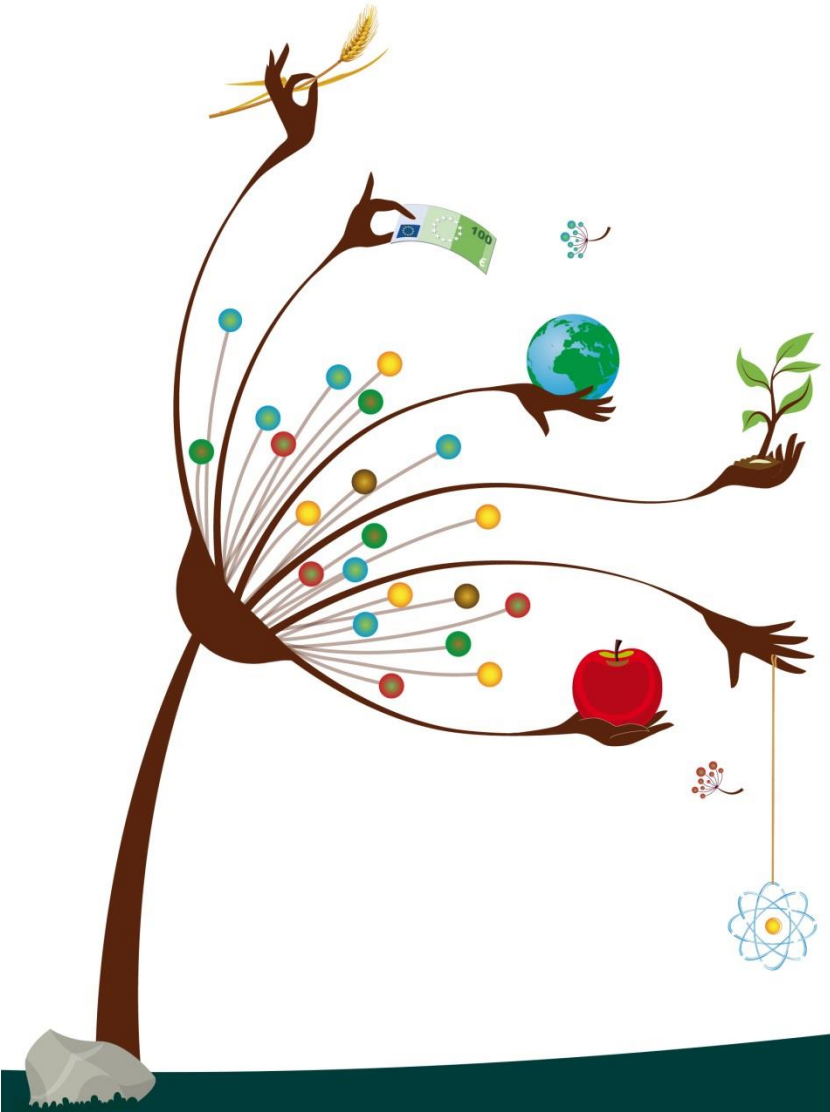

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Joint Research Centre

The Impact of Robots on Labour Productivity

A Panel Data Approach Covering Nine Industries and Twelve Countries

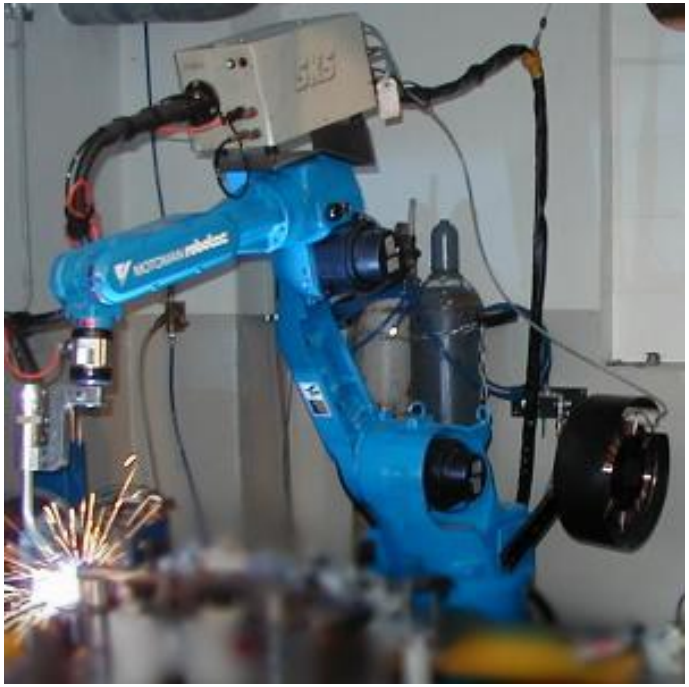
Andre Jungmittag
Annarosa Pesole

European Commission

Roadmap

1. Introduction: Robots and labour productivity
2. The empirical model and the data
3. Empirical results
4. Conclusions

What is the difference between both?



