Automating Labor: Evidence from Firm-level Patent Data

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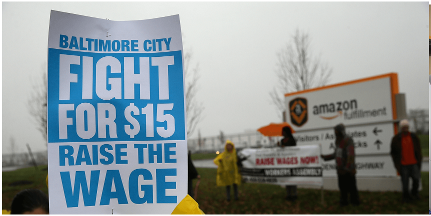
Do Higher Wages Lead to More Innovation in Automation?



- Large body of work on the negative impact of automation technologies on employment and wages for low/middle-skill workers.
- But very little is known about the impact of wages on automation innovations.

This paper

- Goal assessing by how much do (low-skill) wages affect automation innovations?
- Two challenges:
- Identifying *automation innovation:* Use patent data and classify patents as automation / non-automation using text-analysis.
  - Provide a new measure of automation in machinery, broader than what is typically used.
  - Our measure strongly predicts declines in routine occupations in manufacturing
- Establishing *causal effect* of wages on innovation: Exploit firm-level variations in exposure to markets.
  - Use the method of Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (ADHMV, 2016).
  - Large positive effect of low-skill wages on automation.
  - Event study: Hartz reforms.

Literature Review (1)

- Very large empirical literature on the impact of automation technologies on wages/employment:
  - Autor, Levy and Murnane (2003), Autor and Dorn (2013), Acemoglu and Restrepo (2017), many more....
- Some on how wages affect the adoption of automation technology:
  - Acemoglu and Finkelstein (2008), Lewis (2011), Hornbeck and Naidu (2014)
  - Lordan and Neumark (2017): minimum wage hikes displace workers in automatable jobs.
  - Acemoglu and Restrepo (2018): demographics and robot adoption
- Clear theoretical argument that higher wages should lead to more labor-saving innovation:
  - Habakkuk (1962), Zeira (1998), Acemoglu (2010), Hémous and Olsen (2016), Acemoglu and Restrepo (2018).

Literature Review (2)

- Essentially nothing on wages ⇒ innovation of automation technology:
  - Bena and Simintzi (2017): firms with a better access to the Chinese labor market decrease their share of process innovations after the 1999 U.S.-China trade agreement.
- Plenty of evidence on the endogeneity of the direction of technical change from other contexts:
  - Acemoglu and Linn (2004), Hanlon (2015), Newell, Jaffe and Stavins (1999), Popp (2002), Hassler, Krussell and Olovsson (2016), Calel and Dechezleprêtre (2016).
  - ADHMV: use firm-level variations in gas prices to show that higher gas prices lead firms in the auto industry to engage in more clean and less dirty innovations. Adapt the methodology to wages and automation innovations.
    - Method used by Noailly and Smeets (2015), Coelli, Moxnes and Ulltveit-Moe (2017), Aghion, Bénabou, Martin and Roulet (2019).

Outline

Global patent data and text for a subset of patents

- European Patent Office (EPO) provides:
- The World Patent Statistical Database (PATSTAT) contains *bibliographical* information for the universe of patents, including:
  - *Patent family* (same innovation - different geographical offices)
  - *Technological codes* (IPC/CPC);
  - *Year* of first filing;
  - *Location* of inventors;
  - *Firm* link from Orbis (for regressions)
  - $\rightarrow$ Will be used for regression analysis.
- EP full-text database contains the *full text* of patent applications at the EPO.
  - $\rightarrow$ Used to classify patents.

Procedure

- 1) Choose *keywords* concerning automation from the literature;
- 2) Select IPC/CPC codes in “machinery";
- 3) Compute the share of patents with at least one keyword for each IPC/CPC code;
- 4) Identify automation patent codes as those with a share above a cut-off measure;
- 5) Consider all patents with an automation code as automation patents.

Advantages of classifying IPC/CPC codes

- Advantages of classifying IPC/CPC codes (and not directly patents)
  - IPC/CPC codes are informative and used for other classifications (e.g. green technologies)
  - If particular wording is only a signal of underlying characteristic (of IPC code), i.e. an automation patent can be written w/o "automation" words.
  - Allows for the classification of all patents (also those w/o text, non-EPO patents).

Choosing automation keywords based on SMT

- Identify automation technologies from the Survey of Manufacturing Technology used by Doms, Dunne, Troske (1997):
  - **Computer Numerical Control**: (CNC or numeric* controlled) or (NC with key terms).
  - **CAD/CAM:** (computer aided (or similar) with keywords) or (CAD/CAM with key terms).
  - **Flexible manufacturing.** *Flexible manufacturing*
  - **Programmable logic controller**: *Programmable logic controller* or *PLC* (w/o power line),
  - **Robot**: Robot* (w/o surgical or medical)
- Plus a few:
  - **Automation**: *(Automation* or *automatization)* or (*automat** at least 5 times or twice with key terms)
  - **Labor**: Laborious, labor, labour.
  - **3D printing**: (3D print or additive manufacturing)
- key terms: machine, apparatus, equipment, manufacturing, ...

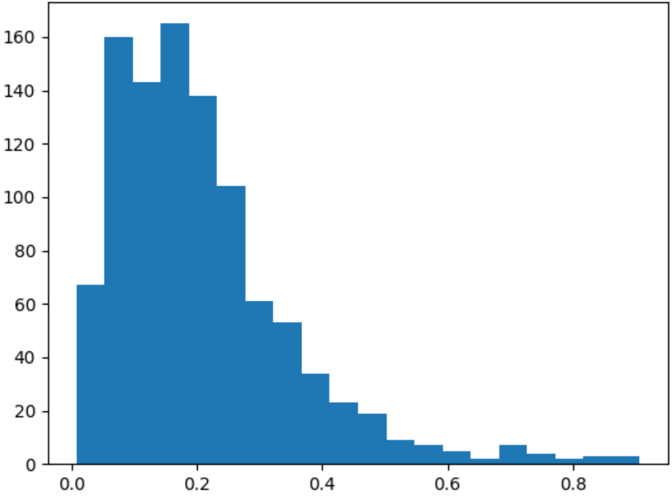
IPC/CPC classification

- IPC/CPC classfication is hierarchical:
  - classes 3 digit codes (B25: “hand tools; portable power-driven tools; handles for hand implements; workshop equipment and manipulators"),
  - subclasses have 4 digit codes (B25J: “manipulators; chambers provided with manipulation devices")
  - Main groups have 5 to 7 digit codes (for instance B25J 9: “programme-controlled manipulators")—referred to as 6 digit codes.

