

Just reallocated? Robots, displacement, and job quality

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Motivation

Automation and Labour

- Technological progress allows firms to **automate** more and more tasks
- **“Optimistic view”**: human labour is not destroyed but rather **reallocated**
 - ▶ Displacement effect is mitigated by several **indirect effects** (Nakamura and Zeira, 2019; Acemoglu and Restrepo, 2018)
- For industrial robots, there is **empirical evidence** in support of this view:
 - ▶ Dauth et al. (2021): ↓ in manufacturing offset by ↑ in services

This study

- Most studies rely on **aggregated measures** (Raj and Seamans, 2018)
 - risk of **inappropriate policy response**
 - Neglect the change in composition of employed workers (Grigoli et al., 2020)
 - Losses of some groups can be covered by gains of others (Kurer and Gallego, 2019)
- We analyse automation's impact from a **different perspective**:
 - ① Shift attention from aggregate employment levels to **workers' welfare**
 - ② Focus on (potential) **losers**

Research questions and findings (preview)

RQ1: New job of worse quality

- Robots can displace **low- and middle-skilled** workers in 2 ways:
 - ▶ Their **firm adopts robots** and replaces production workers with skilled ones (Bonfiglioli et al., 2020; Humlum, 2019)
 - ▶ They work in a **non-adopting firm**, which is pushed out of the market (Acemoglu, LeLarge, et al., 2020; Koch et al., 2019)
- Finding a new good match might be hard:
 - ▶ Shift of labor demand towards a more skilled workforce (Bonfiglioli et al., 2020; Humlum, 2019)
 - ▶ Geographic mismatch
 - ▶ Sector re-education/training

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→ Look at earnings, employment stability and skill-requirement

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 - ▶ **Sector reallocation frictions**

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RQ2: Adjustment mechanisms

→ **Reallocation** is at the base of the optimistic view on automation.

RQ2: Is relocating to a different sector or local labour market an effective adjustment mechanism for automation-exposed displaced workers?

① Change of sector

② Change of local labor market

Flows by NUTS3

Flows by sector

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① Change of sector

Pros: Benefit from positive effects of automation on other sectors

Cons: Sector reallocation frictions

② Change of local labor market

Pros: Expanding labor markets offer more jobs and higher wages

Cons: Shift of labour demand + sector reallocation frictions

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Flows by NUTS3

Flows by sector

Our findings (preview)

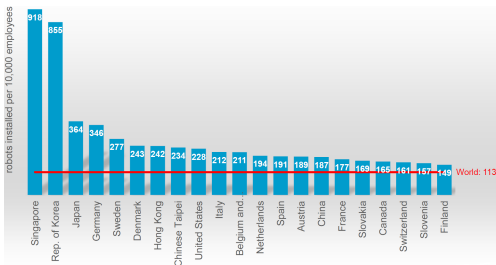
- Exposed middle- and low-skilled workers tend to be re-employed in jobs of **lower quality**
 - Lower pay, skill downgrading, and less stable employment
- Negative effects are quite **persistent** (up to 36 months)
- **Reallocation** offers little to no advantage
- High-skilled are less affected by exposure

Data and Empirical Approach

Why is Spain a good case study?

1 High robot density:

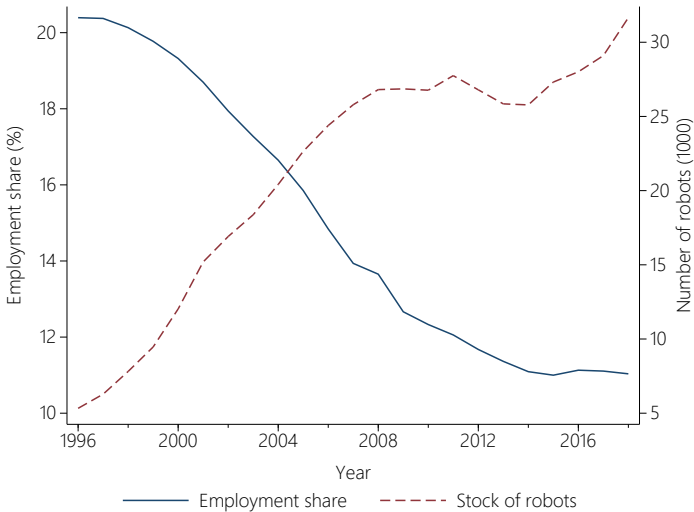
Figure: Robot density in manufacturing - 2019



Source: Müller and Kutzbach (2020)

- 2 There is evidence of **automation-induced displacement** (Koch et al., 2019)
- 3 Spanish workers are sensitive to economic factors when it comes to **internal migration** choices (Alvarez and Royuela, 2020)

Automation in Spain



Sources: INE and IFR, own calculations.

Data

Worker level: Muestra continua de vidas laborales (**MCVL**)

- Anonymised **longitudinal panel** from the Spanish social security records
- Each wave includes 4% of the reference population (about 1 million workers)
- We cover the period **2001-2016**
- The **whole labour history** of each worker can be retrieved
- Basic personal characteristics + Detailed info on each work spell

Robots: International Federation of Robots (**IFR**) dataset

- Based on surveys of robot suppliers
- Covers roughly 90% of the industrial robots market
- Stock of robots by **industry**, **country** and **year** for the period 1993-2018

What is a robot

Descriptives

Balancing

IFR groups

Time series

Sample restriction

- Only consider **involuntary dismissals**
- Keep only **transitions to a different employer**
- Exclude transitions to/from **self-employment**
- Drop very short spells (<30 days)
- Keep individuals aged 18-60
- Trim top and bottom daily earnings

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Empirical approach (i) - Outcomes

$$Y_{iwst\tau} = c + \Omega \cdot X_{i,\tau} + \eta \cdot \theta_{\tau} + \lambda \cdot NUTS2_{i,t} + \psi \cdot Sector_{i,t} + \varphi \cdot Contract_{i,t} + \kappa \cdot \Delta NUTS3_i + \nu \cdot \Delta Sector_i + \pi \cdot \Delta Trade_{s,t-1} + \mu \cdot \Delta ICT_{s,t-1} + \iota \cdot \Xi_w + \beta \cdot \Delta Exp_{s,t-1} + \epsilon_{wist\tau}$$

where, $Y_{iwst\tau}$:

- 1 **dummy** for whether the new job offers a **lower pay**
- 2 **ratio** ($\times 100$) of the current pay over the previous one
- 3 **dummy** for whether the current job requires a **lower qualification**
- 4 **dummy** for whether the new job is with a **temporary contract**
- 5 **dummy** for whether the new job is with a temporary employment agency (TEA)

Empirical approach (ii) - Controls

$$Y_{iwst\tau} = c + \Omega \cdot X_{i,\tau} + \eta \cdot \theta_{\tau} + \lambda \cdot NUTS2_{i,t} + \psi \cdot Sector_{i,t} + \varphi \cdot Contract_{i,t} + \kappa \cdot \Delta NUTS3_i + \nu \cdot \Delta Sector_i + \pi \cdot \Delta Trade_{s,t-1} + \mu \cdot \Delta ICT_{s,t-1} + \iota \cdot \Xi_w + \beta \cdot \Delta Exp_{s,t-1} + \epsilon_{wist\tau}$$

- $X_{i,\tau}$: age, gender, country of birth, weeks unemployed at time τ
- θ_{τ} : year of re-employment
- $NUTS2_{i,t}$: region of previous job
- $Sector_{i,t}$: 1-digit sector of previous job
- $Contract_{i,t}$: type of contract of previous job (permanent vs temporary)
- $\Delta NUTS3_i$: indicator for new job being in a different NUTS3
- $\Delta Sector_i$: indicator for new job being in a different 1-digit sector
- $\Delta Trade_{s,t-1}$: change in net imports from China
- $\Delta ICT_{s,t-1}$: change in real gross fixed capital formation volume for ICT equipment
- Ξ_w : workers' **unobserved ability** (Mincerian wage regression)

Skill groups

Empirical approach (iii) - Exposure

R2

TimeSeries

- **Exposure** to robots:

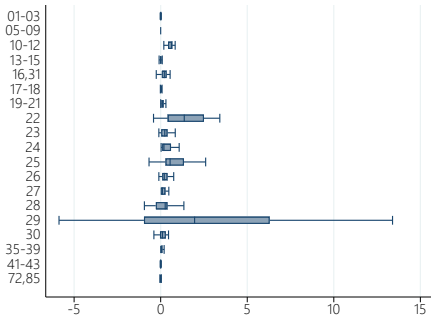
$$\Delta Exp_{s,t-1} = \frac{robots_{s,t-1} - robots_{s,t-2}}{emp_{s,1995}}$$

- Follow Autor et al. (2013), Acemoglu and Restrepo (2020), Dauth et al. (2021)
→ **Instrument** adoption in Spain with **Germany, Italy, France, UK**
- Role of **adjustment mechanisms** captured by replacing $\Delta Exp_{s,t-1}$ with:
 - ▶ $\Delta Exp_{s,t-1} \cdot \Delta NUTS3_i$
 - ▶ $\Delta Exp_{s,t-1} \cdot \Delta Sector_i$

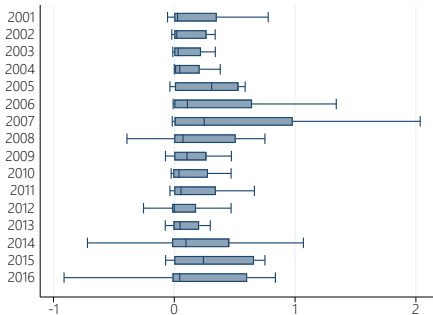
Variation in $\Delta Robots_{s,t-1}$

Figure: Variation of $\Delta Robots_{s,t-1}$ by sector or year

(a) Variation by sector



(b) Variation by year

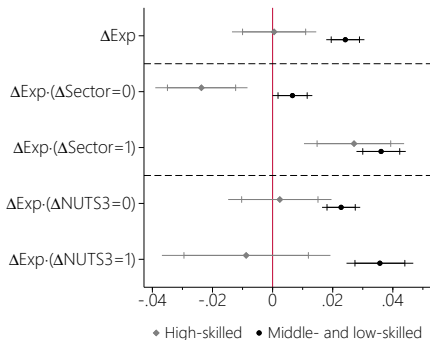
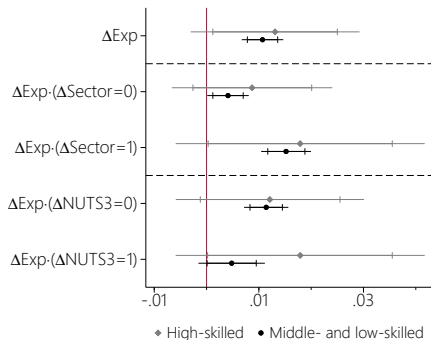


Source: IFR, own calculations.