Both are part of the **physical capital**, but with an embedded difference in **technology**.

Circular saw: Labour augmenting technical progress

Industrial robot: Labour replacing technical progress

Recent theoretical models

- **Acemoglu and Restrepo (2017, 2018):** Tasked-based general equilibrium model with two reverse effects: **Displacement effect** and **productivity effect.**
- **Graetz and Michaels (2018):** Simple model for firms' decisions to use robots in their production → a fall in the robot rental rate leads to a **rise in labour productivity** in robot-using industries.
- **Prettner (2019)** and **Lankisch et al. (2017):** Solow growth models with automation (automation as a perfect substitute for all labour or only for low-skilled labour) → Potential for **perpetual growth of per capita income** driven solely by capital accumulation (and the substitutability between low-skilled and high-skilled labour).

Too early for the advent of a new industrial revolution?

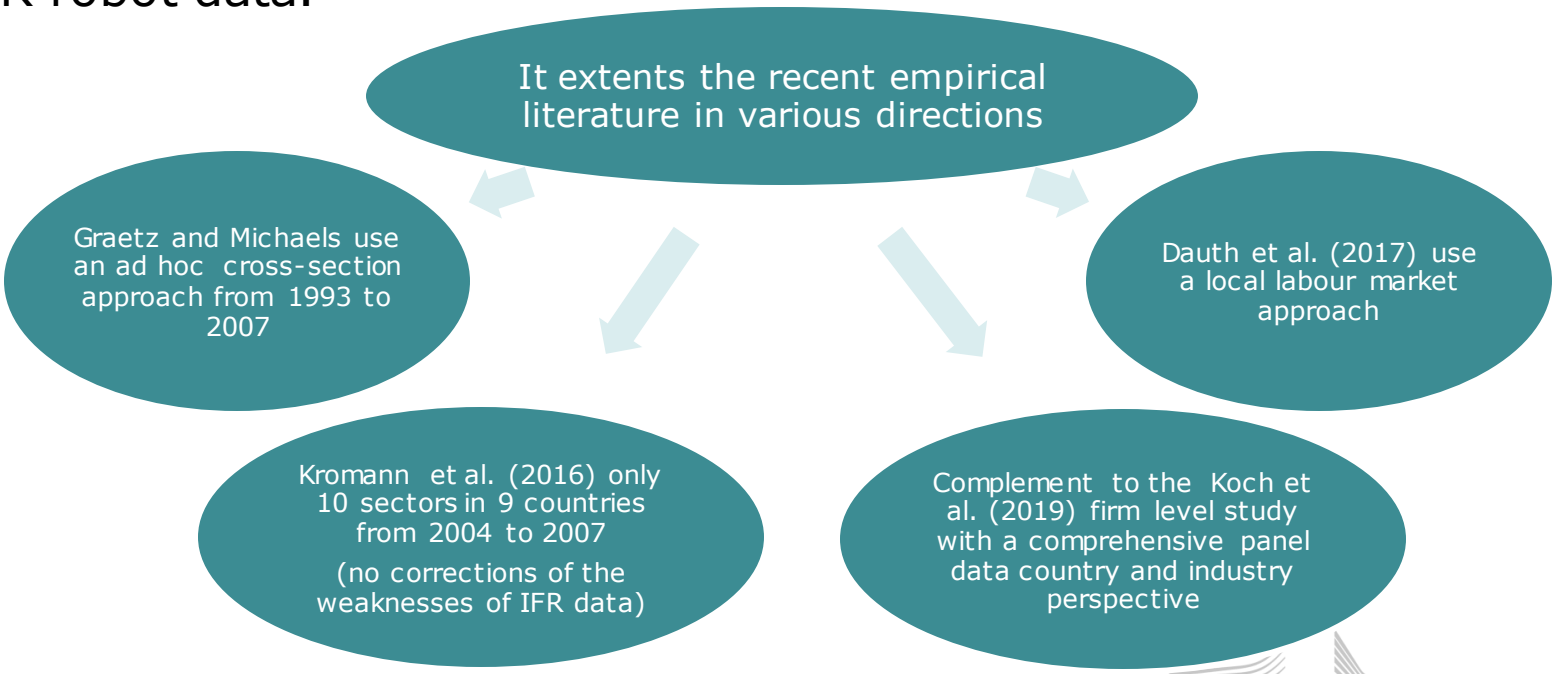
- Industrial robots are "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes" (ISO 8373) with the potential of automating the production processes by executing complete tasks.
- However, the automation process started already more than 100 years ago.
- Fully automated factories with humanoid robots wandering around are very far from reality.
- Modern industrial robots still can only operate in highly structured environments and still require a certain level of human intervention.
- In other words, even if the advance in AI will eventually make robots smarter and gift them with cognitive abilities that may allow them to interacts with humans and among themselves, the current state of the art of industrial robots resolve mostly into handling, assembling and welding tasks.

