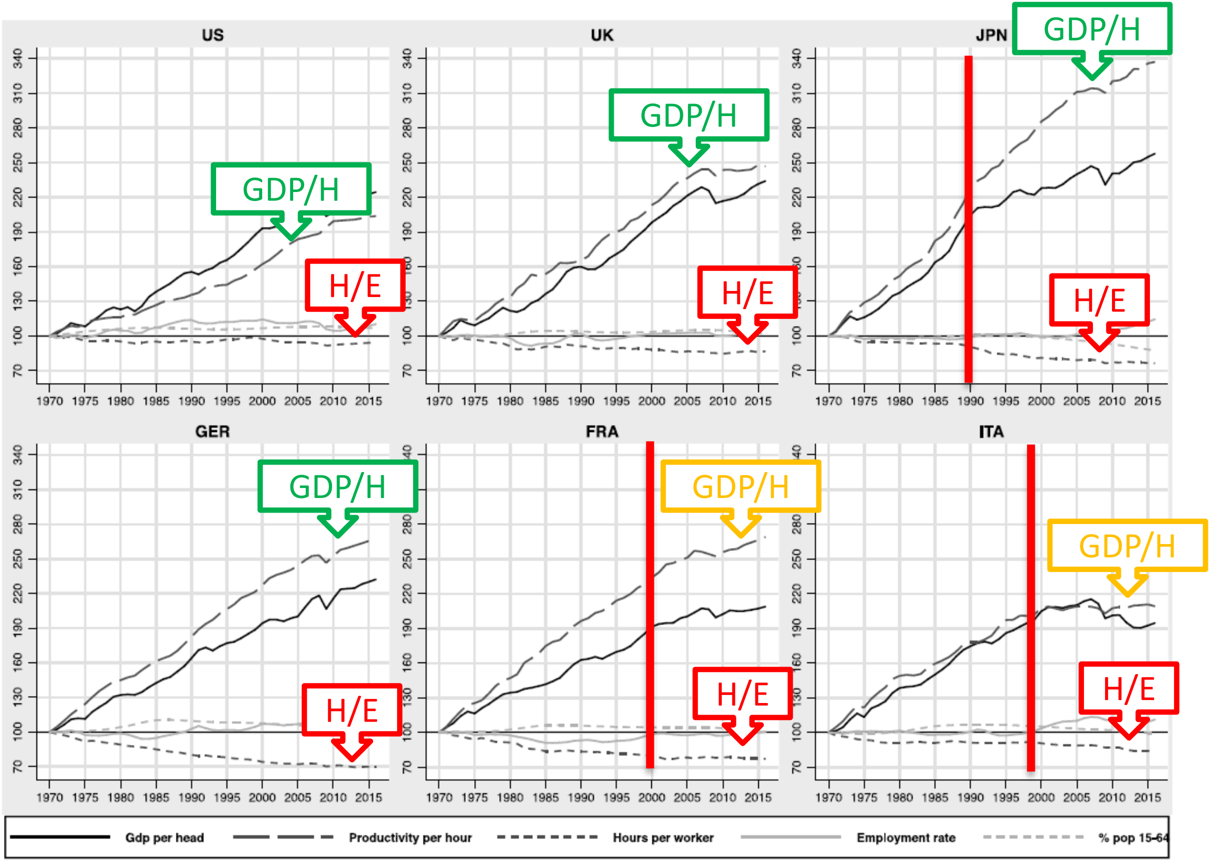