Computing an automation score

- Compute the frequency of patents with one keywords for:
  - 6-digit IPC/CPC codes;
  - pairs of 4-digit IPC/CPC codes;
  - pairs of 4-digit IPC/CPC codes with G05 (controlling; regulating) or G06 (computing; calculating; counting).
  - From 1980 for patent applications in English (1,538,370 patent applications).
- Restrict attention to IPC/CPC codes in machinery: technological fields of *machine tools*, *handling*, *textile and paper machines*, *other special machines* (with some adjustments). tech. fields

Histogram for IPC/CPC 6 digit codes



stats ipc

Defining automation patents

- Choose as thresholds the 90^{th} (0.386) and 95^{th} (0.477) percentiles of the 6 digit code distribution within machinery.
- IPC/CPC codes with a value above the threshold are "automation codes".
- All patents having one automation codes are automation patents (auto90 or auto95), also in PATSTAT.
- For main regression analysis, focus on biadic patents to exclude low quality patents.
  - biadic = patent families with patent applications in at least 2 countries (De Rassenfosse, Dernis, Guellec, Picci and van Pottelsberghe de la Potterie, 2013, and Dechezleprêtre, Ménière and Mohnen, 2017).

Automation patent with keyword in B65G 1

(19) Europäisches Patentamt / European Patent Office / Office européen des brevets

(11) **EP 2 604 550 B1**

(12) **EUROPEAN PATENT SPECIFICATION**

(45) Date of publication and mention of the grant of the patent:
01.10.2014 Bulletin 2014/40

(21) Application number: **10855839.6**

(22) Date of filing: **12.08.2010**

(51) Int Cl.:
B65G 1/137 (2006.01) ***B65G 1/04*** (2006.01)
B66F 9/07 (2006.01) ***A47B 96/02*** (2006.01)
B65G 1/08 (2006.01)

(86) International application number:
PCT/ES2010/070549

(87) International publication number:
WO 2012/020149 (16.02.2012 Gazette 2012/07)

(54) **AUTOMATIC PLANT FOR STORING AND DISPENSING GOODS**

AUTOMATISCHE ANLAGE ZUR AUFBEWAHRUNG UND AUSGABE VON WAREN

INSTALLATION AUTOMATIQUE POUR STOCKER ET DISTRIBUER DES PRODUITS

(84) Designated Contracting States:
AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO SE SI SK SM TR

(43) Date of publication of application:
19.06.2013 Bulletin 2013/25

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(56) References cited:
EP-A1- 2 113 473
CH-A5- 680 434
DE-A1- 4 336 885
DE-A1- 4 339 055
DE-A1- 19 635 396
DE-A1- 19 724 378
DE-U1- 20 021 440
US-A- 3 782 565
US-A1- 2010 168 910

Description

OBJECT OF THE INVENTION

[0001] The present invention, as expressed in the wording of this specification, relates to an automatic plant for storing and dispensing goods, essentially applicable to the pharmaceutical sector, although it is also applicable to any other sector needing to store and dispense different small-sized goods.

[0002] The products are stored in principle in modular shelves, which may be inclined or not, shelves that are part of characteristic modular shelving units that also configure an elongated shelving structure in the longitudinal direction.

[0003] Based on this premise, the essence of the invention is based on characteristic modular horizontal guides along which respective modular subsets (robots) move, for the loading and unloading of products with respect to the shelves of the modular shelving units, modular horizontal guides that can easily adapt to the required length of the elongated structure of shelving units, so that both loading and unloading subsets have a horizontal translation movement parallel to said elongate structure of shelving units and a vertical movement to access the different levels of the shelves where the products are stored.

Automation patent without keyword in B65G 1

(19) Europäisches Patentamt / European Patent Office / Office européen des brevets

(11) **EP 3 290 361 A1**

(12) **EUROPEAN PATENT APPLICATION**
published in accordance with Art. 153(4) EPC

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(51) Int Cl.:
B65G 1/137 *(2006.01)* ***G06K 17/00*** *(2006.01)*
G06Q 10/08 *(2012.01)*

(86) International application number:
PCT/JP2016/063339

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WO 2016/175280 (03.11.2016 Gazette 2016/44)

(84) Designated Contracting States:
AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO RS SE SI SK SM TR
Designated Extension States:
BA ME
Designated Validation States:
MA MD

(30) Priority: **28.04.2015 JP 2015091125**

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(54) **STORAGE CABINET**

TECHNICAL FIELD

[0001] The present invention relates to a storage cabinet that stores contents (items) such as products and goods.

BACKGROUND ART

[0002] A storage cabinet is known that manages contents (items) by using radio frequency identification (RFID) technology. The patent literature 1 for example describes that scanning is performed in a cabinet for monitoring a product including a RF tag for the purpose of searching for an expired product or a product that have been manufactured in a recalled lot.

[0004] The conventional storage cabinet such as one described above may be able to perform scanning an item such as a product in the cabinet by using RFID technology; however, it is necessary for an operator to visually check an expired product or a product that have been manufactured in a recalled lot and remove them from the cabinet. Thus, there is a drawback in the conventional storage cabinet that, in a case in which many products are stored in the storage cabinet for example, the operator cannot immediately recognize whether all products to be removed have been actually retrieved from the storage cabinet.

[0005] Particularly, in a case in which the storage cabinet is not connected to a network, the operator cannot check whether all products to be removed have been actually retrieved from the storage cabinet.

[0006] In view of the above, one of the aspects of the present invention is to provide a storage cabinet from which one can surely retrieve a desired item.

Trends in Automation

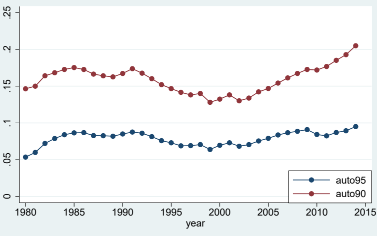

Figure: Share of automation patents in machinery worldwide.