Why this is important for productivity?

- If **current industrial robots** are 'only' a better and (perhaps) cheaper version than previous robots, then the expected boost in labour productivity should come from both an increase in capital investment (robot purchases) and labour quality.
- Then, industrial robots represent more a **qualitative improvement** in industrial mechanisation and automation than a radical innovation.
- **Consequence:** The intensified use of robots leads to a kind of **capital augmenting technical progress**. This means that robots as part of the (non-ICT) capital input have an additional impact on labour productivity compared to traditional non-ICT or ICT capital.
- They not only substitute other types of non-ICT capital and labour, but they **upgrade** the non-ICT capital stock and allow to **improve the quality** of products and to expand the variety of products.

Our empirical paper …

- … uses a **production function approach** to analyse the impact of robots on labour productivity in nine manufacturing sectors of 12 EU countries.
- In order to include the robots per 1 million Euros non-ICT capital in a production function, we calculate robot stocks for the considered country-industry pairs for the period from 1993 to 2015 using the IFR robot data.



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The empirical model

Our empirical model follows the idea of Kromann et al. (2016)

$$Y_{ijt} = A_{ijt} C_{ijt}^{\alpha} Q_{ijt}^{\beta} L_{ijt}^{\gamma},$$

where it is assumed that input of non-ICT capital (including robots) has a quality and a quantity dimension, such that $Q = qK$, where K denotes the quantity of non-ICT capital and q is the (average) quality per unit of non-ICT capital input.

Taking into account the two dimensions of the capital input and taking logarithms yields

$$y_{ijt} - l_{ijt} = a_{ijt} + \alpha(c_{ijt} - l_{ijt}) + \beta \ln(q_{ijt}) + \beta(k_{ijt} - l_{ijt}) + (\alpha + \beta + \gamma - 1) l_{ijt}.$$

The quality of the non-ICT capital input depends on the intensity of industrial robots according to

$$q_{ijt} = e^{\lambda RI_{ijt}},$$

where RI is the number of industrial robots relative to the total non-ICT capital input of an industry-country pair in year t.

The empirical model

The parameter λ reflects the efficiency of a unit of non-ICT capital input with a robot index of *RI* relative to a unit of non-ICT capital input in the absence of robots (*RI* = 0).

Including the robot index into the production function yields

$$y_{ijt} - l_{ijt} = a_{ijt} + \alpha(c_{ijt} - l_{ijt}) + \delta RI_{ijt} + \beta(k_{ijt} - l_{ijt}) + \varepsilon l_{ijt},$$

where $\delta = \beta\lambda$ is the margin return to *RI*. If this parameter is positive, industrial robots have an extra effect compared to other types of non-ICT capital and industries with higher (or faster growing) *RI* realise higher (or faster growing) labour productivity.

In order to estimate the production function, we have to restrict the technical efficiency parameter a_{ijt}. The simplest specification with fixed effects is

$$y_{ijt} - l_{ijt} = a_0 + \alpha(c_{ijt} - l_{ijt}) + \delta RI_{ijt} + \beta(k_{ijt} - l_{ijt}) + \varepsilon l_{ijt}, + b_i + d_j + e_t + u_{ijt},$$

More complex ones are also considered.