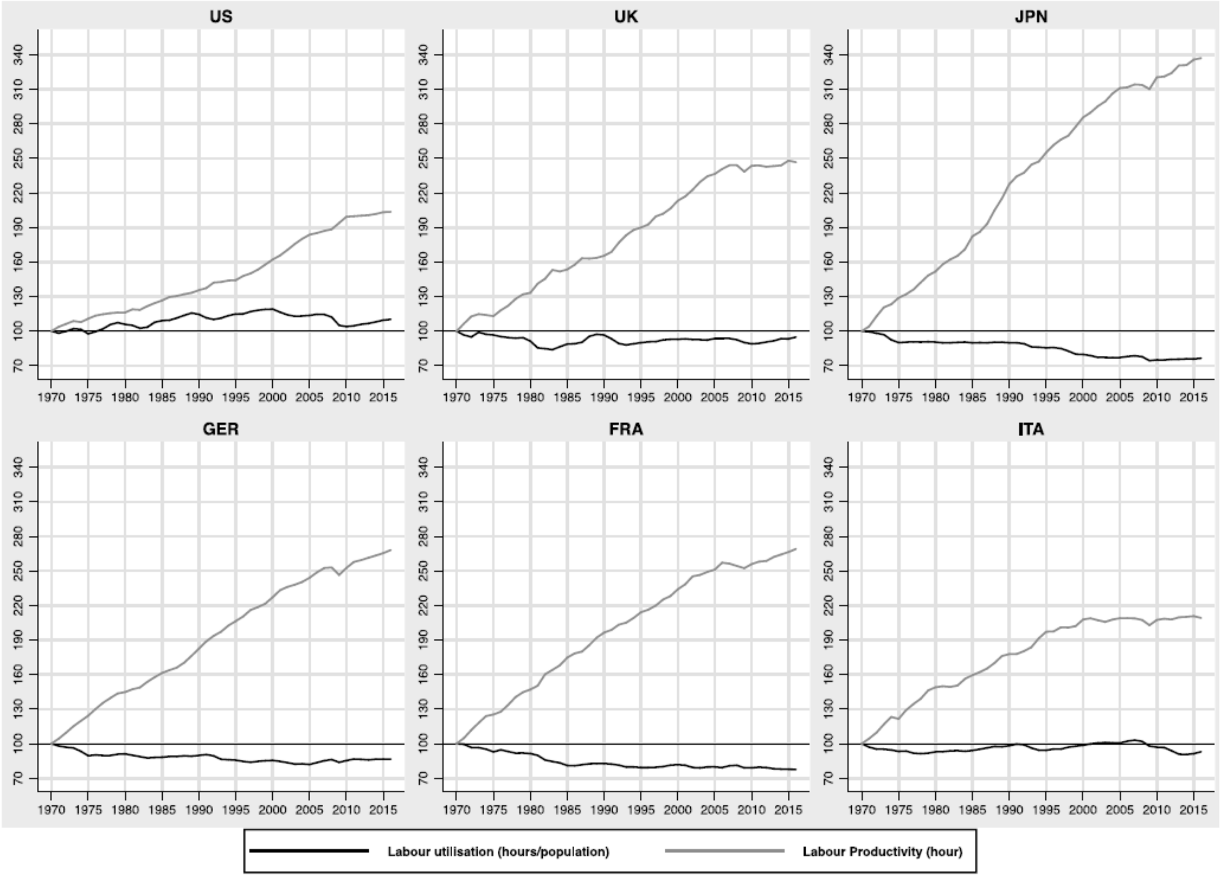