Results

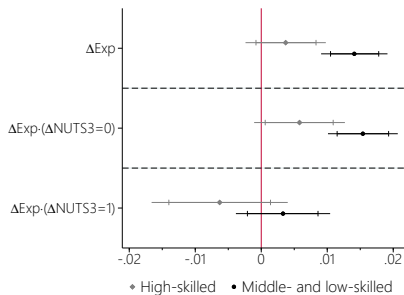
2SLS results (i)

Pay ratio

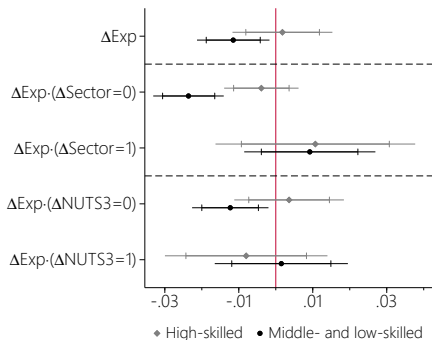
(a) Probability of lower pay**(b) Probability of lower qualification**

2SLS results (ii)

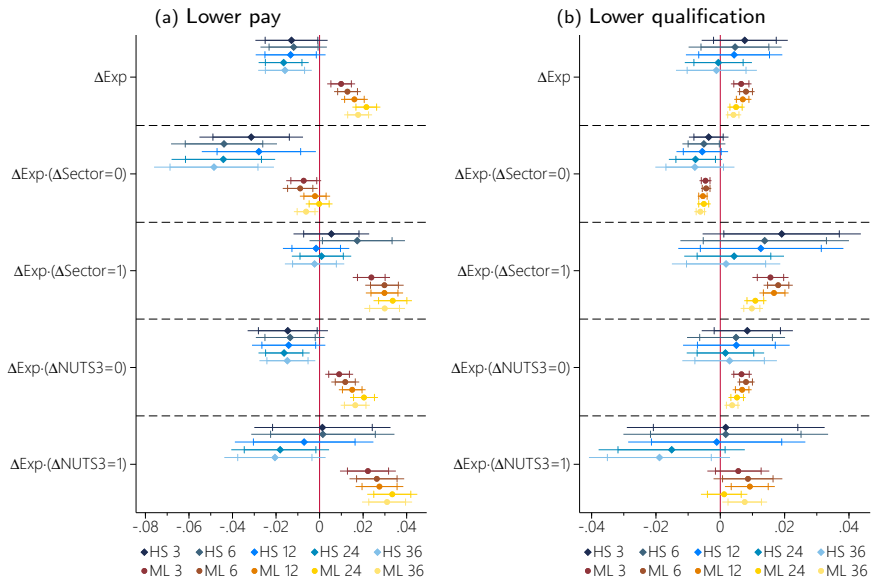
(a) Probability of TEA



(b) Probability of temporary contract

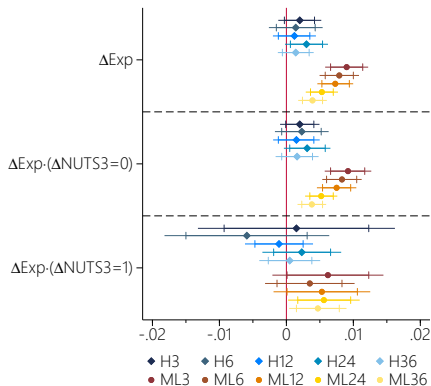


Results 2SLS - Medium term (i)

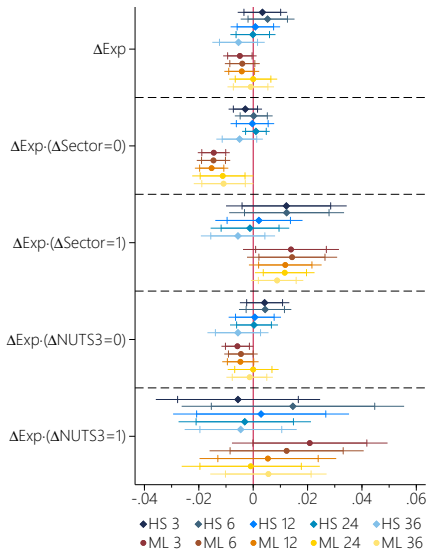


Results 2SLS - Medium term (ii)

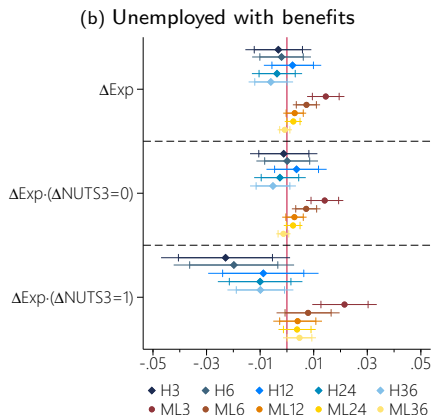
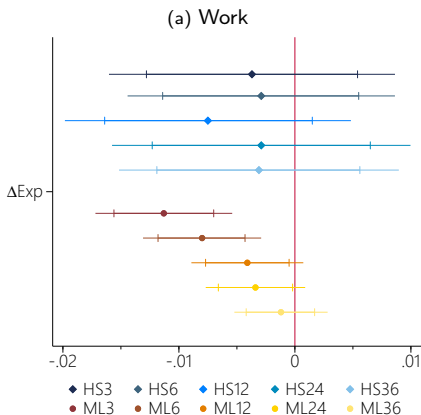
(a) Temporary Employment Agency



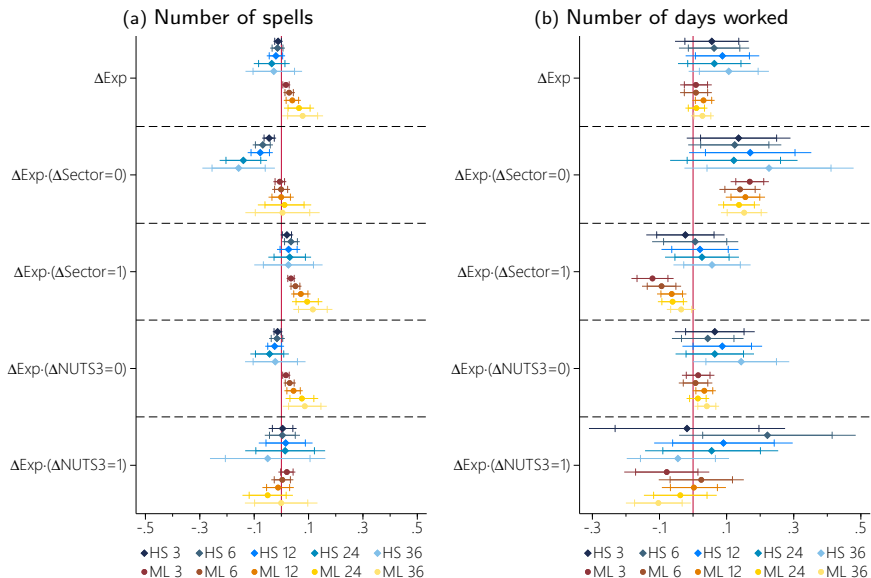
(b) Temporary contract



Results 2SLS - Medium term (iii)



Results 2SLS - Medium term (iv)



Robustness checks

We perform a wide range of robustness checks. Among them:

- Keep only transitions from manufacturing;
- Exclude transitions from the automotive sector;
- For each individual, keep only transition from longest spell;
- Use more detailed sector fixed effects;
- Use a more stringent definition of migration;
- Consider transitions following (a) the end of temporary contracts; (b) collective dismissals;
- Use 5 rather than 2 skill groups.

Conclusion

Conclusion

- Shift focus from employment levels to **quality**
- **Long-lasting negative impact** for middle- and low-skilled workers
- High-skilled workers are less negatively affected by exposure, although they also incur a penalty when changing sector.
- Workers who remain employed in automating sectors benefit from some of its advantages
- Reallocation is not an effective adjustment mechanism
 - **Active labour market policies** might be necessary for a smoother transition

Heterogeneity

Robustness checks

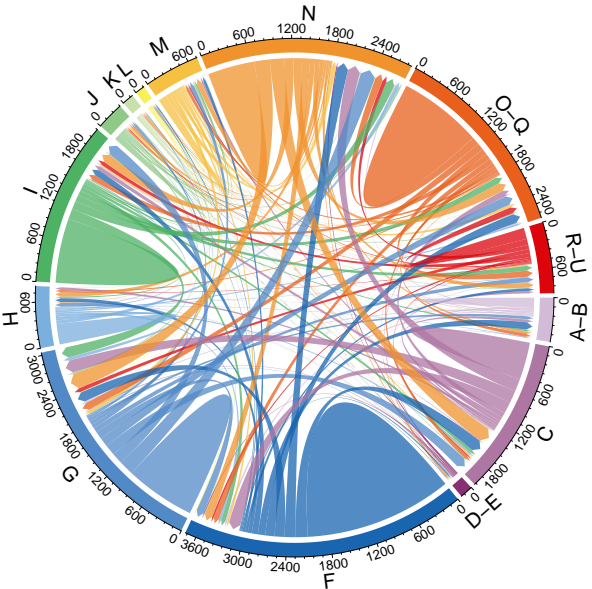
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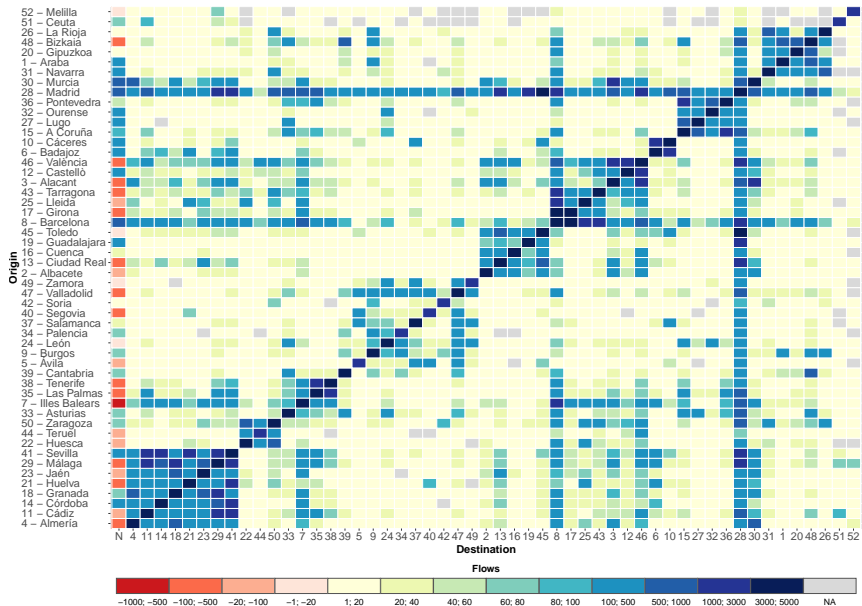
Flows by sector



Source: MCVL, own calculations.