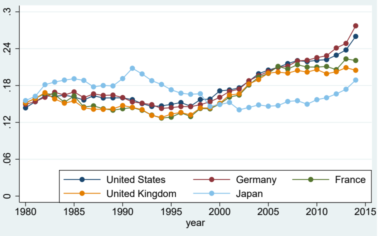

Figure: Share of automation patents (auto95) in machinery conditional on the patent being protected in the designated countries. Details

Outline

Correlation between our measure and robot intensity (IFR)

	(1) Across Countries	(2) Across US Industries	(3) Across German Industries
Share of automation patents in machinery (auto95)	0.383	0.602	0.560
Share of automation patents in machinery (auto90)	0.377	0.483	0.426
Share of robot patents in machinery (robot90)	0.365	0.682	0.546
Share of robot patents in machinery (robot80)	0.461	0.740	0.780
Number of observations	27	17	17

Note: This table reports correlations across countries or industries between shares of automation patents in machinery, robots patents in machinery and robot intensity. Robot intensity is measured as the difference between the stock of robots in 2011 and the stock of robots in 1997 (columns 1 and 3) or 2004 (column 2) over employment in each country (column 1) or each sector (columns 2 and 3) in 1997 (columns 1 and 3) or 2004 (column 2). Shares of automation and robot patents are computed over the time period 1997-2011 for columns (1) and (3) and over 2004-2011 for column (2).

by sector

Validation of automation measure

- Reproduce Autor, Levy and Murnane (ALM, 2003).
- Cross-section analysis on U.S. data from 1960 to 1998 of

$$\Delta T_{jk\theta} = \beta_0 + \beta_C \Delta C_j + \beta_{aut} aut_{jk\theta},$$

- $\Delta T_{jk\theta}$: change in tasks k in industry j during period θ
    - 5 types of tasks: non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual.
    - $\Delta T_{jk\theta}$: 10x the annual within industry change in task input measured in percentile of the 1960 task distribution.
- C_j: computerization in sector j (computed in 1984-1997).
- $aut_{j\theta}$: share of automation patents in machinery for industry j during period θ.
    - Allocate patents to sectors according to their IPC/CPC codes (Lybbert and Zolas, 2014)
- Very low correlation between $aut_{j\theta}$ and C_j: 0.05 or 0.016.

Changes in tasks intensity and automation (auto95) Details

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual	(6) Δ H/L
Panel A: 1970 - 80, n=67						
Share of automation	-1.29	5.42	-17.27***	-11.43**	-1.15	0.27***
patents in machinery	(5.10)	(6.27)	(6.59)	(5.59)	(7.46)	(0.07)
Δ Computer use	-6.86	-3.13	-19.51***	-3.46	14.87*	0.07
1984 - 1997	(5.72)	(7.04)	(7.41)	(6.28)	(8.38)	(0.08)
Intercept	1.06	2.31**	3.07**	2.69***	-1.75	0.05***
	(0.95)	(1.17)	(1.23)	(1.04)	(1.39)	(0.01)
R^2	0.02	0.01	0.20	0.07	0.05	0.21
Weighted mean Δ	-0.05	2.17	-0.90	1.49	0.42	0.07
Panel B: 1980 - 90, n=67						
Share of automation	10.09	19.05**	-30.00***	-21.61***	16.78***	1.33***
patents in machinery	(7.14)	(8.12)	(6.76)	(5.42)	(6.04)	(0.23)
Δ Computer use	24.80**	22.21*	-13.24	-0.42	-6.49	0.29
1984 - 1997	(10.43)	(11.85)	(9.87)	(7.91)	(8.82)	(0.33)
Intercept	-2.62	-0.65	2.15	1.20	-2.13	-0.04
	(1.70)	(1.93)	(1.61)	(1.29)	(1.44)	(0.05)
R^2	0.12	0.14	0.27	0.20	0.11	0.37
Weighted mean Δ	1.86	4.17	-2.22	-0.59	-1.74	0.11
Panel C: 1990 - 98, n=67						
Share of automation	11.06*	16.02*	-22.81***	-12.53**	6.66	0.77***
patents in machinery	(6.08)	(8.18)	(6.54)	(5.42)	(6.28)	(0.15)
Δ Computer use	26.77***	27.00**	-23.15**	-24.87***	7.48	0.66***
1984 - 1997	(8.35)	(11.23)	(8.98)	(7.44)	(8.62)	(0.20)
Intercept	-2.36*	-1.43	1.72	2.27*	-2.40*	-0.06*
	(1.37)	(1.84)	(1.47)	(1.22)	(1.41)	(0.03)
R^2	0.19	0.15	0.25	0.23	0.03	0.41
Weighted mean Δ	2.45	3.79	-3.44	-2.36	-0.79	0.09

Standard errors are in parentheses. Colums (1) to (5) of Panels A to C each presents a separate OLS regression of ten times the annual change in industry-level task input between the endpoints of the indicated time interval (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery (defined with the 95th percentile threshold) and the annual percentage point change in industry computer use during 1984 - 1997 as well as a constant. In Column (6), the dependent variable is the ratio of high-skill (college graduates) to low-skill (high-school graduates and dropouts) workers. Estimates are weighted by mean industry share of total employment in FTEs over the endpoints of the years used to form the dependent variable. * p<0.1; ** p<0.05; *** p<0.01

Outline

A (verbal) toy model

- Suppose a firm (Siemens) can invent new automation technology/machines and sell to customers who are other firms
- These firms can substitute between low-skill labor and a composite of high-skill labor and machines.
- They will be more willing buyers of new machines if
    - low-skill wages are high
    - high-skill wages are low.
- $\rightarrow$ the incentive of the firm (Siemens) to develop new automation technology depends on the wages their customers face. Formal model

Methodology (1)

- We want to carry a regression of the type:

$$\ln Aut_{i,t} = \beta_w \ln w_{i,t-2} + \beta_X X_{i,t-2} + \epsilon_{i,t}$$

  - with $Aut_{i,t}$: automation innovations by equipment manufacturers,
  - $w_{i,t-1}$ low-skill wages of the customers of equipment manufacturers.
  - $X_{i,t-1}$ other factors including high-skill wages.
- Huge concerns of endogeneity (including reverse causality) if
  - i is a country,
  - or i is a firm and $w_{i,t-1}$ is the actual wage paid by the firm's customers.

Methodology (2)

- Our solution is to adapt the methodology of ADHMV:
  - Equipment manufacturers are exporting firms which sell to different countries;
  - Build a weighted average of country-level low-skill wages representative of each firm's market.
- For firm i : Build firm-specific measure of the low-skill wage paid by their potential customers: $w_{i,t}$

$$w_{i,t} = \sum_c \omega_{i,c} w_{c,t}$$

  - $w_{c,t}$ is the low-skill wage in country c
  - $\omega_{i,c}$ is a fixed measure of the importance of market c for firm i, computed pre-sample.
- Identify the effect of wages on automation by exploiting how country-level trends in wages affect firms differently depending on their history (in the spirit of a shift-share instrument).