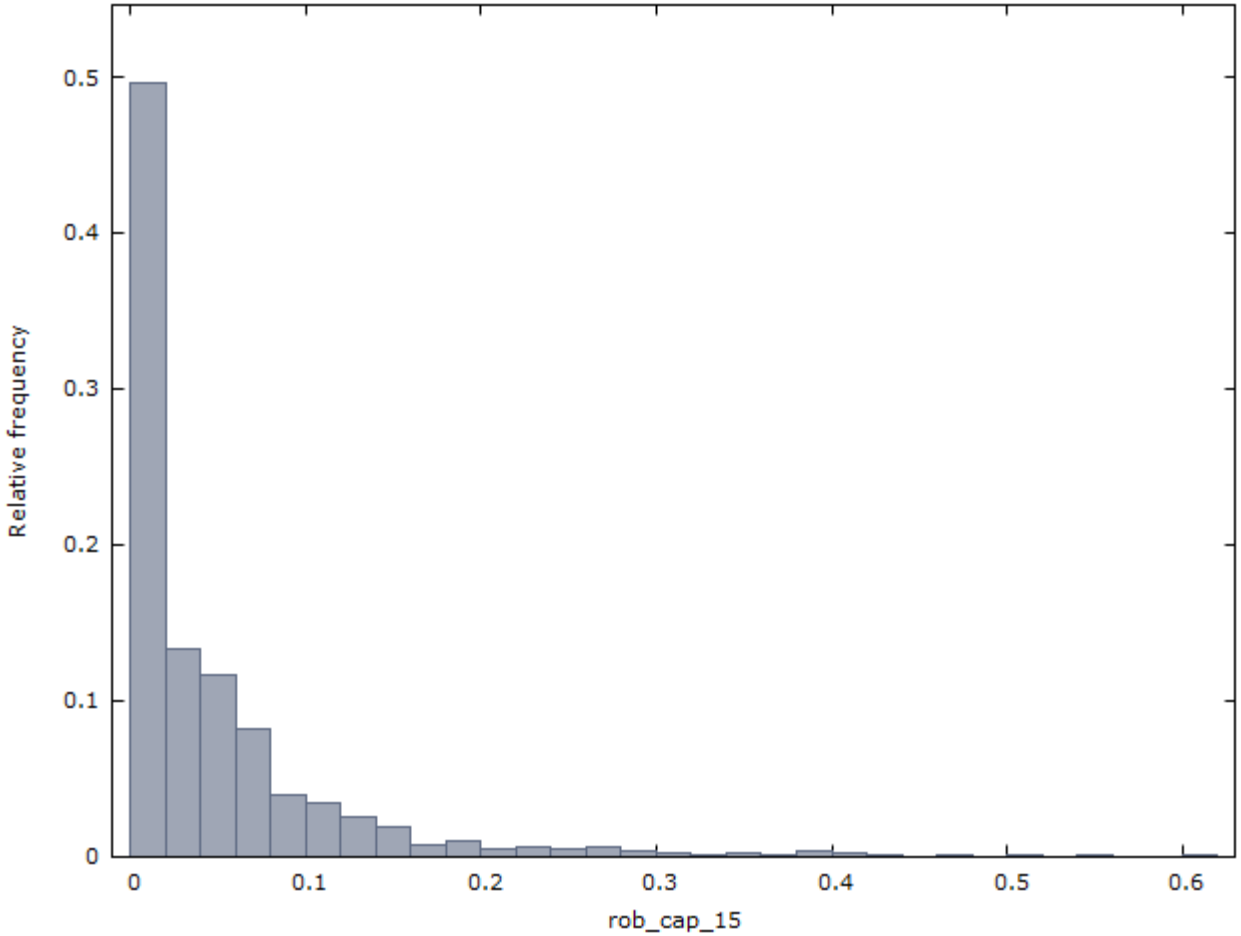
Data issues

- Main source of information on robots is the **International Federation of Robotics** (IFR, 2017).
- The IFR collects data on annual shipment (sales) from 1993 to 2016 and compiles a measure of robot stock based on the assumption that the average service life of a robot is approximately 12 years.
- Given that the service life of robots might be affected by the introduction of new technology with subsequent effects on its capital service, we recomputed the stock of robots using the **perpetual inventory method** assuming depreciation rates of 5%, 10% and 15%.
- Two adjustments on the original IFR data.
  1. For some of the countries in the initial years there is only aggregate country data. In order to disaggregate the data for the total economy at industry level we take the average industry share for all the years with available information and reallocate the total consequently.
  2. Starting from 2008 the number of robots in the "unspecified" category grows discernibly. For these countries we use the same average industry share as above to redistribute the unspecified category.

Data issues

- The second source of information is the **EU KLEMS database** (2017 release) that reports information on inputs, outputs and prices at industry-country level up to 2015.
- IFR and EU KLEMS use different industry classifications and report data for different level of industry aggregation.
- We used the most detailed breakdown available in the EU KLEMS and we consistently match these data with the IFR data.
- Our analysis covers nine different manufacturing industries over the period 1995-2015 in 12 EU countries.
- **Labour productivity** is calculated as real value added divided by total hours worked by persons engaged.
- **Labour input** is total hours worked by persons engaged.
- **Real ICT capital** and **real non-ICT capital** inputs are calculated by multiplying the volume indices of ICT and non-ICT capital services (2010 = 100) by the respective capital stock in 2010.

Frequency distribution of robots per 1 million Euro non-ICT capital input



Robot stocks with perpetual inventory method and 15% depreciation rate

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Descriptive statistics for the robot densities

Industry	Mean	Median	Standard deviation	Inter-quartile range	Mini-mum	Maxi-mum	Nobs
All nine industries	0.046	0.021	0.067	0.056	0.000	0.619	2010
10-12: food products, beverages, tobacco	0.021	0.012	0.021	0.028	0.000*	0.085	225
13-15: textiles, wearing apparel, etc.	0.012	0.004	0.017	0.013	0.000*	0.100	225
16-18: wood and paper product, etc.	0.014	0.006	0.019	0.010	0.000*	0.096	225
20-21: chemical products, etc.	0.003	0.001	0.003	0.004	0.000	0.014	210
22-23: rubber and plastics products, etc.	0.088	0.068	0.062	0.081	0.010	0.277	225
24-25: metals and metal products	0.053	0.048	0.039	0.057	0.003	0.164	225
26-27: electrical and optical equipment	0.022	0.017	0.016	0.020	0.000*	0.090	225
28: machinery and equipment	0.045	0.044	0.032	0.048	0.001	0.154	225
29-30: transport equipment	0.157	0.125	0.113	0.136	0.010	0.619	225

* Greater than zero, but smaller than 0.000.