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Flows by NUTS3



Source: MCVL, own calculations.

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Summary statistics, transition level

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Qualitative	MLS		HS		Total	
	%	Corr.	%	Corr.	%	Corr.
Worse pay	41.19		40.24		40.96	
Worse security	8.25	-0.002	10.92	0.081	8.87	0.019
Lower skill	10.78	0.069	34.65	0.186	16.36	0.098
Employed in ETT firm	4.93	0.012	2.40	0.028	4.34	0.016
Female	36.24	-0.013	53.22	0.025	40.21	-0.005
Change sector	47.82	0.058	42.07	0.107	46.48	0.070
Change NUTS3	15.30	0.018	21.43	0.007	16.74	0.015
Temporary contract (prev.)	83.21	0.046	57.71	0.090	77.25	0.058
Manufacturing (prev.)	11.98	0.022	5.86	-0.007	10.55	0.017
Birth Place						
Spain	80.72	-0.010	91.44	-0.012	83.23	-0.012
Center and South America	8.03	0.009	3.82	0.010	7.05	0.010
EU28	4.68	-0.000	3.06	0.006	4.31	0.001
Africa	4.58	0.006	0.71	0.002	3.67	0.006
Other	1.99	0.004	0.97	0.002	1.75	0.004
Year of start						
2001 - 2003	18.95	-0.008	16.81	-0.051	18.45	-0.017
2004 - 2006	25.09	-0.032	21.06	-0.054	24.15	-0.036
2007 - 2009	23.39	-0.004	22.30	-0.020	23.13	-0.008
2010 - 2012	18.18	0.032	21.74	0.061	19.01	0.039
2013 - 2015	9.22	0.021	11.89	0.060	9.84	0.031
2016 - 2018	5.17	0.002	6.19	0.019	5.41	0.006
Quantitative						
	MLS		HS		Total	
	Mean	Corr.	Mean	Corr.	Mean	Corr.
Pay ratio	111.307	-0.633	108.243	-0.612	110.591	-0.627
Δ robots	0.080	0.024	0.030	-0.008	0.068	0.019
Δ imports from China	0.076	0.004	0.038	-0.001	0.067	0.003
Δ ICT stock	0.386	-0.002	0.565	0.000	0.428	-0.002
Age	34.622	-0.011	35.954	-0.046	34.933	-0.019
Weeks unemployed	33.591	-0.028	28.062	0.056	32.299	-0.010
Unobs. ability	-0.040	0.038	0.058	0.028	-0.017	0.034
N	1,065,361		324,881		1,390,242	

Notes: Summary statistics on the estimation sample. Columns "Corr." report the correlation between each variable and the dummy for "Worse pay". Sources: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Balancing analysis, individual level (June 2001)

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	Unconditional		Conditional	
	Coefficient	SE	Coefficient	SE
<i>All workers</i>				
Monthly earnings	16.9943***	0.1613	7.4972***	0.6102
Female	-0.0119***	0.0002	-0.0017***	0.0006
Foreign	-0.0016***	0.0001	0.0002	0.0001
Age	0.0177***	0.0040	-0.0228	0.0188
Middle- and low-skilled	0.0102***	0.0002	0.0036***	0.0004
Permanent contract	0.0160***	0.0002	0.0018**	0.0007
Temporary contract	-0.0029***	0.0002	-0.0000	0.0006
Self employed	-0.0069***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0031***	0.0001	-0.0025***	0.0004
10-49 Employees	0.0007***	0.0001	-0.0046***	0.0006
50-249 Employees	0.0034***	0.0001	-0.0006	0.0006
More than 250 Employees	0.0088***	0.0001	0.0126***	0.0022
N	546,657		546,657	
<i>Manufacturing workers</i>				
Monthly earnings	13.4952***	0.2088	4.8352***	0.4883
Female	-0.0037***	0.0002	-0.0010	0.0007
Foreign	-0.0003***	0.0001	-0.0000	0.0001
Age	0.0192***	0.0054	-0.0437***	0.0165
Middle- and low-skilled	0.0032***	0.0002	0.0024***	0.0004
Permanent contract	0.0064***	0.0002	0.0006	0.0006
Temporary contract	-0.0023***	0.0002	-0.0002	0.0005
Self employed	-0.0037***	0.0001	-0.0000	0.0001
1-9 Employees	-0.0030***	0.0001	-0.0018***	0.0003
10-49 Employees	-0.0038***	0.0002	-0.0031***	0.0005
50-249 Employees	0.0010***	0.0002	-0.0011*	0.0006
More than 250 Employees	0.0148***	0.0002	0.0110***	0.0021
N	96,463		96,463	

Notes: Coefficients from 2SLS regressions of the respective transition characteristics on the change in robots exposure per 1,000 workers between 2001 and 2016 (instrumented with robot installations across industries in other European countries). The sample includes *all* workers with an on-going working spell on June 1, 2001. The "Unconditional" column reports coefficient and standard error when the listed variables are regressed on predicted robot exposure and a constant, while column "Conditional" adds a series of standard control variables. In each regression, all controls that are constructed from the dependent variable are not included in the estimation. Standard errors are clustered by 1-digit sector and NUTS3 area.

Sources: MCVL, IFR, INE and Eurostat, own calculations.

IFR categories and aggregation schemes

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Code	Name	15 Groups	19 Groups
A-B	Agriculture, forestry, fishing	01-03	01-03
C	Mining and quarrying	05-09	05-09
D	Manufacturing		
10-12	Food and beverages	10-12	10-12
13-15	Textiles	13-15	13-15
16	Wood and furniture	16,31	16,31
17-18	Paper	17-18	17-18
19-22	Plastic and chemical products	19-22	
19	Pharmaceuticals, cosmetics	19-22	19-21
20-21	other chemical products n.e.c.	19-22	19-21
22	Rubber and plastic products (non-automotive)	19-22	22
229	Chemical products, unspecified		
23	Non-metallic mineral products	23	23
24-28	Metal	24,25,28	
24	Basic metals	24,25,28	24
25	Metal products (non-automotive)	24,25,28	25
28	Industrial machinery	24,25,28	28
289	Metal, unspecified		
26-27	Electrical/electronics	26-27	
275	Household/domestic appliances		27
271	Electrical machinery n.e.c. (non-automotive)		27
260	Electronic components/devices		26
261	Semiconductors, LCD, LED		26
262	Computers and peripheral equipment		26
263	Communication equipment		26
265	Medical, precision, optical instruments		26
279	Electrical/electronics unspecified		
29	Automotive	29	29
291	Motor vehicles, engines and bodies		
293	Automotive parts		
2931	Metal (AutoParts)		
2932	Rubber and plastic (AutoParts)		
2933	Electrical/electronic (AutoParts)		
2934	Glass (AutoParts)		
2939	Other (AutoParts)		
2999	Unspecified AutoParts		
299	Automotive unspecified		
30	Other vehicles	30	30
91*	All other manufacturing branches		
E	Electricity, gas, water supply	35-39	35-39
F	Construction	41-43	41-43
P	Education/research/development	72,85	72,85
90*	All other non-manufacturing branches		
99*	Unspecified		

Notes: "*" indicates residual categories whose robots are excluded from all aggregation schemes.

Separate estimations for **high-skilled** versus **middle- and low-skilled** workers

- **High-skilled** → Previous social security skill-group was:
 - ▶ Engineers, graduates and senior management
 - ▶ Technical engineers, technicians and assistants
 - ▶ Administrative and workshop managers

- **Medium-Low skilled** → Previous social security skill-group was:
 - ▶ Non-graduate assistants
 - ▶ Administrative officers
 - ▶ Subordinates
 - ▶ Administrative assistants
 - ▶ First and second officers
 - ▶ Third officers and specialists
 - ▶ Unskilled (over 18)

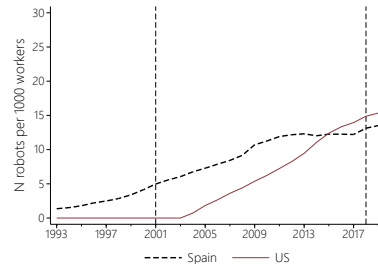
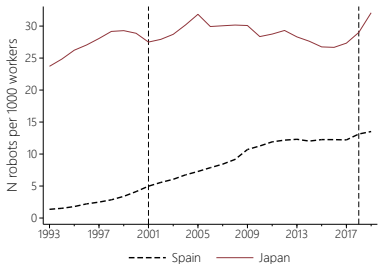
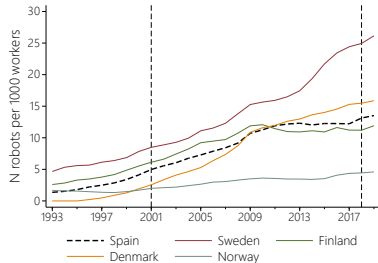
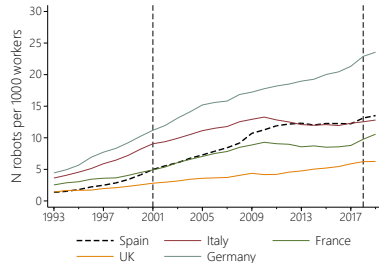
- For every job j held by worker w we estimate:

$$\begin{aligned} \ln(\text{earning}_{wj}) = & \alpha + \Xi' \cdot \zeta_w + \\ & \pi \cdot \text{Age}_{wj} + \sigma \cdot \text{Unempl}_{wj} + \xi \cdot \text{Tenure}_{wj} + \\ & \varphi' \cdot \text{Skill}_{wj} + \omega \cdot \text{FullPart}_{wj} + \nu \cdot \text{Stab}_{wj} + \rho' \cdot \text{YearStart}_{wj} + \\ & \mu' \cdot \text{Sector}_j + \lambda' \cdot \text{NUTS3}_j + \psi \cdot \text{NumWorkers}_j + \epsilon_{wj} \end{aligned}$$

- Worker fixed effect ζ_w should capture workers' unobserved ability.
- Hence, we include Ξ as an additional control in the main equation.

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Trends in robot density



Source: IFR and ILO, own calculations.