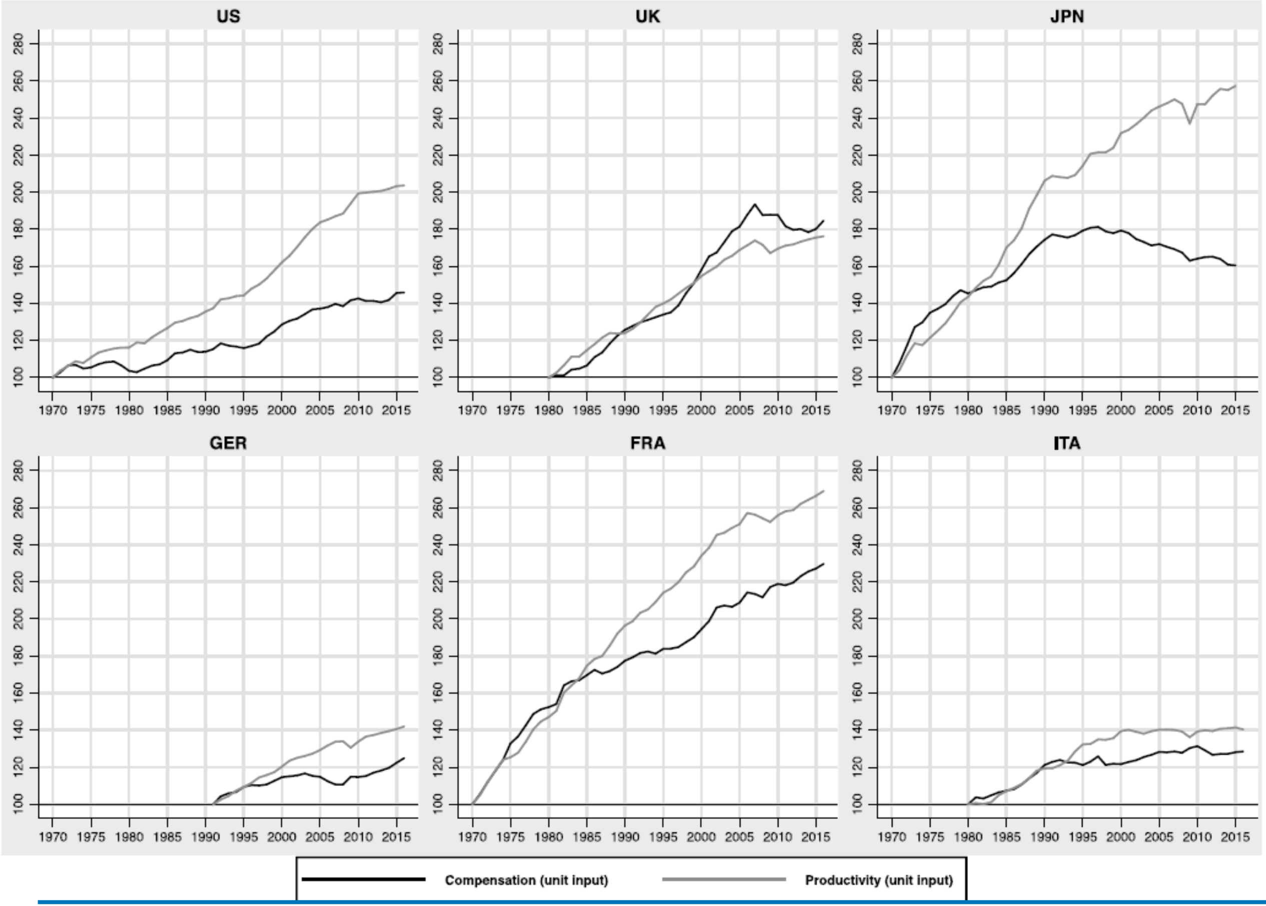