Implied Regression

- Firm's innovation in automation is described by Poisson:

$$PAT_{Aut,i,t} = \exp\left(\ \beta_{w_L} \ln w_{L,i,t-2} + \beta_X X_{i,t-2} + \delta_i + \delta_t\ \right) + \epsilon_{i,t}.$$

  - $PAT_{Aut,i,t}$: number of automation innovations by firm i at time t.
  - $w_{Li,t-2}$ low-skill wage faced by the **customers of firm** i at $t-2$, expect $\beta_{w_L} > 0$.
  - δ_i firm fixed effects and δ_t year fixed effects.

- $X_{i,t-2}$ vector of controls include:
  - other macro variables: high-skill wages (in log), GDP per capita, labor productivity in manufacturing, GDP gap.
  - firm's knowledge stocks in automation and other tech
  - firm's exposure to spillovers in automation and other tech.
- Time period 1995-2009 for RHS (because of wage data).

Macroeconomic Data

- Use macro data (low-skill wages, high-skill wages, GDP, etc...) from WIOD + Switzerland (Swiss statistics)
  - Focus on wages in the manufacturing sector.
  - Deflate by local manuf PPI and conv. to 1995 USD by exchange rate.
  - For 1995-2009 consistent data for 41 countries: all EU (except Croatia) + US, Canada, Japan, India, China, Korea, etc...

Country	Low-skill wages (1995$)		Skill-premium (HS wages/LS wages)	
	1995	2009	1995	2009
India	0.19	0.28	4.79	4.98
Mexico	0.89	0.61	3.90	4.21
Bulgaria	1.29	0.71	3.32	2.25
USA	11.57	13.67	2.46	3.02
Belgium	29.50	41.89	1.56	1.46
Sweden	19.92	42.16	1.73	1.33
Finland	23.41	43.63	1.20	1.46

Note: Wages data, taken from the World Input Output Database. Table shows manufacturing low-skill wages deflated by (manufacturing) producer price index and converted to US dollars using average 1995 exchange rates. Skill-premium is the ratio of high-skill to low-skill wages. Table shows the three countries with the lowest low-skill wages in 2009, the three with the highest and the United States.

Weights calculated using patent history and GDP

- $\omega_{i,c}$ is computed using a firm's patent history pre-sample (proxy for firm's market shares)
  - Firms only pay to patent where they intend to sell
  - We compute pre-sample from 1970- the share of patents protected in country i: $\Omega_{i,c}$.
  - Include market size effect (Eaton, Kortum and Kramarz, 2011):
$$\omega_{i,c} = \frac{\Omega_{i,c} GDP_c^{0.35}}{\sum_{c'} \Omega_{i,c'} GDP_{c'}^{0.35}}.$$
- Similar approach for controls: (high-skill wages, GDP gap, GDP, etc...)
- Approach validated on a sample of car companies in ADHMV, on bilateral trade flows in Coelli, Moxnes and Ulltveit-Moe (2017).

Controlling for knowledge stocks

- Potential Spillovers from other innovations (Jaffe, 1986, ADHMV)
- Build $\Lambda_{i,t}$ is exposure-weighted stock of automation patents

$$\Lambda_{i,t} = \sum_{c} \widetilde{\omega}_{i,c} \Lambda_{c,t},$$

  - $\Lambda_{c,t}$ is stock of automation patents in country c,
  - $\widetilde{\omega}_{i,c}$ share of inventors of firm i located in country c, computed pre-sample.

Descriptive Statistics

Variable	Auto95		Auto90			Auto95	Auto90
Automation pantents	per year	1997-2011	per year	1997-2011	Weights		
Mean	0.7	11.22	0.84	13.24	Largest country	0.47	0.46
Standard deviation	3.46	48.71	4.04	56.76	Second largest	0.17	0.18
p50	0	2	0	3	US	0.21	0.21
p75	0.27	6	0.33	7	Japan	0.17	0.15
p90	1.4	19	1.6	22	Germany	0.2	0.21
p95	3	41	3.27	50	France	0.09	0.09
p99	12	173	13.73	194	UK	0.09	0.09
Number of firms	3341		4903				

Note: Summary statistics for the firms used in our baseline regression.

- Exclude purely domestic firms.

Outline

Baseline results for auto95 (95th pct cutoff) country cluster

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.2000***	2.8254***	1.8160**	1.9058**	1.9992**	2.2954***	2.4627***	2.4266***	3.7365***
	(0.5123)	(0.7332)	(0.7421)	(0.7729)	(0.8223)	(0.8198)	(0.8351)	(0.8658)	(0.9116)
High-skill wage		-0.9210	-0.9009	-0.9695	-0.8698	-0.2971	-1.6180**	-1.6700*	-0.4838
		(0.7082)	(0.6715)	(0.6913)	(0.7511)	(0.6802)	(0.8033)	(0.8634)	(0.7650)
Stock automation			-0.1275***	-0.1269**	-0.1270**	-0.1239**	-0.1441***	-0.1443***	-0.1504***
			(0.0495)	(0.0496)	(0.0495)	(0.0495)	(0.0509)	(0.0510)	(0.0510)
Stock other			0.6311***	0.6296***	0.6309***	0.6260***	0.6408***	0.6407***	0.6489***
			(0.0579)	(0.0581)	(0.0581)	(0.0574)	(0.0600)	(0.0600)	(0.0595)
GDP gap				0.0210	0.0214	0.0179	0.0279*	0.0278*	0.0265*
				(0.0159)	(0.0157)	(0.0157)	(0.0158)	(0.0157)	(0.0156)
Labor productivity					-0.2551			0.1285	
					(0.8644)			(0.9199)	
GDP per capita						-1.5635*			-3.3618***
						(0.8765)			(0.8917)
Spillovers automation							0.5442*	0.5478*	0.8587***
							(0.3135)	(0.3151)	(0.3213)
Spillovers other							-0.3014	-0.3089	-0.5853**
							(0.2248)	(0.2315)	(0.2303)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

- Slightly weaker results for auto90: auto90

Regression Challenges

- Are we doing better than country-level regressions?
  - Yes, if firms are sufficiently multinational (i.e. Siemens doesn't just sell to Germany)
  - Check: "Remove" largest country by country-year fixed effects
  - Provided that initial weights are exogenous to future trends, we capture the effect of different country trends on firms' innovations.
- Do we capture the effect of wages or other omitted variables?
  - Use controls and effect on other (placebo) innovations.
- But wages are still an equilibrium outcome in labor markets:
  - Interpretation: average effect of an increase in wages given the controls (for whatever reasons).
  - Later: effect of Hartz labor market reforms.