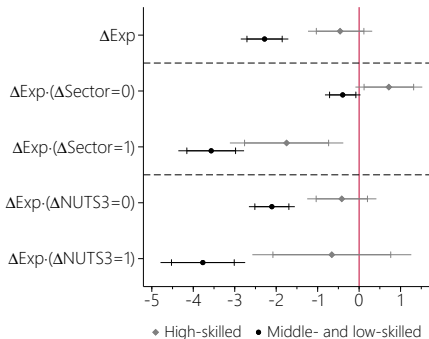
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Instrument choice

Back

	R-squared	Overid.	F-statistic
Year and sector FE	0.273		
All 8 European countries	0.831	0.000	440.9
Italy, France, UK, Germany	0.800	0.000	474.9
Italy, France, UK	0.788	0.000	585.0
Sweden, Denmark, Finland, Norway	0.426	0.000	64.8
Japan	0.280		5.1
Average: all 8 European countries	0.629		356.9
Average: Italy, France, UK, Germany	0.632		374.6
Average: Italy, France, UK	0.662		276.0
Average: Sweden, Denmark, Finland, Norway	0.285		117.3
N	361	1,390,242	1,390,242
Year and sector FE	0.251		
All 8 European countries	0.657	0.000	41.1
All 8 European countries + US	0.657	0.000	37.3
Italy, France, UK, Germany	0.573	0.000	77.4
Italy, France, UK, Germany, US	0.576	0.000	58.5
Italy, France, UK	0.483	0.000	46.6
Sweden, Denmark, Finland, Norway	0.414	0.000	18.8
Japan	0.251		3.2
US	0.296		0.4
Average: all 8 European countries	0.292		333.7
Average: Italy, France, UK, Germany	0.284		274.9
Average: Italy, France, UK	0.277		72.4
Average: Italy, France, UK, Germany, US	0.254		12.9
Average: Sweden, Denmark, Finland, Norway	0.281		57.6
N	209	495,441	495,441

(a) Earnings ratio ($\times 100$)



For middle- and low-skilled (high-skilled):

$N = 1,095,924$ (281,852)

Montiel Olea and Pflueger (2013) F-Stat = 203.6 (165.1)

Heterogeneity (I) - Lower pay

Back

	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Gender						
ΔExp	-0.003	-0.003	-0.001	0.032 ***	0.020 ***	0.011 ***
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.036 **	-0.020 ***	-0.016	0.016 ***	0.003	0.013 ***
$\Delta Exp \cdot (\Delta Sector = 1)$	0.019 **	0.028 ***	-0.009	0.040 ***	0.035 ***	0.006
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.001	-0.001	0.002	0.031 ***	0.019 ***	0.012 **
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.032	-0.008	-0.023	0.043 ***	0.031 ***	0.012
<i>N</i>	170,552	140,459		432,886	717,384	
Age						
ΔExp	-0.004	0.000	-0.004	0.018 **	0.025 ***	-0.007
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.018 ***	-0.024 ***	0.005	0.004	0.007 ***	-0.003
$\Delta Exp \cdot (\Delta Sector = 1)$	0.023 **	0.025 ***	-0.002	0.034 ***	0.037 ***	-0.003
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.004	0.003	-0.006	0.017 **	0.023 ***	-0.006
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.008	-0.014	0.006	0.023 ***	0.037 ***	-0.014
<i>N</i>	90,922	220,089		339,244	811,026	
Urbanisation						
ΔExp	0.003	-0.007	0.009	0.021 ***	0.025 ***	-0.004
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.020 ***	-0.025 ***	0.004	0.005 *	0.007 **	-0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.030 ***	0.019 **	0.011	0.033 ***	0.039 ***	-0.006
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	-0.005	0.009	0.020 ***	0.024 ***	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.011	-0.013	0.002	0.040 ***	0.032 ***	0.008
<i>N</i>	128,242	182,769		355,923	794,347	
Empl. in Manufacturing						
ΔExp	0.008	-0.011 *	0.019 **	0.025 ***	0.021 ***	0.004
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.010 *	-0.032 ***	0.022 **	0.011 ***	0.000	0.010 ***
$\Delta Exp \cdot (\Delta Sector = 1)$	0.029 ***	0.021 **	0.008	0.034 ***	0.037 ***	-0.003
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.009	-0.009	0.018 *	0.023 ***	0.020 ***	0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.000	-0.017	0.017	0.038 ***	0.028 ***	0.010
<i>N</i>	73,851	237,160		253,825	896,445	

Notes: Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40 , (2) < 40 . Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. Sources: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Heterogeneity (II) - Pay ratio

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	Group 1	HS Group 2	Diff	Group 1	MLS Group 2	Diff
Gender						
ΔExp	-0.454	-0.350	-0.104	-3.083 ***	-1.923 ***	-1.160 ***
$\Delta Exp \cdot (\Delta Sector = 0)$	1.034	0.583 ***	0.452	-1.090 ***	-0.175	-0.915 ***
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.455 **	-1.949 ***	0.495	-4.166 ***	-3.348 ***	-0.819 *
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.282	-0.329	0.048	-2.964 ***	-1.751 ***	-1.213 ***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-1.739	-0.460	-1.280	-4.408 ***	-3.330 ***	-1.079
<i>N</i>	170,552	140,459		432,886	717,384	
Age						
ΔExp	0.009	-0.727 **	0.736	-1.720 ***	-2.387 ***	0.666 *
$\Delta Exp \cdot (\Delta Sector = 0)$	0.697 **	0.431	0.267	-0.319	-0.456 **	0.138
$\Delta Exp \cdot (\Delta Sector = 1)$	-1.320	-1.931 ***	0.611	-3.304 ***	-3.659 ***	0.355
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.065	-0.586 *	0.521	-1.532 ***	-2.234 ***	0.702 **
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.454	-1.494 *	1.949	-4.198 ***	-3.635 ***	-0.563
<i>N</i>	90,922	220,089		339,244	811,026	
Urbanisation						
ΔExp	-0.751 **	0.055	-0.807	-2.140 ***	-2.322 ***	0.181
$\Delta Exp \cdot (\Delta Sector = 0)$	0.356	0.957 ***	-0.600	-0.653 ***	-0.233	-0.420
$\Delta Exp \cdot (\Delta Sector = 1)$	-2.102 ***	-1.296	-0.806	-3.171 ***	-3.930 ***	0.758
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.725 **	0.225	-0.949 *	-2.033 ***	-2.107 ***	0.074
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.993	-0.567	-0.426	-3.415 ***	-3.861 ***	0.445
<i>N</i>	128,242	182,769		355,923	794,347	
Empl. in Manufacturing						
ΔExp	-0.887 ***	0.029	-0.917 **	-2.280 ***	-2.086 ***	-0.194
$\Delta Exp \cdot (\Delta Sector = 0)$	0.478	0.735 **	-0.257	-0.771 ***	-0.009	-0.762 **
$\Delta Exp \cdot (\Delta Sector = 1)$	-2.487 ***	-1.033	-1.454 *	-3.338 ***	-3.691 ***	0.353
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.866 ***	0.180	-1.047 **	-2.160 ***	-1.907 ***	-0.253
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-1.085	-0.578	-0.508	-3.488 ***	-3.466 ***	-0.022
<i>N</i>	73,851	237,160		253,825	896,445	

Notes: Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40 , (2) < 40 . Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. Sources: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Heterogeneity (III) - Lower skill

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	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Gender						
ΔExp	0.013	0.007	0.006	0.012 ***	0.009 ***	0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	0.001	0.005	-0.004	0.010 ***	0.002	0.008 **
$\Delta Exp \cdot (\Delta Sector = 1)$	0.020 *	0.010	0.010	0.013 ***	0.015 ***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.012	0.006	0.006	0.013 ***	0.009 ***	0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.014	0.011	0.003	0.004	0.005 **	-0.001
<i>N</i>	170,552	140,459		432,886	717,384	
Age						
ΔExp	0.005	0.011 *	-0.006	0.002	0.012 ***	-0.009 ***
$\Delta Exp \cdot (\Delta Sector = 0)$	0.004	0.004	0.001	-0.000	0.004 ***	-0.005 *
$\Delta Exp \cdot (\Delta Sector = 1)$	0.006	0.018 **	-0.012	0.005	0.016 ***	-0.011 ***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.003	0.011	-0.008	0.003	0.012 ***	-0.010 ***
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.018	0.009	0.010	0.000	0.006 **	-0.005
<i>N</i>	90,922	220,089		339,244	811,026	
Urbanisation						
ΔExp	0.007	0.011 *	-0.004	0.011 ***	0.008 ***	0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	0.001	0.009	-0.009	0.000	0.005 ***	-0.005 *
$\Delta Exp \cdot (\Delta Sector = 1)$	0.014	0.013	0.001	0.019 ***	0.010 ***	0.008 **
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.008	0.008	-0.001	0.011 ***	0.009 ***	0.003
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.002	0.021 *	-0.024	0.007	0.004	0.003
<i>N</i>	128,242	182,769		355,923	794,347	
Empl. in Manufacturing						
ΔExp	0.005	0.011	-0.006	0.012 ***	0.006 ***	0.006 **
$\Delta Exp \cdot (\Delta Sector = 0)$	0.002	0.006	-0.005	0.004 *	0.002	0.002
$\Delta Exp \cdot (\Delta Sector = 1)$	0.009	0.018	-0.009	0.018 ***	0.009 ***	0.009 **
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.004	0.011	-0.007	0.012 ***	0.007 ***	0.005 *
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.019	0.011	0.008	0.011 ***	-0.000	0.011 **
<i>N</i>	73,851	237,160		253,825	896,445	

Notes: Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40 , (2) < 40 . Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. Sources: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Heterogeneity (IV) - Temporary contract