Robot stocks with perpetual inventory method and 15% depreciation rate

FE estimation results (15% depreciation rate)

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.325***		0.302***		0.302***		0.454***	
	(0.039)		(0.039)		(0.037)		(0.113)	
ln(cap_ict/hours)		-0.014		-0.005		-0.000		0.008
		(0.033)		(0.033)		(0.032)		(0.109)
ln(cap_oth/hours)		0.339***		0.311***		0.306***		0.432***
		(0.048)		(0.046)		(0.044)		(0.111)
ln(hours)	0.088***	0.089***	0.087***	0.088***	0.098***	0.098***	0.322**	0.308**
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.442***	0.459***	0.478***	0.492***	0.532***	0.541***	0.603*	0.594**
	(0.148)	(0.149)	(0.149)	(0.149)	(0.144)	(0.144)	(0.311)	(0.304)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.917	0.920	0.921	0.920	0.920	0.969	0.969
Log-likelihood	641.0	659.0	804.7	821.9	780.6	792.6	1906.1	1907.9
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

FE estimation results (15% depreciation rate), two subsamples

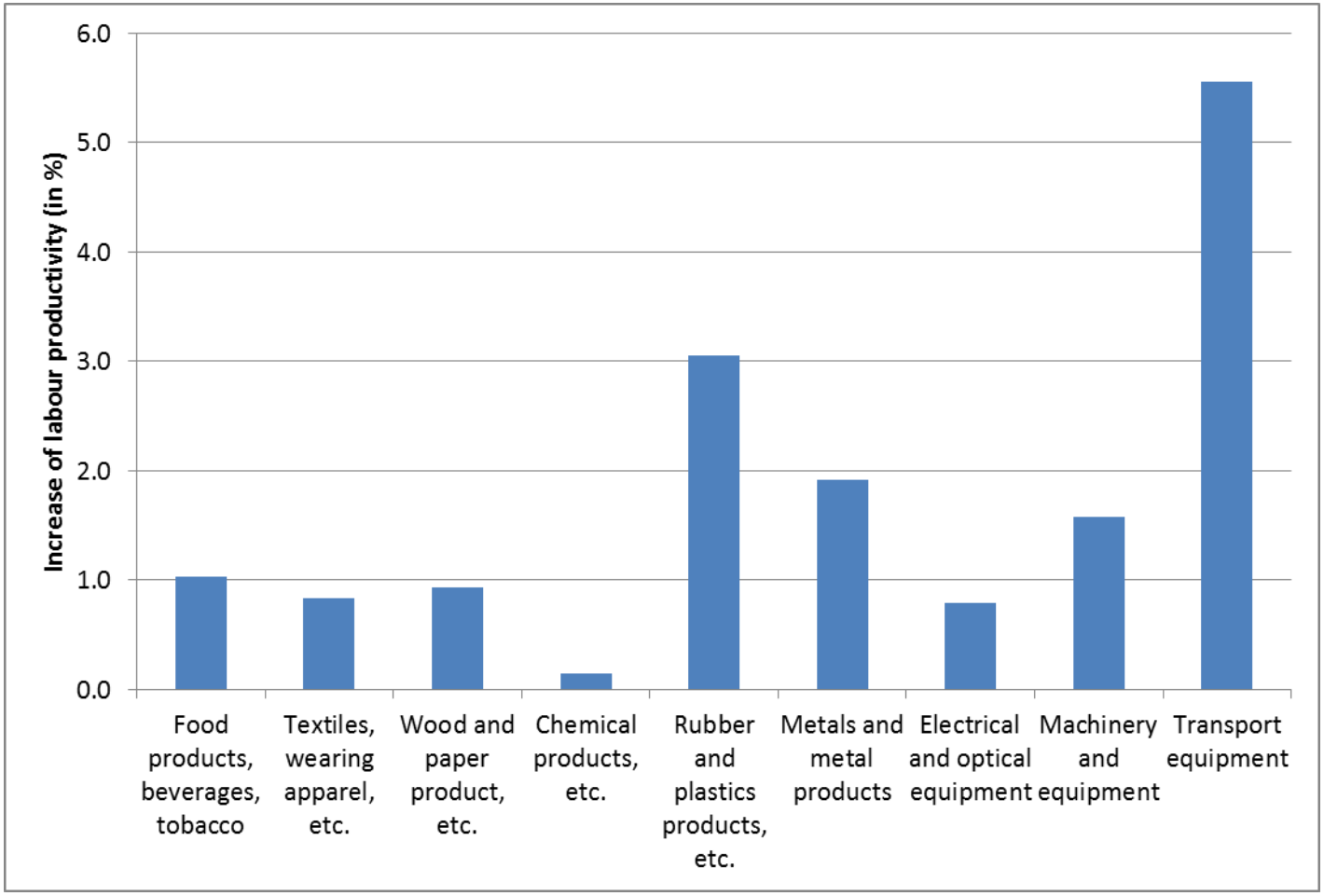
	Dependent variable: ln(value added/hours)							
	Period 1995 – 2007							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.300***		0.281***		0.290***		0.526***	
	(0.044)		(0.048)		(0.046)		(0.180)	
ln(cap_ict/hours)		-0.009		-0.007		-0.000		-0.016
		(0.037)		(0.038)		(0.037)		(0.125)
ln(cap_oth/hours)		0.312***		0.292***		0.296***		0.524***
		(0.052)		(0.054)		(0.053)		(0.178)
ln(hours)	0.064*	0.066*	0.070*	0.071*	0.065*	0.065	0.346*	0.320*
	(0.037)	(0.039)	(0.038)	(0.040)	(0.039)	(0.040)	(0.192)	(0.176)
Robot index	0.408**	0.422**	0.502**	0.513***	0.436**	0.442**	0.011	0.000
	(0.192)	(0.191)	(0.198)	(0.196)	(0.205)	(0.203)	(0.384)	(0.380)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
R^2	0.920	0.921	0.921	0.922	0.917	0.918	0.984	0.984
Log-likelihood	410.3	420.9	473.8	484.5	438.8	447.1	1561.7	1569.0
NOBS	1207	1207	1207	1207	1207	1207	1207	1207