Country-year fixed effects

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.8852*	2.1429*	3.0411**	3.4891***	4.3023***	3.7989**	3.6420***	4.3362***	3.8663**
	(1.0367)	(1.1505)	(1.2232)	(1.2958)	(1.4482)	(1.6370)	(1.3146)	(1.4473)	(1.6288)
High-skill wage	-2.4820**	-1.9117*	-1.7526	-3.5161***	-2.4740*	-3.3526**	-3.7549***	-2.8325**	-3.6398***
	(1.0115)	(1.0157)	(1.1046)	(1.2515)	(1.4209)	(1.3633)	(1.2805)	(1.4364)	(1.3692)
GDP gap	0.0623*	0.0620*	0.0646*	0.0044	0.0016	0.0044	0.0031	0.0001	0.0031
	(0.0343)	(0.0342)	(0.0343)	(0.0492)	(0.0492)	(0.0492)	(0.0494)	(0.0494)	(0.0494)
Labor productivity		-1.2851			-1.7494			-1.5475	
		(1.6381)			(1.4131)			(1.3896)	
GDP per capita			-2.8260			-0.5289			-0.3829
			(2.0242)			(1.9347)			(1.8713)
Stock automation	-0.1511***	-0.1506***	-0.1541***	-0.1522***	-0.1523***	-0.1526***	-0.1530***	-0.1532***	-0.1533***
	(0.0528)	(0.0527)	(0.0523)	(0.0525)	(0.0523)	(0.0525)	(0.0524)	(0.0521)	(0.0524)
Stock other	0.6549***	0.6556***	0.6555***	0.6494***	0.6471***	0.6490***	0.6496***	0.6475***	0.6493***
	(0.0602)	(0.0602)	(0.0598)	(0.0602)	(0.0601)	(0.0600)	(0.0601)	(0.0601)	(0.0599)
Spillovers automation	1.4782***	1.4762***	1.4715***	1.4396***	1.4128***	1.4355***	1.4380***	1.4161***	1.4357***
	(0.4992)	(0.5000)	(0.4998)	(0.4872)	(0.4895)	(0.4899)	(0.4866)	(0.4896)	(0.4887)
Spillovers other	-1.2259***	-1.2020***	-1.2436***	-1.2377***	-1.2268***	-1.2436***	-1.2252***	-1.2141***	-1.2300***
	(0.3805)	(0.3820)	(0.3789)	(0.3748)	(0.3730)	(0.3716)	(0.3731)	(0.3725)	(0.3697)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50070	50070	50070	50070	50070	50070	50070
Firms	3338	3338	3338	3338	3338	3338	3338	3338	3338

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Multinationals weighted fe auto90 fe

Define “Placebo” patents in machinery

- Low-automation codes = codes with a frequency of keywords below the 60^{th} percentile of the distribution of IPC/CPC 6 digit codes in machinery (0.209).
- Low-automation patents whose machinery codes are all low-automation.

Effect on placebo patents

Dependent Variable	Placebo Machinery								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	0.2962	0.5837	1.6587**	-0.0486	0.0964	0.6381	-0.7470	-1.0568	-0.9430
	(0.6209)	(0.7013)	(0.6573)	(0.8089)	(0.9245)	(0.9903)	(1.2590)	(1.4477)	(1.3045)
High-skill wage	-0.1907	0.3251	0.8911	-0.3499	-0.0648	0.0238	0.4969	0.1238	0.4016
	(0.6953)	(0.6428)	(0.7506)	(0.9539)	(0.9122)	(1.0053)	(1.3193)	(1.3073)	(1.4470)
GDP gap	-0.0307***	-0.0292***	-0.0292***	-0.0072	-0.0071	-0.0062	0.0117	0.0120	0.0114
	(0.0105)	(0.0103)	(0.0104)	(0.0188)	(0.0187)	(0.0188)	(0.0319)	(0.0319)	(0.0319)
Labor productivity		-1.1140			-0.6087			0.6174	
		(0.7467)			(1.1021)			(1.1452)	
GDP per capita			-3.4367***			-1.5038			0.3079
			(0.8242)			(1.3776)			(1.3051)
Stock own	0.0866**	0.0879**	0.0892**	0.0952**	0.0956**	0.0957**	0.0958**	0.0954**	0.0956**
	(0.0408)	(0.0411)	(0.0405)	(0.0405)	(0.0406)	(0.0404)	(0.0405)	(0.0406)	(0.0406)
Stock other	0.4797***	0.4811***	0.4758***	0.4854***	0.4861***	0.4847***	0.4862***	0.4871***	0.4866***
	(0.0464)	(0.0464)	(0.0463)	(0.0460)	(0.0459)	(0.0459)	(0.0448)	(0.0449)	(0.0449)
Spillovers own	2.6849***	2.7419***	1.9983***	1.1394***	1.1505***	1.0777**	1.1398***	1.1215**	1.1469***
	(0.4153)	(0.4163)	(0.4423)	(0.4410)	(0.4435)	(0.4411)	(0.4393)	(0.4428)	(0.4418)
Spillovers other	-2.4198***	-2.4342***	-1.8132***	-1.2443**	-1.2469**	-1.1918**	-1.2694**	-1.2450**	-1.2706**
	(0.5298)	(0.5348)	(0.5386)	(0.5052)	(0.5056)	(0.5047)	(0.4965)	(0.5008)	(0.4965)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	115575	115575	115575	115515	115515	115515	115515	115515	115515
Firms	7705	7705	7705	7701	7701	7701	7701	7701	7701

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and year fixed effects, while (4)-(9) include firm and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(6), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

1/skill premium

Correlations Placebo sp Monte Carlo 1

Dependent variable	Auto95					
	Domestic + Foreign				Foreign	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill / High-skill wage	1.9423**	1.9008**	2.1995**	2.2870**	3.5089***	3.5012***
	(0.7552)	(0.7478)	(0.9170)	(0.9166)	(1.2083)	(1.2021)
GDP gap	0.0263*	0.0251	0.0627*	0.0632*	0.0049	0.0030
	(0.0157)	(0.0156)	(0.0343)	(0.0344)	(0.0526)	(0.0502)
GDP per capita		-0.6817		-1.5302		-0.1073
		(0.6943)		(1.2805)		(0.9038)
Stock automation	-0.1448***	-0.1466***	-0.1505***	-0.1531***	-0.1522***	-0.1523***
	(0.0509)	(0.0511)	(0.0530)	(0.0524)	(0.0526)	(0.0525)
Stock other	0.6407***	0.6424***	0.6546***	0.6555***	0.6495***	0.6491***
	(0.0599)	(0.0597)	(0.0603)	(0.0600)	(0.0602)	(0.0600)
Spillovers automation	0.5783*	0.6625**	1.4755***	1.4766***	1.4397***	1.4386***
	(0.3153)	(0.3340)	(0.4968)	(0.5013)	(0.4868)	(0.4888)
Spillovers other	-0.2349	-0.2543	-1.2535***	-1.2160***	-1.2387***	-1.2362***
	(0.2129)	(0.2112)	(0.3717)	(0.3807)	(0.3669)	(0.3720)
Fixed effects	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY
Observations	50115	50115	50070	50070	50070	50070
Firms	3341	3341	3338	3338	3338	3338