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	HS			MLS		
	Group 1	Group 2	Diff	Group 1	Group 2	Diff
Gender						
ΔExp	-0.006	0.002	-0.008	-0.012 *	-0.009 ***	-0.002
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.003	-0.005 *	0.002	-0.029 ***	-0.019 ***	-0.009
$\Delta Exp \cdot (\Delta Sector = 1)$	-0.010	0.017 **	-0.027 *	0.004	0.011	-0.007
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.004	0.002	-0.005	-0.015 **	-0.010 ***	-0.005
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.026	0.002	-0.028	0.024 **	-0.004	0.028 **
<i>N</i>	44,831	52,770		84,354	96,147	
Age						
ΔExp	-0.001	0.002	-0.003	-0.012 ***	-0.009 **	-0.003
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.003	-0.007	0.004	-0.024 ***	-0.019 ***	-0.005
$\Delta Exp \cdot (\Delta Sector = 1)$	0.004	0.016	-0.012	0.015 *	0.007	0.008
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.001	0.000	0.001	-0.011 **	-0.011 **	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.016	0.013	-0.028	-0.019	0.013 **	-0.032 **
<i>N</i>	41,032	56,569		74,911	105,590	
Urbanisation						
ΔExp	0.003	-0.003	0.006	-0.016 ***	-0.002	-0.014 **
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.003	-0.006	0.003	-0.024 ***	-0.017 ***	-0.007
$\Delta Exp \cdot (\Delta Sector = 1)$	0.012	0.003	0.009	-0.003	0.026 ***	-0.029 ***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.003	-0.003	0.006	-0.017 ***	-0.003	-0.014 **
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.003	-0.005	0.002	-0.005	0.010	-0.015
<i>N</i>	49,975	47,626		69,487	111,014	
Empl. in Manufacturing						
ΔExp	-0.003	0.002	-0.004	-0.015 ***	-0.006	-0.009
$\Delta Exp \cdot (\Delta Sector = 0)$	-0.005	-0.004	-0.002	-0.022 ***	-0.021 ***	-0.001
$\Delta Exp \cdot (\Delta Sector = 1)$	0.001	0.014	-0.013	-0.004	0.025 ***	-0.029 ***
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	-0.003	0.003	-0.006	-0.016 ***	-0.007	-0.009
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.001	-0.004	0.003	0.001	0.004	-0.003
<i>N</i>	25,983	71,618		47,536	132,965	

Notes: Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40 , (2) < 40 . Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. Sources: MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Heterogeneity (V) - TEA

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	Group 1	HS Group 2	Diff	Group 1	MLS Group 2	Diff
Gender						
ΔExp	0.006	0.003	0.004	0.019 ***	0.012 ***	0.007 *
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.011 **	0.003	0.007	0.020 ***	0.014 ***	0.006
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.021 **	-0.001	-0.020 **	0.018 ***	-0.001	0.019 ***
<i>N</i>	73,851	237,160		253,825	896,445	
Age						
ΔExp	0.001	0.005	-0.004	0.012 ***	0.014 ***	-0.002
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.001	0.009 **	-0.008 *	0.012 ***	0.016 ***	-0.004
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	0.003	-0.012 **	0.014 *	0.008	0.002	0.006
<i>N</i>	73,851	237,160		253,825	896,445	
Urbanisation						
ΔExp	0.007 *	-0.000	0.007	0.013 ***	0.013 ***	0.000
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.008 *	0.002	0.007	0.014 ***	0.015 ***	-0.001
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.006	0.002	0.005	0.002	0.003
<i>N</i>	73,851	237,160		253,825	896,445	
Empl. in Manufacturing						
ΔExp	0.004	0.002	0.002	0.013 ***	0.012 ***	0.000
$\Delta Exp \cdot (\Delta NUTS3 = 0)$	0.005	0.005 *	0.001	0.015 ***	0.013 ***	0.002
$\Delta Exp \cdot (\Delta NUTS3 = 1)$	-0.004	-0.006	0.002	-0.005 *	0.008 *	-0.013 **
<i>N</i>	73,851	237,160		253,825	896,445	

Notes: Group 1 and Group 2 are defined as follows. Gender: (1) Female, (2) Male. Age: (1) ≥ 40 , (2) < 40 . Urbanisation (at least 60% of previous province's population is in municipalities with more than 50.000 inhabitants): (1) yes, (2) no. Employment in Manufacturing (previous province had more than 25% of employment in manufacturing in 2000): (1) yes, (2) no. *Sources:* MCVL, IFR, INE, EU-KLEMS and Eurostat, own calculations.

Robustness checks - Lower pay (HS)

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	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0005	-0.0237***	0.0271***	0.0024	-0.0088	281,852
<i>Subsamples</i>						
Manufacturing	0.0018	-0.0114**	0.0161***	0.0029	-0.0035	14,079
One transition	0.0001	-0.0171***	0.0257***	0.0007	-0.0036	130,907
Previous 6 months	0.0002	-0.0179***	0.0235***	0.0019	-0.0086	161,118
4 months unemployed	0.0086*	-0.0095	0.0153**	0.0152**	-0.0109	162,925
24 months unemployed	0.0125*	-0.0031	0.0177**	0.0232***	-0.0218	86,975
Previous permanent	0.0040	-0.0134**	0.0310***	0.0026	0.0114	81,197
Previous not automotive	0.0212**	-0.0238	0.0433***	0.0324***	-0.0347	281,383
Only general regime	0.0003	-0.0236***	0.0266***	0.0022	-0.0092	275,414
<i>IFR aggregation schemes</i>						
15 Groups	-0.0078	-0.0332***	0.0262***	-0.0074	-0.0099	281,852
17 Groups	-0.0038	-0.0313***	0.0264***	-0.0009	-0.0172	281,852
20 Groups	0.0009	-0.0232***	0.0273***	0.0028	-0.0085	281,852
<i>Migration</i>						
Non-neighbouring NUTS3	0.0006	-0.0237***	0.0272***	0.0012	-0.0046	281,852
<i>Spell length</i>						
> 180 days	-0.0069	-0.0207***	0.0123*	-0.0049	-0.0166*	167,473
> 360 days	-0.0021	-0.0157***	0.0175**	0.0000	-0.0133	103,398
<i>Controls</i>						
Drop indiv. effect	0.0007	-0.0240***	0.0278***	0.0026	-0.0087	281,852
Drop ΔICT	0.0005	-0.0237***	0.0271***	0.0024	-0.0088	281,852
Drop indiv. effect and ΔICT	0.0007	-0.0240***	0.0278***	0.0026	-0.0087	281,852
<i>Fixed effects</i>						
Add Current spell FE	0.0002	-0.0171***	0.0189***	0.0022	-0.0099	281,852
<i>Sector</i>						
1-dig Δ 1-dig	0.0005	-0.0237***	0.0271***	0.0024	-0.0088	281,852
1-dig Δ IFR15(2-dig)	-0.0006	-0.0336***	0.0185***	0.0016	-0.0110	281,852
1-dig Δ IFR19(2-dig)	-0.0006	-0.0361***	0.0192***	0.0016	-0.0110	281,852
IFR15(1-dig) Δ 1-dig	0.0045	-0.0231***	0.0287***	0.0065	-0.0055	281,852
IFR15(1-dig) Δ IFR15(2-dig)	0.0037	-0.0321***	0.0210***	0.0059	-0.0075	281,852
IFR15(1-dig) Δ IFR19(2-dig)	0.0034	-0.0351***	0.0208***	0.0055	-0.0078	281,852
IFR15(2-dig) Δ 1-dig	0.0047	-0.0220***	0.0281***	0.0065	-0.0046	281,852
IFR15(2-dig) Δ IFR15(2-dig)	0.0039	-0.0301***	0.0204***	0.0060	-0.0068	281,852
IFR15(2-dig) Δ IFR19(2-dig)	0.0035	-0.0331***	0.0202***	0.0056	-0.0070	281,852
IFR19(1-dig) Δ 1-dig	-0.0007	-0.0273***	0.0233***	0.0012	-0.0104	281,852
IFR19(1-dig) Δ IFR15(2-dig)	-0.0012	-0.0355***	0.0162**	0.0009	-0.0121	281,852
IFR19(1-dig) Δ IFR19(2-dig)	-0.0016	-0.0385***	0.0161**	0.0005	-0.0124	281,852
IFR19(2-dig) Δ 1-dig	-0.0005	-0.0262***	0.0227***	0.0013	-0.0095	281,852
IFR19(2-dig) Δ IFR15(2-dig)	-0.0009	-0.0334***	0.0155**	0.0011	-0.0113	281,852
IFR19(2-dig) Δ IFR19(2-dig)	-0.0014	-0.0365***	0.0154**	0.0006	-0.0117	281,852

Sources: MCVL and IFR, own calculations.

Robustness checks - Lower pay (MLS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0242***	0.0066***	0.0361***	0.0228***	0.0357***	1,095,924
<i>Subsamples</i>						
Manufacturing	0.0221***	0.0109***	0.0298***	0.0206***	0.0345***	120,189
One transition	0.0242***	0.0062*	0.0393***	0.0227***	0.0370***	393,620
Previous 6 months	0.0276***	0.0091***	0.0429***	0.0258***	0.0426***	440,058
4 months unemployed	0.0301***	0.0220***	0.0331***	0.0294***	0.0350***	727,763
24 months unemployed	0.0321***	0.0236***	0.0346***	0.0317***	0.0350***	379,546
Previous permanent	0.0076*	-0.0055	0.0300***	0.0055	0.0398***	162,694
Previous not automotive	0.0242***	-0.0026	0.0384***	0.0239***	0.0263***	1,090,528
Only general regime	0.0238***	0.0063**	0.0360***	0.0225***	0.0349***	1,025,150
<i>IFR aggregation schemes</i>						
15 Groups	0.0280***	0.0077***	0.0426***	0.0263***	0.0427***	1,095,924
17 Groups	0.0248***	0.0067***	0.0372***	0.0233***	0.0376***	1,095,924
20 Groups	0.0241***	0.0067***	0.0359***	0.0227***	0.0355***	1,095,924
<i>Migration</i>						
Non-neighbouring NUTS3	0.0242***	0.0067***	0.0362***	0.0240***	0.0289***	1,095,924
<i>Spell length</i>						
> 180 days	0.0270***	0.0136***	0.0420***	0.0254***	0.0396***	435,709
> 360 days	0.0242***	0.0115**	0.0416***	0.0219***	0.0483***	204,360
<i>Controls</i>						
Drop indiv. effect	0.0241***	0.0065***	0.0361***	0.0227***	0.0356***	1,095,924
Drop ΔICT	0.0242***	0.0066***	0.0361***	0.0228***	0.0357***	1,095,924
Drop indiv. effect and ΔICT	0.0241***	0.0065***	0.0361***	0.0227***	0.0356***	1,095,924
<i>Fixed effects</i>						
Add Current spell FE	0.0230***	0.0134***	0.0295***	0.0215***	0.0353***	1,095,924
<i>Sector</i>						
1-dig $\Delta 1$ -dig	0.0242***	0.0066***	0.0361***	0.0228***	0.0357***	1,095,924
1-dig $\Delta IFR15(2$ -dig)	0.0236***	-0.0043	0.0318***	0.0221***	0.0357***	1,095,924
1-dig $\Delta IFR19(2$ -dig)	0.0238***	-0.0042	0.0316***	0.0224***	0.0360***	1,095,924
IFR15(1-dig) $\Delta 1$ -dig	0.0046*	-0.0127***	0.0158***	0.0029	0.0165***	1,095,924
IFR15(1-dig) $\Delta IFR15(2$ -dig)	0.0046*	-0.0221***	0.0129***	0.0029	0.0171***	1,095,924
IFR15(1-dig) $\Delta IFR19(2$ -dig)	0.0048*	-0.0233***	0.0124***	0.0031	0.0175***	1,095,924
IFR15(2-dig) $\Delta 1$ -dig	0.0044*	-0.0129***	0.0157***	0.0028	0.0166***	1,095,924
IFR15(2-dig) $\Delta IFR15(2$ -dig)	0.0044*	-0.0224***	0.0129***	0.0027	0.0171***	1,095,924
IFR15(2-dig) $\Delta IFR19(2$ -dig)	0.0047*	-0.0236***	0.0124***	0.0029	0.0175***	1,095,924
IFR19(1-dig) $\Delta 1$ -dig	0.0056**	-0.0117***	0.0169***	0.0039	0.0179***	1,095,924
IFR19(1-dig) $\Delta IFR15(2$ -dig)	0.0056**	-0.0210***	0.0140***	0.0039	0.0185***	1,095,924
IFR19(1-dig) $\Delta IFR19(2$ -dig)	0.0056**	-0.0225***	0.0133***	0.0038	0.0185***	1,095,924
IFR19(2-dig) $\Delta 1$ -dig	0.0055*	-0.0119***	0.0168***	0.0038	0.0179***	1,095,924
IFR19(2-dig) $\Delta IFR15(2$ -dig)	0.0055*	-0.0213***	0.0139***	0.0037	0.0185***	1,095,924
IFR19(2-dig) $\Delta IFR19(2$ -dig)	0.0054*	-0.0228***	0.0132***	0.0037	0.0185***	1,095,924