FE estimation results (15% depreciation rate), two subsamples

	Period 2008 – 2015							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.296***		0.291***		0.294***		0.268*	
	(0.034)		(0.036)		(0.035)		(0.138)	
ln(cap_ict/hours)		0.024		0.026		0.022		0.270
		(0.035)		(0.038)		(0.036)		(0.216)
ln(cap_oth/hours		0.279***		0.273***		0.278***		0.261**
)		(0.044)		(0.046)		(0.045)		(0.121)
ln(hours)	0.129***	0.126***	0.130***	0.127***	0.130***	0.127***	0.061	0.313
	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.191)	(0.270)
Robot index	0.660***	0.668***	0.642***	0.650***	0.666***	0.674***	0.735**	0.736**
	(0.159)	(0.158)	(0.170)	(0.169)	(0.166)	(0.164)	(0.328)	(0.327)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	yes
R^2	0.939	0.939	0.936	0.937	0.937	0.938	0.978	0.978
Log-likelihood	450.6	454.1	472.0	476.0	471.1	474.5	993.1	996.6
NOBS	803	803	803	803	803	803	803	803

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The impact of a one standard deviation increase of robot densities



Robot stocks with perpetual inventory method and 15% depreciation rate

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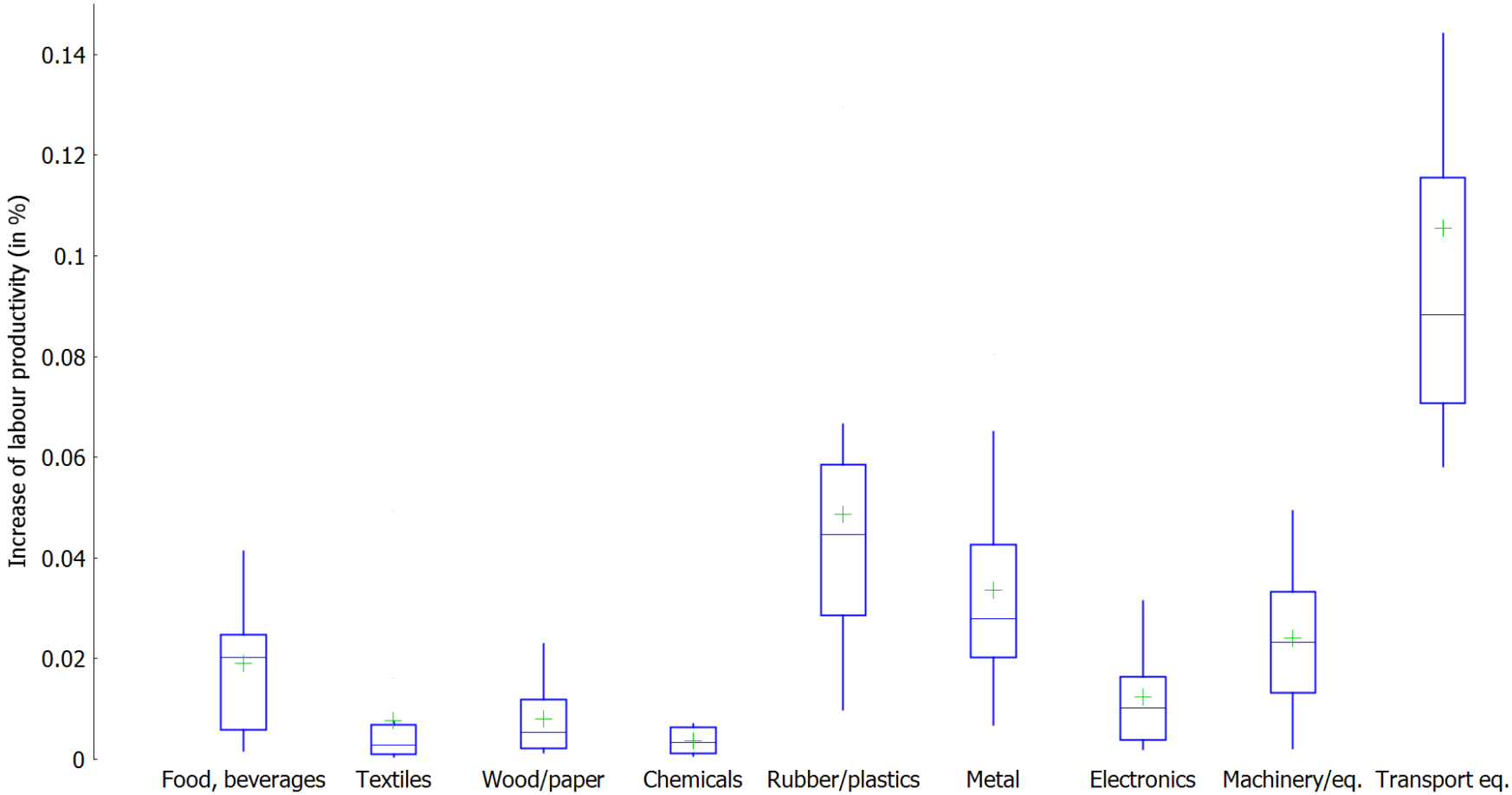
The impact of a one percent increase of robot stocks in 2014