Fig. 1. GDP per head $\left(\frac{GDP}{N}\right)$, productivity $\left(\frac{GDP}{H}\right)$, hours worked per worker $\left(\frac{H}{E}\right)$, employment rate $\left(\frac{E}{Na}\right)$, population 15–64 ratio $\left(\frac{Na}{N}\right)$. $\frac{GDP}{N} = \frac{GDP}{H}\frac{H}{E}\frac{E}{Na}\frac{Na}{N}$. Indexes, 1970 = 100.

Empirical evidence: Jobless Growth



Empirical evidence: Jobless Growth



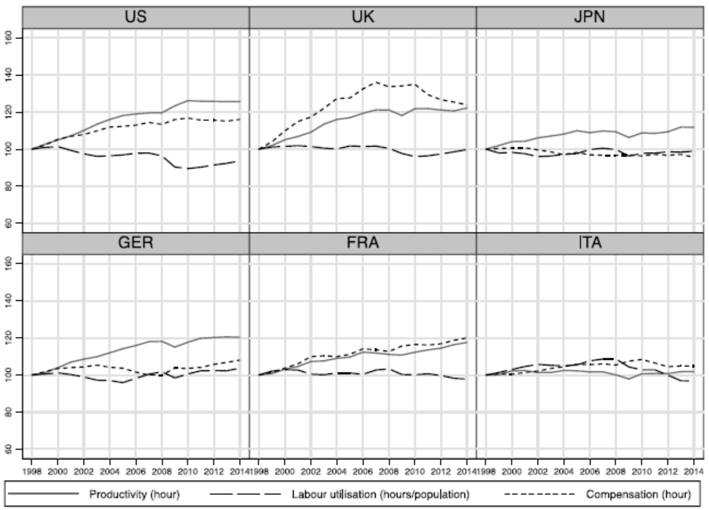
Empirical evidence: Decoupling

Summary.

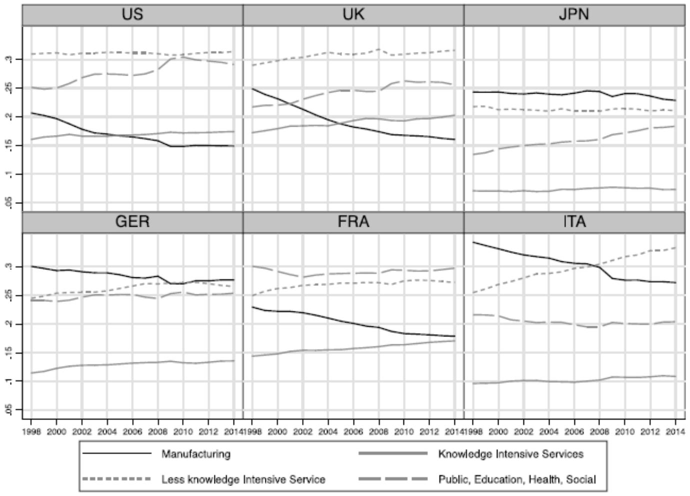
	Productivity ↑ Compensation ↑	Productivity ↑ Compensation ⟵ or ↓ or augmenting less than productivity ("decoupling")	Productivity ⟵ Compensation ⟵ or ↓
Productivity ↑ Labour ↑		US (1970 to mid-1990s)	
Productivity ↑ Labour ⟵	UK ITA (1970 to mid-1990s)	ITA (mid-1990s to 2000)	
Productivity ↑ Labour ↓ ("jobless growth")	JPN (1970 to mid-1990s) GER (1970 to mid-1990s) FRA (1970 to mid-1980s)	US (from mid-1990s) JPN (from mid-1990s) GER (from mid-1990s) FRA (from mid-1980s)	
Productivity ⟵ Labour ⟵ or ↓			ITA (from 2000)