Sources: MCVL and IFR, own calculations.

Robustness checks - Pay ratio (HS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-0.4582	0.7175**	-1.7492***	-0.4174	-0.6581	281,852
<i>Subsamples</i>						
Manufacturing	-0.5571**	0.1552	-1.3241**	-0.5986**	-0.3505	14,079
One transition	-0.4005	0.6536**	-1.9785***	-0.3609	-0.6182	130,907
Previous 6 months	-0.4112	0.6318**	-1.7589***	-0.4802	-0.0626	161,118
4 months unemployed	-0.9065*	1.2995	-1.7281***	-1.1918**	-0.0674	162,925
24 months unemployed	-1.3216**	0.2636	-1.8433***	-1.9471***	0.6878	86,975
Previous permanent	-0.3954	0.4843**	-1.7617***	-0.2744	-1.0697*	81,197
Previous not automotive	-1.0694*	1.0129	-2.0922***	-1.0168	-1.3321	281,383
Only general regime	-0.4065	0.7152**	-1.6462***	-0.3662	-0.6049	275,414
<i>IFR aggregation schemes</i>						
15 Groups	-0.1944	1.3435***	-2.2627***	-0.2868	0.2078	281,852
17 Groups	-0.2969	0.9139***	-1.6247***	-0.5269	0.7759	281,852
20 Groups	-0.5263*	0.6366**	-1.8026***	-0.4681	-0.8118	281,852
<i>Migration</i>						
Non-neighbouring NUTS3	-0.4601	0.7208**	-1.7569***	-0.5529*	0.3211	281,852
<i>Spell length</i>						
> 180 days	-0.0821	0.6914**	-1.1589**	-0.0499	-0.2372	167,473
> 360 days	-0.3715	0.5341	-1.6762***	-0.3286	-0.6022	103,398
<i>Controls</i>						
Drop indiv. effect	-0.4501	0.7014**	-1.7144***	-0.4092	-0.6508	281,852
Drop ΔICT	-0.4598	0.7133**	-1.7481***	-0.4189	-0.6610	281,852
Drop indiv. effect and ΔICT	-0.4518	0.6970**	-1.7132***	-0.4107	-0.6538	281,852
<i>Fixed effects</i>						
Add Current spell FE	-0.4100	0.1457	-1.0138*	-0.3860	-0.5274	281,852
<i>Sector</i>						
1-dig $\Delta 1$ -dig	-0.4582	0.7175**	-1.7492***	-0.4174	-0.6581	281,852
1-dig $\Delta IFR15(2\text{-dig})$	-0.4456	0.8656**	-1.2008***	-0.4087	-0.6270	281,852
1-dig $\Delta IFR19(2\text{-dig})$	-0.4455	0.9240***	-1.2079***	-0.4085	-0.6272	281,852
IFR15(1-dig) $\Delta 1$ -dig	-0.8812*	0.4688	-2.0638***	-0.8534*	-1.0241	281,852
IFR15(1-dig) $\Delta IFR15(2\text{-dig})$	-0.8732*	0.5678	-1.5700***	-0.8492*	-0.9966	281,852
IFR15(1-dig) $\Delta IFR19(2\text{-dig})$	-0.8682*	0.6226	-1.5447***	-0.8438*	-0.9940	281,852
IFR15(2-dig) $\Delta 1$ -dig	-0.9010*	0.3424	-1.9900***	-0.8610*	-1.1064	281,852
IFR15(2-dig) $\Delta IFR15(2\text{-dig})$	-0.8920*	0.3693	-1.5018***	-0.8588*	-1.0629	281,852
IFR15(2-dig) $\Delta IFR19(2\text{-dig})$	-0.8841*	0.4234	-1.4773***	-0.8501*	-1.0586	281,852
IFR19(1-dig) $\Delta 1$ -dig	-0.5875	0.7107	-1.7564***	-0.5555	-0.7533	281,852
IFR19(1-dig) $\Delta IFR15(2\text{-dig})$	-0.5834	0.7620	-1.2649**	-0.5550	-0.7302	281,852
IFR19(1-dig) $\Delta IFR19(2\text{-dig})$	-0.5773	0.8182	-1.2473**	-0.5485	-0.7264	281,852
IFR19(2-dig) $\Delta 1$ -dig	-0.6105	0.5822	-1.6842***	-0.5664	-0.8389	281,852
IFR19(2-dig) $\Delta IFR15(2\text{-dig})$	-0.6078	0.5614	-1.2000**	-0.5702	-0.8025	281,852
IFR19(2-dig) $\Delta IFR19(2\text{-dig})$	-0.5981	0.6182	-1.1820**	-0.5599	-0.7962	281,852

Sources: MCVL and IFR, own calculations.

Robustness checks - Pay ratio (MLS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-2.2805***	-0.3955**	-3.5677***	-2.1045***	-3.7693***	1,095,924
<i>Subsamples</i>						
Manufacturing	-2.0387***	-0.8433***	-2.8667***	-1.8684***	-3.4816***	120,189
One transition	-2.4289***	-0.4196**	-4.1103***	-2.2530***	-3.9145***	393,620
Previous 6 months	-2.5219***	-0.3580*	-4.3200***	-2.2916***	-4.4186***	440,058
4 months unemployed	-3.0283***	-1.2288***	-3.6989***	-2.8839***	-3.9816***	727,763
24 months unemployed	-3.3412***	-1.1650***	-3.9917***	-3.2625***	-3.8649***	379,546
Previous permanent	-0.9537***	0.2785	-3.0565***	-0.7666***	-3.7844***	162,694
Previous not automotive	-1.5998***	2.1023***	-3.5649***	-1.2920***	-3.4770***	1,090,528
Only general regime	-2.2410***	-0.4030**	-3.5168***	-2.0805***	-3.6327***	1,025,150
<i>IFR aggregation schemes</i>						
15 Groups	-2.7692***	-0.4194**	-4.4433***	-2.5783***	-4.3995***	1,095,924
17 Groups	-2.3606***	-0.4214**	-3.6947***	-2.1920***	-3.7914***	1,095,924
20 Groups	-2.2725***	-0.4068**	-3.5461***	-2.0962***	-3.7637***	1,095,924
<i>Migration</i>						
Non-neighbouring NUTS3	-2.2780***	-0.3939**	-3.5646***	-2.2202***	-3.6103***	1,095,924
<i>Spell length</i>						
> 180 days	-2.5298***	-0.7306***	-4.5426***	-2.2826***	-4.4799***	435,709
> 360 days	-2.4713***	-0.7612**	-4.8254***	-2.1907***	-5.4042***	204,360
<i>Controls</i>						
Drop indiv. effect	-2.1735***	-0.2277	-3.5030***	-1.9938***	-3.6937***	1,095,924
Drop ΔICT	-2.2803***	-0.3955**	-3.5674***	-2.1043***	-3.7690***	1,095,924
Drop indiv. effect and ΔICT	-2.1734***	-0.2277	-3.5028***	-1.9937***	-3.6935***	1,095,924
<i>Fixed effects</i>						
Add Current spell FE	-2.1625***	-0.9147***	-3.0209***	-1.9766***	-3.7340***	1,095,924
<i>Sector</i>						
1-dig $\Delta 1$ -dig	-2.2805***	-0.3955**	-3.5677***	-2.1045***	-3.7693***	1,095,924
1-dig $\Delta IFR15(2$ -dig)	-2.2757***	0.4283**	-3.0752***	-2.0987***	-3.7731***	1,095,924
1-dig $\Delta IFR19(2$ -dig)	-2.2791***	0.3750*	-3.0130***	-2.1022***	-3.7762***	1,095,924
IFR15(1-dig) $\Delta 1$ -dig	-0.2908	1.5940***	-1.5128***	-0.0832	-1.8099***	1,095,924
IFR15(1-dig) $\Delta IFR15(2$ -dig)	-0.2882	2.2905***	-1.0966***	-0.0796	-1.8141***	1,095,924
IFR15(1-dig) $\Delta IFR19(2$ -dig)	-0.2898	2.3531***	-1.0076***	-0.0811	-1.8168***	1,095,924
IFR15(2-dig) $\Delta 1$ -dig	-0.2773	1.6018***	-1.4955***	-0.0697	-1.7962***	1,095,924
IFR15(2-dig) $\Delta IFR15(2$ -dig)	-0.2744	2.3083***	-1.0840***	-0.0659	-1.7998***	1,095,924
IFR15(2-dig) $\Delta IFR19(2$ -dig)	-0.2759	2.3705***	-0.9945***	-0.0673	-1.8024***	1,095,924
IFR19(1-dig) $\Delta 1$ -dig	-0.4312*	1.4539***	-1.6628***	-0.2225	-1.9888***	1,095,924
IFR19(1-dig) $\Delta IFR15(2$ -dig)	-0.4290*	2.1437***	-1.2371***	-0.2195	-1.9934***	1,095,924
IFR19(1-dig) $\Delta IFR19(2$ -dig)	-0.4283*	2.2148***	-1.1527***	-0.2187	-1.9932***	1,095,924
IFR19(2-dig) $\Delta 1$ -dig	-0.4183*	1.4612***	-1.6460***	-0.2096	-1.9759***	1,095,924
IFR19(2-dig) $\Delta IFR15(2$ -dig)	-0.4159	2.1607***	-1.2251***	-0.2063	-1.9799***	1,095,924
IFR19(2-dig) $\Delta IFR19(2$ -dig)	-0.4152	2.2314***	-1.1404***	-0.2056	-1.9797***	1,095,924

Sources: MCVL and IFR, own calculations.