Robot stocks with perpetual inventory method and 15% depreciation rate

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Conclusions

- We provide the first study of the impact of industrial robots on labour productivity **within a production function framework** with panel data for nine manufacturing industries and 12 EU countries over a longer time period of 21 years.
- Our estimation results show that robots deployed in industrial production have – compared to other non-ICT capital – an **additional impact** on labour productivity.
- This capital augmenting effect of robots contributes to total factor productivity and via this channel also increases labour productivity.
- However, the country-sector distribution of robots presented suggests that they represent the **latest iteration of a very long-term process** of industrial automation more than a break-through innovation.

Conclusions

- Thus, it is plausible that the expected gains in productivity and employment will restrain to those countries and industries with an **already consistent stock of industrial robots** and that the **positive spillovers** will depend on how difficult will be the automation process in different industries and countries.
- Indeed, the analysis shows that with the current level of robot technology, the substantial effects are limited to **a few industries** with an already large deployment of robots (transport equipment industry, rubber and plastic products industry, metals and metal products industry and machinery and equipment industry).
- Particularly in these sectors robots seem to **upgrade the non-ICT capital stock** and allow to improve the quality of products and to expand the variety of products.

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3000 staff

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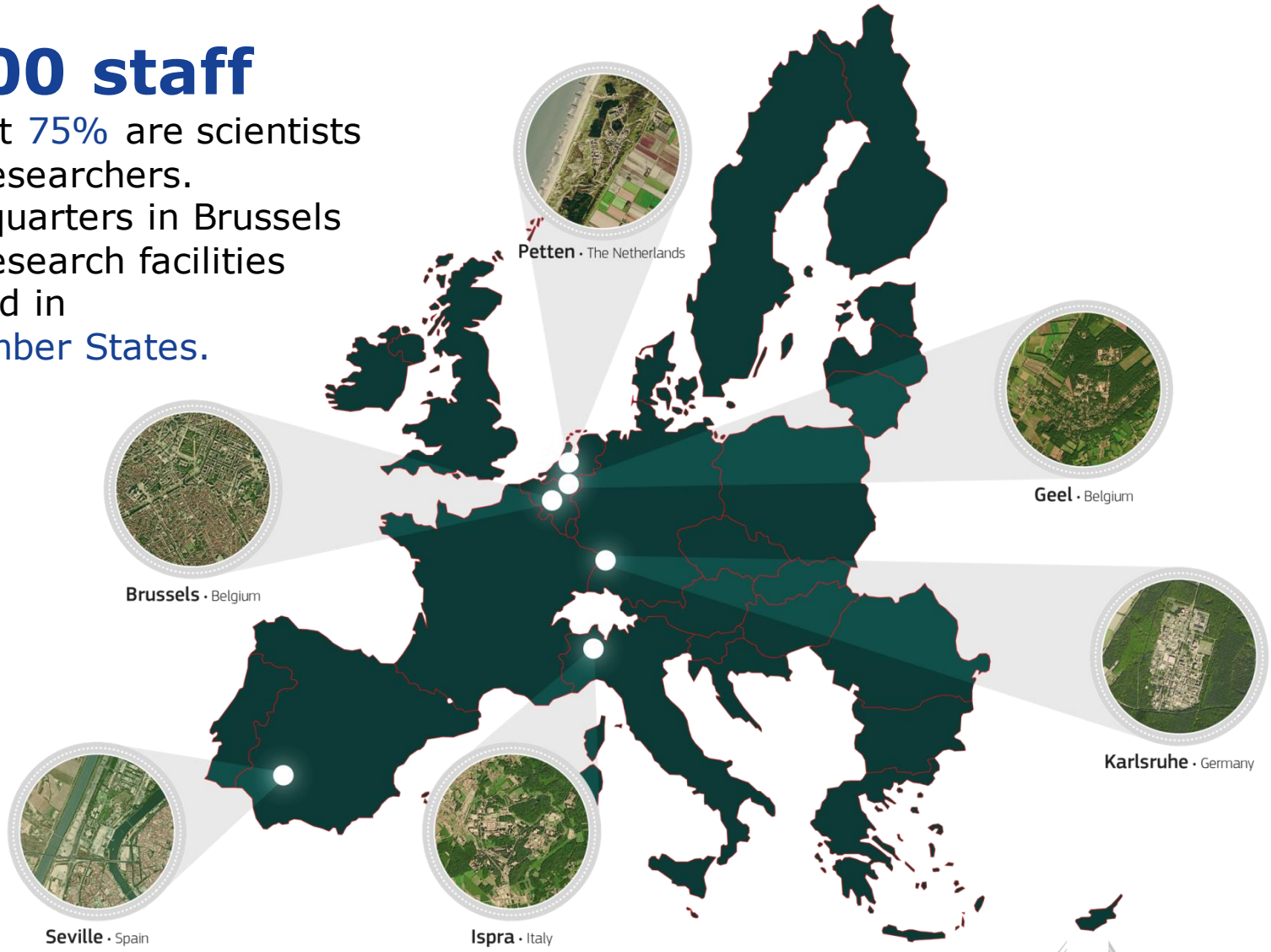

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FE estimation results (10% depreciation rate)

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.325***		0.302***		0.302***		0.459***	
	(0.039)		(0.039)		(0.037)		(0.114)	
ln(cap_ict/hours)		-0.014		-0.005		-0.001		0.007
		(0.033)		(0.033)		(0.032)		(0.110)
ln(cap_oth/hours)		0.340***		0.311***		0.306***		0.436***