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(2) include firm fixed effects and year dummies. Columns (3)-(6) include firm and country-year fixed effects. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Columns (5)-(6) use the log difference between foreign low-skill wages interacted with the share of foreign low-skill wages in total low-skill wages at the beginning of the sample and foreign high-skill wages similarly interacted; GDP gap and GDP per capita are also their interacted foreign components. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Other regressions

- Alternative timing: Go
- Subcomponents: Go
- Other indicators of quality of innovations: Go
- Middle-skill wages: Go

Robustness checks

- Nickell's bias: Go
- Other wages and deflators: Go
- Other weights: Go
- Recent literature on Bartik instruments: Go

Outline

Case Study: German Hartz Reforms

- German labor market reforms Hartz I-IV came into effect between 2003 and 2005. Attempt to address "Sick man of Europe" syndrome of high unemployment
  - Hartz I-II: A number of changes: job centers, vocational training, mini - and minijobs (low wage and hours): 2003.
- Prediction: more flexible labor markets: less need to automate from 2003 onward.
- Focus on firms from the country with the largest exposure to Germany: Austria, France, Italy, Japan, the Netherlands, Spain, Switzerland, the United Kingdom and the United States.
- First Poisson regression:

$$PAT_{Aut,i,t+2} = \exp\begin{pmatrix} \beta_{DE,t} \cdot \delta_t \omega_{i,DE} + \delta_i + \delta_{c,t} \\ +\beta_{Ka} \cdot \delta_k \ln K_{Aut,i,t} + \beta_{Ko} \cdot \delta_k \ln K_{other,i,t} \end{pmatrix} + \epsilon_{k,i,t}.$$

German exposure

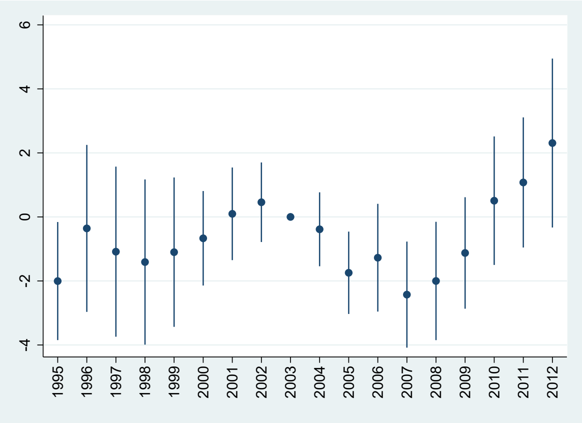

Figure: Coefficients on the interaction between the German weight and a set of year fixed effects.

- -2 in 2008: a firm with a German weight of 0.1 (mean is 0.11) did 20% less automation innovations in 2010 than in 2005 compared to a firm with no German exposure.

German exposure: auto95 versus other machinery time trend

$$PAT_{k,i,t+2} = \exp\left(\begin{array}{c} \beta_{DE,t} \cdot \delta_t \omega_{i,DE} + \beta^{aut}_{DE,t} \cdot \delta_t \omega_{i,DE} 1_{k=aut} + \delta_{k,i} + \delta_{k,c,t} \\ + \beta_{Ka} \cdot \delta_k \ln K_{Aut,i,t} + \beta_{Ko} \cdot \delta_k \ln K_{other,i,t} \end{array} \right) + \epsilon_{k,i}$$

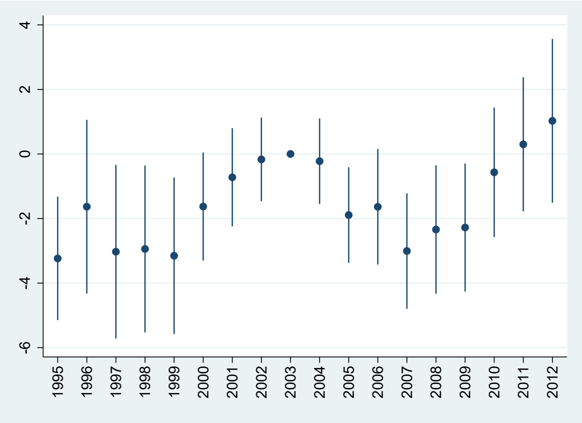

Figure: Coefficients on the triple interaction between the German weight, a dummy for auto95 innovations and a set of year fixed effects.

Outline

Conclusion

- We identify and classify patents according as relating to automation or not
  - Upward trend since late 90s. Varies across countries and strong predictive power on occupational distribution
- Use wages in countries where firms sell to estimate elasticity
  - positive elasticity of 2-4 for low-skill wages
  - negative elasticity for controls: high-skill wages, gdp per capita or labor productivity.
- Hartz reforms discouraged automation innovation by making labor market more flexible.
- Measure can be used to study effect of automation on labor share (Sulaja and Zanella, 2019), or on wages (future work).

Technological fields

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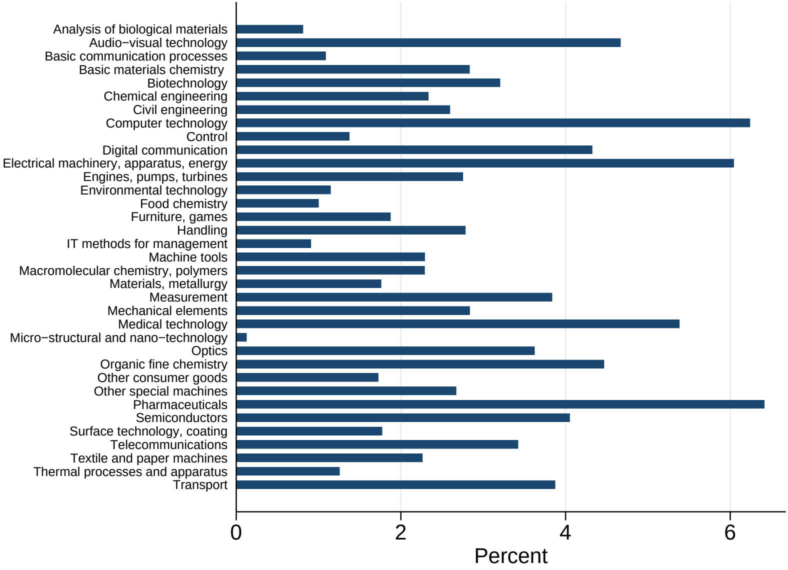