Robustness checks - Lower skill (HS)

[Back](#)

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0131**	0.0087	0.0179**	0.0121*	0.0179**	281,852
<i>Subsamples</i>						
Manufacturing	0.0070	-0.0051	0.0200***	0.0074	0.0047	14,079
One transition	0.0056	0.0034	0.0090	0.0046	0.0117	130,907
Previous 6 months	0.0090	0.0079	0.0104	0.0079	0.0147	161,118
4 months unemployed	0.0040	0.0332**	-0.0068	0.0021	0.0097	162,925
24 months unemployed	0.0038	0.0296*	-0.0047	0.0050	-0.0001	86,975
Previous permanent	0.0018	-0.0025	0.0085	0.0011	0.0058	81,197
Previous not automotive	0.0495***	0.0720***	0.0385***	0.0550***	0.0223	281,383
Only general regime	0.0131**	0.0088	0.0179**	0.0119*	0.0192**	275,414
<i>IFR aggregation schemes</i>						
15 Groups	-0.0010	0.0042	-0.0079	-0.0054	0.0186*	281,852
17 Groups	0.0072	0.0038	0.0108	0.0068	0.0087	281,852
20 Groups	0.0131**	0.0086	0.0180**	0.0121*	0.0182**	281,852
<i>Migration</i>						
Non-neighbouring NUTS3	0.0130**	0.0089	0.0175*	0.0124*	0.0182*	281,852
<i>Spell length</i>						
> 180 days	0.0050	0.0060	0.0037	0.0033	0.0133	167,473
> 360 days	0.0021	0.0036	0.0001	0.0032	-0.0037	103,398
<i>Controls</i>						
Drop indiv. effect	0.0140**	0.0070	0.0217**	0.0130	0.0187**	281,852
Drop ΔICT	0.0131**	0.0088	0.0179**	0.0121*	0.0179**	281,852
Drop indiv. effect and ΔICT	0.0140**	0.0070	0.0217**	0.0130	0.0187**	281,852
<i>Fixed effects</i>						
Add Current spell FE	0.0126**	0.0050	0.0209**	0.0116*	0.0178**	281,852
<i>Sector</i>						
1-dig Δ 1-dig	0.0131**	0.0087	0.0179**	0.0121*	0.0179**	281,852
1-dig Δ IFR15(2-dig)	0.0099*	0.0029	0.0139*	0.0096	0.0115	281,852
1-dig Δ IFR19(2-dig)	0.0099*	0.0001	0.0153**	0.0095	0.0116	281,852
IFR15(1-dig) Δ 1-dig	0.0217***	0.0180**	0.0249***	0.0209**	0.0259***	281,852
IFR15(1-dig) Δ IFR15(2-dig)	0.0191***	0.0125**	0.0223***	0.0190**	0.0200**	281,852
IFR15(1-dig) Δ IFR19(2-dig)	0.0181***	0.0085	0.0225***	0.0178**	0.0194*	281,852
IFR15(2-dig) Δ 1-dig	0.0216***	0.0163**	0.0262***	0.0209**	0.0247**	281,852
IFR15(2-dig) Δ IFR15(2-dig)	0.0191***	0.0111*	0.0230***	0.0192**	0.0189*	281,852
IFR15(2-dig) Δ IFR19(2-dig)	0.0181***	0.0071	0.0231***	0.0181**	0.0184*	281,852
IFR19(1-dig) Δ 1-dig	0.0161**	0.0132*	0.0187*	0.0153*	0.0204**	281,852
IFR19(1-dig) Δ IFR15(2-dig)	0.0144**	0.0088	0.0172**	0.0142*	0.0155	281,852
IFR19(1-dig) Δ IFR19(2-dig)	0.0132*	0.0046	0.0173**	0.0129*	0.0147	281,852
IFR19(2-dig) Δ 1-dig	0.0159**	0.0114	0.0200**	0.0153*	0.0193*	281,852
IFR19(2-dig) Δ IFR15(2-dig)	0.0144**	0.0074	0.0179**	0.0144*	0.0145	281,852
IFR19(2-dig) Δ IFR19(2-dig)	0.0132*	0.0032	0.0179**	0.0131*	0.0136	281,852

Sources: MCVL and IFR, own calculations.

Robustness checks - Lower skill (MLS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0107***	0.0041***	0.0152***	0.0114***	0.0048**	1,095,924
<i>Subsamples</i>						
Manufacturing	0.0099***	0.0039***	0.0140***	0.0099***	0.0100***	120,189
One transition	0.0091***	0.0002	0.0165***	0.0096***	0.0047	393,620
Previous 6 months	0.0109***	0.0017	0.0185***	0.0113***	0.0076**	440,058
4 months unemployed	0.0136***	0.0135***	0.0137***	0.0150***	0.0043	727,763
24 months unemployed	0.0139***	0.0168***	0.0131***	0.0150***	0.0066	379,546
Previous permanent	-0.0017	-0.0063***	0.0061*	-0.0019	0.0006	162,694
Previous not automotive	0.0019	0.0004	0.0027	0.0039*	-0.0102**	1,090,528
Only general regime	0.0109***	0.0035**	0.0160***	0.0115***	0.0057**	1,025,150
<i>IFR aggregation schemes</i>						
15 Groups	0.0104***	0.0032**	0.0155***	0.0113***	0.0024	1,095,924
17 Groups	0.0106***	0.0036**	0.0154***	0.0113***	0.0047*	1,095,924
20 Groups	0.0107***	0.0041***	0.0152***	0.0114***	0.0049**	1,095,924
<i>Migration</i>						
Non-neighbouring NUTS3	0.0107***	0.0041***	0.0152***	0.0112***	-0.0004	1,095,924
<i>Spell length</i>						
> 180 days	0.0063***	0.0047***	0.0080***	0.0067***	0.0033	435,709
> 360 days	0.0033**	0.0010	0.0064**	0.0031**	0.0053	204,360
<i>Controls</i>						
Drop indiv. effect	0.0105***	0.0037**	0.0151***	0.0111***	0.0047*	1,095,924
Drop ΔICT	0.0107***	0.0041***	0.0153***	0.0114***	0.0048**	1,095,924
Drop indiv. effect and ΔICT	0.0105***	0.0037**	0.0151***	0.0111***	0.0047*	1,095,924
<i>Fixed effects</i>						
Add Current spell FE	0.0095***	0.0057***	0.0122***	0.0101***	0.0048**	1,095,924
<i>Sector</i>						
1-dig $\Delta 1$ -dig	0.0107***	0.0041***	0.0152***	0.0114***	0.0048**	1,095,924
1-dig $\Delta IFR15(2$ -dig)	0.0101***	-0.0058***	0.0149***	0.0108***	0.0049**	1,095,924
1-dig $\Delta IFR19(2$ -dig)	0.0104***	-0.0057***	0.0149***	0.0110***	0.0051**	1,095,924
IFR15(1-dig) $\Delta 1$ -dig	0.0016	-0.0048**	0.0058***	0.0023	-0.0034	1,095,924
IFR15(1-dig) $\Delta IFR15(2$ -dig)	0.0016	-0.0129***	0.0062***	0.0023	-0.0028	1,095,924
IFR15(1-dig) $\Delta IFR19(2$ -dig)	0.0019	-0.0133***	0.0060***	0.0025	-0.0025	1,095,924
IFR15(2-dig) $\Delta 1$ -dig	0.0017	-0.0048**	0.0059***	0.0023	-0.0032	1,095,924
IFR15(2-dig) $\Delta IFR15(2$ -dig)	0.0017	-0.0129***	0.0062***	0.0023	-0.0027	1,095,924
IFR15(2-dig) $\Delta IFR19(2$ -dig)	0.0019	-0.0134***	0.0061***	0.0025	-0.0023	1,095,924
IFR19(1-dig) $\Delta 1$ -dig	0.0007	-0.0056***	0.0049**	0.0014	-0.0043	1,095,924
IFR19(1-dig) $\Delta IFR15(2$ -dig)	0.0008	-0.0136***	0.0053**	0.0014	-0.0038	1,095,924
IFR19(1-dig) $\Delta IFR19(2$ -dig)	0.0007	-0.0144***	0.0049**	0.0013	-0.0037	1,095,924
IFR19(2-dig) $\Delta 1$ -dig	0.0008	-0.0057***	0.0050**	0.0014	-0.0041	1,095,924
IFR19(2-dig) $\Delta IFR15(2$ -dig)	0.0008	-0.0136***	0.0053***	0.0014	-0.0036	1,095,924
IFR19(2-dig) $\Delta IFR19(2$ -dig)	0.0007	-0.0144***	0.0049**	0.0013	-0.0035	1,095,924

Sources: MCVL and IFR, own calculations.