		(0.048)		(0.046)		(0.044)		(0.112)
ln(hours)	0.088***	0.090***	0.087***	0.088***	0.098***	0.099***	0.328**	0.313**
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.308***	0.324***	0.365***	0.377***	0.382***	0.391***	0.542**	0.534**
	(0.110)	(0.110)	(0.111)	(0.111)	(0.104)	(0.104)	(0.234)	(0.231)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.916	0.920	0.921	0.919	0.920	0.969	0.969
Log-likelihood	639.0	657.0	804.5	821.8	778.0	790.1	1908.5	1910.2
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

FE estimation results (5% depreciation rate)

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.325***		0.302***		0.302***		0.459***	
	(0.039)		(0.039)		(0.037)		(0.116)	
ln(cap_ict/hours)		-0.014		-0.006		-0.001		0.003
		(0.033)		(0.033)		(0.032)		(0.112)
ln(cap_oth/hours)		0.340***		0.311***		0.307***		0.438***
		(0.048)		(0.046)		(0.044)		(0.113)
ln(hours)	0.089***	0.090***	0.088***	0.088***	0.099***	0.099***	0.333**	0.315**
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.189**	0.203**	0.256***	0.265***	0.245***	0.253***	0.389**	0.383**
	(0.080)	(0.080)	(0.078)	(0.077)	(0.075)	(0.075)	(0.175)	(0.174)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.916	0.920	0.921	0.919	0.920	0.969	0.969
Log-likelihood	636.6	654.6	803.8	821.8	774.6	786.7	1908.3	1910.1
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

FE estimation results (stepwise 12 years depr.)

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.324***		0.301***		0.301***		0.448***	
	(0.039)		(0.039)		(0.037)		(0.113)	
ln(cap_ict/hours)		-0.013		-0.005		-0.000		0.005
		(0.033)		(0.033)		(0.032)		(0.111)
ln(cap_oth/hours)		0.338***		0.310***		0.305***		0.427***
		(0.048)		(0.046)		(0.044)		(0.111)
ln(hours)	0.088***	0.089***	0.087***	0.088***	0.098***	0.099***	0.328**	0.312**
	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.187**	0.197**	0.239***	0.247***	0.242***	0.247***	0.303*	0.297**
	(0.080)	(0.080)	(0.081)	(0.080)	(0.077)	(0.077)	(0.169)	(0.304)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.917	0.920	0.921	0.919	0.920	0.969	0.969
Log-likelihood	636.5	654.1	802.1	819.2	774.6	786.5	1904.0	1905.8
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano) in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.