Classification

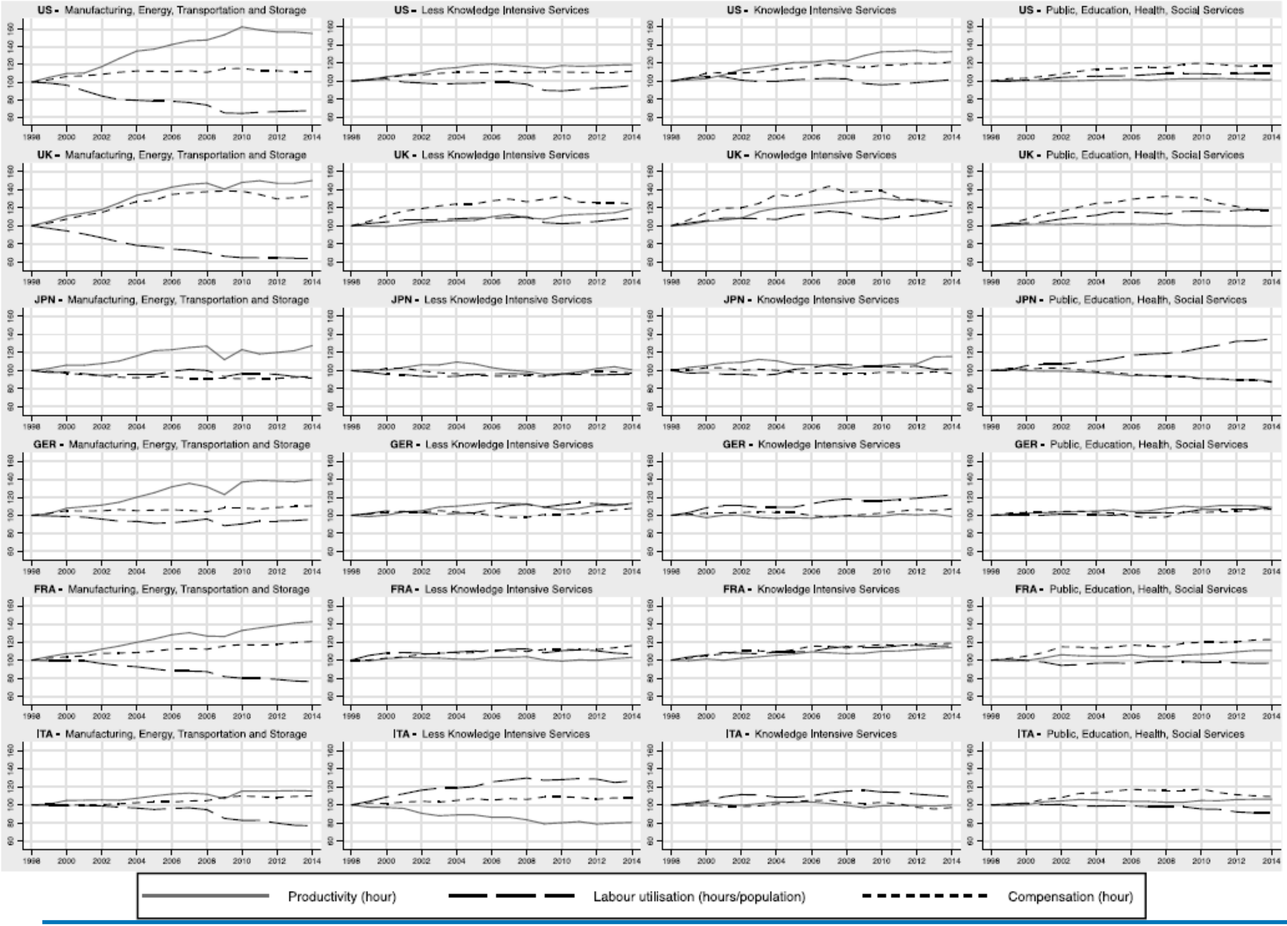
(a) Total economy: productivity, labour utilisation and compensation



(b) Sectoral Composition



Sectoral analysis



Sectoral decomposition

OECD-STructural ANalysis + IFR

OSR cannot be easily matched with sectors of the ISIC rev.4:

- all industries in the Services sector are grouped in only two categories: “all other non-manufacturing” and “education/research”
- Mining and quarrying”, “Electricity, gas, water supply” and “Agriculture, Forestry and Fishing”, all sectors showing a very small room for robotization at present time
- High fluctuation on growth rates

Dropping outliers is generally not a good practice whenever there is no clear evidence of measurement errors:

- first, we drop those sector/country with less than three observations different from zero
- we computed the standard deviation of robots’ growth rates for each sector/country
- since a high standard deviation value could be a signal of the bad quality of data for the concerned sector, we perform the Blocked Adaptive Computationally efficient Outlier Nominators (BACON) algorithm proposed by Billor, Hadi, and Velleman (2000) using a 5% cut-off parameter to identify outliers

-> we drop 11 combinations sector/country out of a total of 104

OECD-STructural ANalysis + IFR

STAN database:

- HRSE (“Hours worked, employee”)
- VALK (“Value added, volumes”)
- WAGE (“Wages and Salaries”)
- VALP (“Value added deflator”)
- Hourly productivity is derived from VALK and HRSE
- Real wages are computed deflating sectoral wages using the sectoral deflator and GDP deflator
  - The former gives the “employer point of view”
  - The latter the “employee point of view”

P-VAR

PVAR methodology is often used to capture the dynamic interdependencies among variables using a minimal set of restrictions while studying interdependent economies.