Statistics on the classification

	IPC/CPC 6 digit				IPC4 + (G05 or G06)				IPC 4 pairs			
Share	all	robot	automat*	CNC	all	robot	automat*	CNC	all	robot	automat*	CNC
Mean	20.9	4.3	11.2	2.4	53.2	15.4	32.4	11.2	18.5	4.5	8.8	1.8
S. d.	14.4	8.4	9.5	5.8	19.3	17.7	11	16.5	16.3	10	9.9	4.7
p25	10.5	0.8	4.2	0	40	6.7	26.6	0.8	7.7	0.6	2.5	0
p50	18	2	8.7	0.4	54.3	10	31.9	3	13.6	1.8	5.2	0.4
p75	26.6	4.5	15.3	1.8	63.8	16	40.3	15.5	23	4.2	10.7	1.4
p90	38.7	9.1	24.3	6.1	77.9	36.4	43.3	38.2	36.8	8.9	21.7	4.4
p95	47.7	13.7	29.4	12.7	85.6	44.3	45.2	55.3	51.8	14.5	31	7.7
p99	75	35.8	43.8	33.1	90.1	82.9	59.9	56.6	84.5	60	45.3	23.1

Note: This table computes summary statistics on the share of patents with any automation keywords, robot keywords, automat* keywords or CNC keywords for each type of technological categories (6 digit codes, pairs of 4 digit codes and combinations of ipc4 codes with G05 or G06) within machinery with at least 100 patents.

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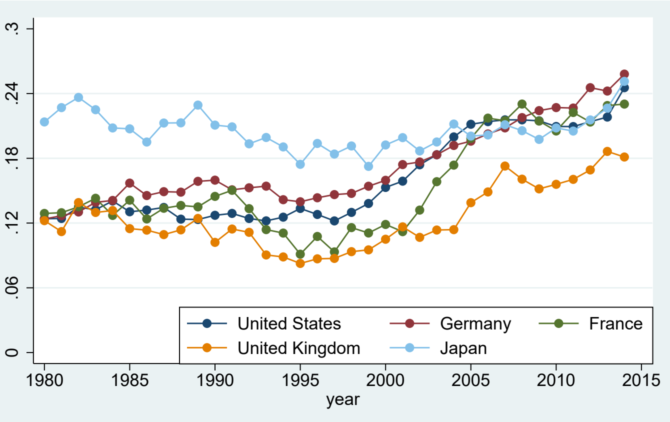
Share of automation (auto95) in machinery by applicant



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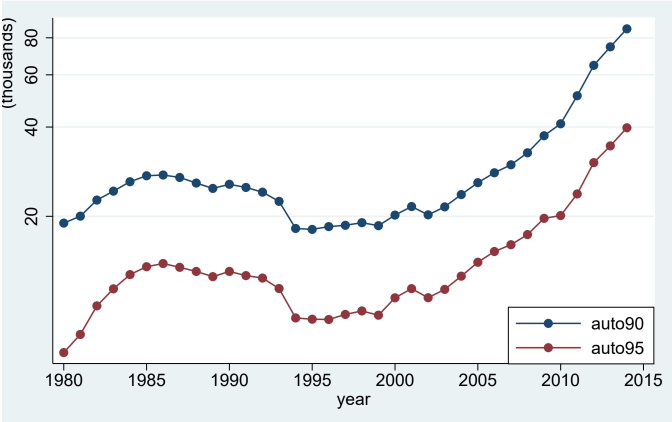
Raw number of biadic patent applications



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Automation by sectors Back

ISIC Rev. 4	Title	Share of automation patents in machinery 1997 - 2011 (in %)					
		Germany		United States		All Countries	
		auto95	auto90	auto95	auto90	auto95	auto90
A	Agriculture, forestry and fishing	5.7	12.4	6.4	14.8	6.8	13.8
B	Mining and quarrying	10.0	17.6	9.9	18.2	9.8	17.2
10-12	Food, beverages and tobacco products	4.6	12.9	5.6	15.2	5.0	12.6
13-15	Textiles, wearing apparel, leather and related products	3.9	9.0	4.7	11.4	4.2	10.3
16	Wood and products of wood and cork	4.3	9.3	4.7	11.9	4.9	10.9
17-18	Paper, paper products and printing	2.6	6.8	2.8	7.5	2.8	7.6
19-22	Coke, chemicals, pharmaceuticals, rubber and plastic products	2.9	6.9	3.8	8.2	3.0	7.0
23	Other non-metallic mineral products	6.1	11.7	6.7	13.9	5.9	12.0
24	Basic metals	10.8	26.0	12.4	29.4	11.1	27.0
25	Fabricated metal products	7.7	22.3	8.8	24.3	8.4	23.7
26-27	Computer, electronic, optical and electrical products	30.7	39.4	30.1	40.1	29.4	39.1
28	Machinery and equipment n.e.c.	17.4	30.5	18.1	30.7	18.8	31.5
29	Motor vehicles, trailers and semi-trailers	32.6	36.8	30.0	35.7	31.9	36.8
30	Other transport equipment	24.5	29.3	22.8	29.1	26.1	31.9
91	All other manufacturing branches	15.7	23.2	18.7	27.9	18.9	27.7
E	Water supply; sewerage, waste management and remediation activities	6.6	13.2	8.2	16.5	7.9	14.7
F	Construction	7.7	11.7	9.4	15.5	8.4	13.3

Change in routine cognitive tasks and automation intensity (1980-1998)