Robustness checks - Temporary contract (HS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
<i>Subsamples</i>						
Manufacturing	0.0003	-0.0074*	0.0116	0.0026	-0.0131	7,378
One transition	-0.0005	-0.0061	0.0101	0.0014	-0.0122	59,307
Previous 6 months	-0.0007	-0.0041	0.0051	0.0019	-0.0163*	67,544
4 months unemployed	-0.0135*	-0.0009	-0.0179**	-0.0085	-0.0258**	38,153
24 months unemployed	-0.0220**	-0.0149	-0.0240**	-0.0134	-0.0458***	23,832
Previous permanent	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
Previous not automotive	0.0337***	0.0319***	0.0347**	0.0358***	0.0204	80,924
Only general regime	0.0021	-0.0037	0.0111	0.0036	-0.0063	79,745
<i>IFR aggregation schemes</i>						
15 Groups	-0.0117***	-0.0104**	-0.0141	-0.0106**	-0.0167*	81,197
17 Groups	-0.0050	-0.0102**	0.0029	-0.0028	-0.0168*	81,197
20 Groups	0.0020	-0.0040	0.0115	0.0039	-0.0082	81,197
<i>Migration</i>						
Non-neighbouring NUTS3	0.0018	-0.0040	0.0108	0.0038	-0.0139*	81,197
<i>Spell length</i>						
> 180 days	-0.0037	-0.0038	-0.0034	-0.0025	-0.0105	68,569
> 360 days	-0.0019	-0.0012	-0.0032	-0.0020	-0.0016	56,063
<i>Controls</i>						
Drop indiv. effect	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
Drop ΔICT	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
Drop indiv. effect and ΔICT	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
<i>Fixed effects</i>						
Add Current spell FE	0.0040	-0.0037	0.0158	0.0060	-0.0071	81,197
<i>Sector</i>						
1-dig Δ 1-dig	0.0018	-0.0039	0.0107	0.0036	-0.0080	81,197
1-dig Δ IFR15(2-dig)	0.0001	-0.0062**	0.0057	0.0020	-0.0109	81,197
1-dig Δ IFR19(2-dig)	-0.0001	-0.0060*	0.0051	0.0019	-0.0110	81,197
IFR15(1-dig) Δ 1-dig	0.0071	-0.0005	0.0163	0.0088	-0.0036	81,197
IFR15(1-dig) Δ IFR15(2-dig)	0.0055	-0.0025	0.0113	0.0074	-0.0067	81,197
IFR15(1-dig) Δ IFR19(2-dig)	0.0043	-0.0031	0.0095	0.0062	-0.0075	81,197
IFR15(2-dig) Δ 1-dig	0.0070	-0.0011	0.0167	0.0087	-0.0035	81,197
IFR15(2-dig) Δ IFR15(2-dig)	0.0056	-0.0023	0.0114	0.0076	-0.0065	81,197
IFR15(2-dig) Δ IFR19(2-dig)	0.0045	-0.0030	0.0097	0.0064	-0.0074	81,197
IFR19(1-dig) Δ 1-dig	0.0015	-0.0052	0.0099	0.0031	-0.0084	81,197
IFR19(1-dig) Δ IFR15(2-dig)	0.0007	-0.0059	0.0060	0.0026	-0.0106	81,197
IFR19(1-dig) Δ IFR19(2-dig)	-0.0005	-0.0066	0.0042	0.0013	-0.0115	81,197
IFR19(2-dig) Δ 1-dig	0.0015	-0.0057	0.0104	0.0030	-0.0082	81,197
IFR19(2-dig) Δ IFR15(2-dig)	0.0009	-0.0057	0.0062	0.0028	-0.0104	81,197
IFR19(2-dig) Δ IFR19(2-dig)	-0.0003	-0.0065	0.0044	0.0015	-0.0113	81,197

Sources: MCVL and IFR, own calculations.

Robustness checks - Temporary contract (MLS)

Back

	ΔExp	$\Delta Sec = 0$	$\Delta Sec = 1$	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
<i>Subsamples</i>						
Manufacturing	-0.0094***	-0.0218***	0.0109	-0.0102***	0.0026	25,562
One transition	-0.0127***	-0.0265***	0.0107*	-0.0133***	-0.0042	123,643
Previous 6 months	-0.0118***	-0.0229***	0.0074	-0.0126***	0.0001	128,201
4 months unemployed	-0.0007	0.0050	-0.0031	-0.0005	-0.0020	91,647
24 months unemployed	-0.0010	0.0026	-0.0020	-0.0007	-0.0027	56,406
Previous permanent	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
Previous not automotive	0.0091	-0.0187**	0.0287***	0.0119	-0.0154	161,515
Only general regime	-0.0102***	-0.0227***	0.0115*	-0.0114***	0.0083	154,127
<i>IFR aggregation schemes</i>						
15 Groups	-0.0166***	-0.0243***	-0.0016	-0.0180***	0.0053	162,694
17 Groups	-0.0125***	-0.0249***	0.0091	-0.0136***	0.0042	162,694
20 Groups	-0.0113***	-0.0233***	0.0093	-0.0121***	0.0014	162,694
<i>Migration</i>						
Non-neighbouring NUTS3	-0.0115***	-0.0238***	0.0094	-0.0116***	-0.0087	162,694
<i>Spell length</i>						
> 180 days	-0.0090***	-0.0162***	0.0060	-0.0100***	0.0108	122,746
> 360 days	-0.0081***	-0.0112***	-0.0017	-0.0076**	-0.0170	91,795
<i>Controls</i>						
Drop indiv. effect	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
Drop ΔICT	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
Drop indiv. effect and ΔICT	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
<i>Fixed effects</i>						
Add Current spell FE	-0.0103***	-0.0203***	0.0066	-0.0109***	-0.0006	162,694
<i>Sector</i>						
1-dig $\Delta 1$ -dig	-0.0115***	-0.0236***	0.0092	-0.0123***	0.0015	162,694
1-dig $\Delta IFR15(2\text{-dig})$	-0.0127***	-0.0354***	0.0074	-0.0134***	-0.0006	162,694
1-dig $\Delta IFR19(2\text{-dig})$	-0.0121***	-0.0352***	0.0074	-0.0130***	0.0012	162,694
IFR15(1-dig) $\Delta 1$ -dig	0.0025	-0.0121***	0.0228***	0.0014	0.0162**	162,694
IFR15(1-dig) $\Delta IFR15(2\text{-dig})$	0.0024	-0.0226***	0.0215***	0.0014	0.0151**	162,694
IFR15(1-dig) $\Delta IFR19(2\text{-dig})$	0.0030	-0.0228***	0.0211***	0.0019	0.0179**	162,694
IFR15(2-dig) $\Delta 1$ -dig	0.0027	-0.0125***	0.0239***	0.0015	0.0177**	162,694
IFR15(2-dig) $\Delta IFR15(2\text{-dig})$	0.0027	-0.0227***	0.0220***	0.0016	0.0162**	162,694
IFR15(2-dig) $\Delta IFR19(2\text{-dig})$	0.0033	-0.0229***	0.0216***	0.0021	0.0190***	162,694
IFR19(1-dig) $\Delta 1$ -dig	-0.0021	-0.0156***	0.0178**	-0.0030	0.0104	162,694
IFR19(1-dig) $\Delta IFR15(2\text{-dig})$	-0.0022	-0.0261***	0.0169***	-0.0031	0.0094	162,694
IFR19(1-dig) $\Delta IFR19(2\text{-dig})$	-0.0023	-0.0266***	0.0158**	-0.0033	0.0113	162,694
IFR19(2-dig) $\Delta 1$ -dig	-0.0020	-0.0160***	0.0188**	-0.0030	0.0117	162,694
IFR19(2-dig) $\Delta IFR15(2\text{-dig})$	-0.0020	-0.0262***	0.0173***	-0.0029	0.0104	162,694
IFR19(2-dig) $\Delta IFR19(2\text{-dig})$	-0.0020	-0.0267***	0.0162**	-0.0031	0.0123*	162,694

Sources: MCVL and IFR, own calculations.

Robustness checks - TEA (HS)

Back

	ΔExp	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0037	0.0058**	-0.0063	278,770
<i>Subsamples</i>				
Manufacturing	0.0042*	0.0055**	-0.0020	14,079
One transition	0.0008	0.0020	-0.0059	130,907
Previous 6 months	0.0022	0.0037	-0.0053*	161,118
4 months unemployed	0.0022	0.0063	-0.0100*	162,925
24 months unemployed	0.0072	0.0117*	-0.0073*	86,975
Previous permanent	0.0009	0.0011	0.0001	81,197
Previous not automotive	0.0097**	0.0142***	-0.0127	281,383
Only general regime	0.0036	0.0056**	-0.0063	275,414
<i>IFR aggregation schemes</i>				
15 Groups	0.0012	0.0032	-0.0074**	281,852
17 Groups	0.0020	0.0043	-0.0086**	281,852
20 Groups	0.0033	0.0051**	-0.0060	281,852
<i>Migration</i>				
Non-neighbouring NUTS3	0.0037	0.0052**	-0.0091**	281,852
<i>Spell length</i>				
> 180 days	0.0006	0.0004	0.0015	167,473
> 360 days	0.0002	0.0001	0.0008	103,398
<i>Controls</i>				
Drop indiv. effect	0.0037	0.0057**	-0.0062	281,852
Drop ΔICT	0.0037	0.0057**	-0.0062	281,852
Drop indiv. effect and ΔICT	0.0037	0.0057**	-0.0062	281,852
<i>Fixed effects</i>				
Add Current spell FE	0.0014	0.0033*	-0.0081**	281,852
<i>Sector</i>				
IFR15(1-dig)	0.0002	0.0021	-0.0097**	281,852
IFR15(2-dig)	0.0002	0.0021	-0.0097**	281,852
IFR19(1-dig)	-0.0008	0.0011	-0.0108**	281,852
IFR19(2-dig)	-0.0008	0.0011	-0.0108**	281,852

Sources: MCVL and IFR, own calculations.

Robustness checks - TEA (MLS)

Back

	ΔExp	$\Delta NUTS = 0$	$\Delta NUTS = 1$	N
Baseline	0.0141***	0.0154***	0.0033	1,025,572
<i>Subsamples</i>				
Manufacturing	0.0114***	0.0120***	0.0064**	120,189
One transition	0.0125***	0.0136***	0.0034	393,620
Previous 6 months	0.0141***	0.0150***	0.0065	440,058
4 months unemployed	0.0170***	0.0188***	0.0052*	727,763
24 months unemployed	0.0160***	0.0180***	0.0025	379,546
Previous permanent	0.0021	0.0016	0.0099	162,694
Previous not automotive	0.0101***	0.0123***	-0.0037	1,090,528
Only general regime	0.0142***	0.0154***	0.0037	1,025,150
<i>IFR aggregation schemes</i>				
15 Groups	0.0157***	0.0174***	0.0018	1,095,924
17 Groups	0.0147***	0.0161***	0.0028	1,095,924
20 Groups	0.0140***	0.0153***	0.0029	1,095,924
<i>Migration</i>				
Non-neighbouring NUTS3	0.0142***	0.0150***	-0.0050*	1,095,924
<i>Spell length</i>				
> 180 days	0.0038***	0.0040***	0.0022	435,709
> 360 days	0.0006	0.0009*	-0.0032	204,360
<i>Controls</i>				
Drop indiv. effect	0.0146***	0.0159***	0.0033	1,095,924
Drop ΔICT	0.0142***	0.0156***	0.0031	1,095,924
Drop indiv. effect and ΔICT	0.0146***	0.0159***	0.0033	1,095,924
<i>Fixed effects</i>				
Add Current spell FE	0.0080***	0.0090***	-0.0006	1,095,924
<i>Sector</i>				
IFR15(1-dig)	0.0002	0.0017	-0.0102***	1,095,924
IFR15(2-dig)	0.0001	0.0015	-0.0103***	1,095,924
IFR19(1-dig)	0.0006	0.0020	-0.0098***	1,095,924
IFR19(2-dig)	0.0005	0.0018	-0.0100***	1,095,924

Sources: MCVL and IFR, own calculations.