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:

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

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

where $\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{t}}$ is a vector of dependent variables, while $\boldsymbol{u}_{\boldsymbol{i},\boldsymbol{t}}$ and $\boldsymbol{e}_{\boldsymbol{i},\boldsymbol{t}}$ are vectors of dependent variable-specific fixed effects and idiosyncratic errors, respectively. The matrices $\boldsymbol{A}_{\boldsymbol{1}}$, $\boldsymbol{A}_{\boldsymbol{2}}$..., $\boldsymbol{A}_{\boldsymbol{p}}$ are the parameters to be estimated.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Dep. var:	Total Hours	Real Hourly Wage (ind. level deflator)	Total Wages (ind. level deflator)	Real Hourly Wage (GDP deflator)	Total Wages (GDP deflator)	Ind. Level deflator
Robot (t-1)	-0.119*** [0.036]	0.083*** [0.031]	-0.010 [0.043]	0.057** [0.027]	-0.043* [0.025]	-0.130* [0.070]
Hours (t-1)	0.631*** [0.140]					
Real Hourly Wage (ind. Level deflator) (t-1)		0.191*** [0.070]				
Total Wages (ind. Level deflator) (t-1)			0.186** [0.077]			
Real Hourly Wage (GDP deflator) (t-1)				0.238** [0.105]		
Total Wages (GDP deflator) (t-1)					0.312*** [0.115]	
Industry level deflator (t-1)						0.152 [0.140]

Dep var:	Robot	Robot	Robot	Robot	Robot	Robot
Robot (t-1)	0.325*** [0.085]	0.342*** [0.085]	0.321*** [0.086]	0.350*** [0.085]	0.330*** [0.089]	0.372*** [0.093]
Hours (t-1)	0.357** [0.153]					
Real Hourly Wage (ind. Level deflator) (t-1)		0.166 [0.148]				
Total Wages (ind. Level deflator) (t-1)			0.275** [0.109]			
Real Hourly Wage (GDP deflator) (t-1)				-0.255 [0.244]		
Total Wages (GDP deflator) (t-1)					0.258 [0.180]	
Industry Level deflator (t-1)						0.223** [0.101]
GMM criterion Q(b)	5.45e-34	3.97e-34	4.85e-35	1.47e-34	8.10e-35	1.26e-34
CD	0.92	0.90	0.90	0.91	0.90	0.89
N_clust	90	90	90	90	90	90
N	309	309	309	309	309	309
t min - t max	2012 - 2015	2012 - 2015	2012 - 2015	2012 - 2015	2012 - 2015	2012 - 2015
t mean	3.433	3.433	3.433	3.433	3.433	3.433

OECD-STructural ANalysis + IFR

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

- a significant decrease in growth rates of hours worked;
- a significant increase in real hourly wage growth rates (deflated using industry-level deflator);
- a non-significant (negative) effect on total wages (deflated using industry-level deflator) growth rates;
- a significant increase of real hourly wage growth rate (computed using GDP deflator);
- a significant decrease of total wages growth rates (computed using GDP deflator);
- a significant decrease of industry sectoral deflator hence for prices growth rates.

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

- hours worked growth significantly and positively affect the growth of robotization;
- hourly wages growth (deflated by industry level deflator) has a non-significant effect on robotization;
- total wages (deflated by industry level deflator) significantly and negatively affect robotization growth;
- hourly wages growth (deflated by GDP deflator) has a non-significant effect on robotization;
- total wages growth rates (computed using GDP deflator) has a non-significant effect on robotization (column 4)
- sectoral prices growth rates significantly and positively affect robotization.