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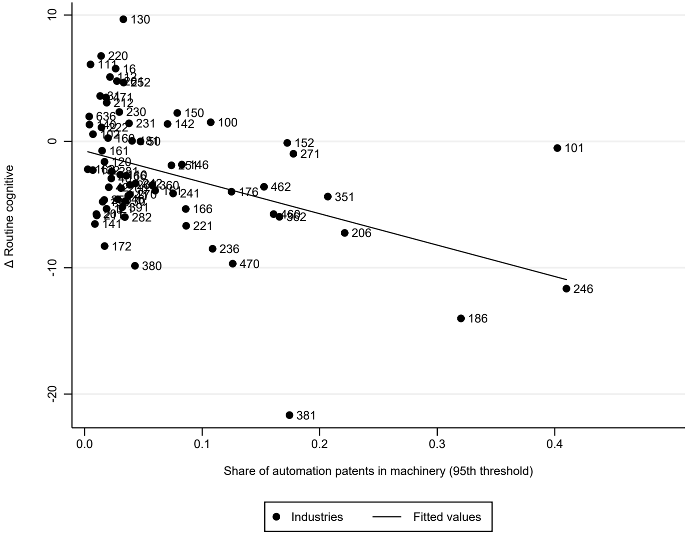
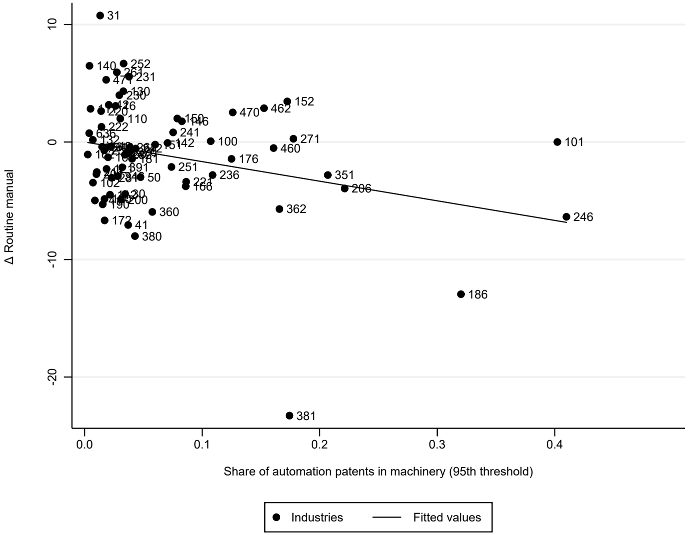


Change in routine manual tasks and automation intensity (1980-1998) Back



List of sectors for ALM regressions Back

ind6090	Title
16	Ag production crops & livestock; Ag services; Horticultural services
30	Forestry
31	Fishing, hunting and trapping
40	Metal mining
41	Coal mining
42	Crude petroleum and natural gas extraction
50	Nonmetallic mining & quarrying, except fuel
66	Construction
100	Meat products
101	Dairy products
102	Canned and preserved fuits and vegetables
110	Gain mill products
111	Bakery products
112	Sugar and confectionary products
120	Beverage industries
121	Misc. food preparations, kindred products
130	Tobacco manufactures
132	Knitting mills
140	Dyeing and finishing textiles, except wool and knit goods
141	Floor coverings, except hard surfaces
142	Yarn, thread, and fabric mills
146	Primary aluminum and other primary metal industries
150	Misc. textile mill products
151	Apparel and accessories, except knit
152	Misc. fabricated textile products
160	Pulp, paper, and paperboard mills
161	Misc. paper and pulp products
162	Paperboard containers and boxes
166	Screw machine products; Metal forgings & stampings; Misc. fabricated metal products
172	Printing, publishing, and allied industries except newspapers
176	Engine and turbines; Construction & material handling machines; Metalworking machinery; Machinery, except electrical, n.e.c.; Not specified machinery
181	Drugs
186	Electronic computing equipment; Office and accounting machines
190	Paints, varnishes, and related products
200	Petroleum refining
201	Misc. petroleum and coal products
206	Household appliances; Radio, TV & communications equipment; Electric machinery, equipment & supplies, n.e.c., not specified electrical machinery, equipment & supplies
211	Other rubber products, and plastics footwear and belting + tires & inner tubes
212	Misc. plastic products
220	Leather tanning and finishing
221	Footwear, except rubber and plastic
222	Leather products, except footwear
230	Logging
231	Sawmills, planning mills, and millwork
236	Railroad locomotives & equipment; Cycles & misc transporation equipment; Wood buildings & mobile homes
241	Misc. wood products
242	Furniture and fixtures
246	Scientific and controlling instruments; Optical and health service supplies
250	Glass products
251	Cement, concrete, gypsum & plaster
252	Structural clay products
261	Pottery and related products
262	Misc. nonmetallic mineral & stone products
270	Blast furnaces, steelworks, rolling and
271	Iron and stell foundaries
281	Cutlery, handtools, and other hardware
282	Fabricated structural metal products
346	Plastics, synthetics & resins; Soaps & cosmetics; Agricultural chemicals; Industrial & miscellaneous chemicals
351	Transportation equipment
360	Ship and boat building and repairing
362	Guided missiles, space vehicles, and parts,
380	Photographic equipment and supplies
381	Watches, clocks, and clockwork operated
391	Misc. manufacturing industries and toys,
460	Electric light and power
462	Eletric and gas, and other combinations
470	Water supply and irrigation
471	Sanitary services
636	Grocery stores; Retail bakeries; Food

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual
Panel A: Aggregated within-industry change					
Share of automation patents in machinery	9.53**	17.97***	-26.66***	-17.09***	12.57***
	(4.53)	(5.39)	(4.83)	(3.90)	(4.30)
Δ Computer use 1984 - 1997	24.91***	23.81***	-17.75***	-11.53**	0.47
	(6.36)	(7.56)	(6.79)	(5.48)	(6.03)
Intercept	-2.36**	-1.01	2.05*	1.73*	-2.37**
	(1.03)	(1.22)	(1.10)	(0.89)	(0.98)
R^2	0.26	0.27	0.39	0.29	0.12
Weighted mean Δ	2.05	3.88	-2.62	-1.29	-1.34
Panel B: Within industry: High school dropouts					
Share of automation patents in machinery	2.41	13.61	-26.19***	-5.80	4.56
	(7.89)	(10.85)	(6.94)	(6.22)	(6.35)
Δ Computer use 1984 - 1997	11.70	18.08	15.84	8.68	-9.95
	(11.08)	(15.24)	(9.74)	(8.73)	(8.91)
Intercept	-4.47**	-8.45***	0.87	0.55	1.16
	(1.79)	(2.47)	(1.58)	(1.41)	(1.44)
R^2	0.02	0.05	0.19	0.02	0.02
Weighted mean Δ	-2.56	-4.73	1.20	1.39	0.04
Panel C: Within industry: High school graduates					
Share of automation patents in machinery	-7.08	6.50	-26.09***	-13.43***	9.62*
	(5.47)	(7.05)	(5.64)	(4.25)	(5.37)
Δ Computer use 1984 - 1997	9.30	-0.76	-14.39*	-2.86	6.71
	(7.69)	(9.90)	(7.92)	(5.96)	(7.54)
Intercept	-2.86**	2.19	2.25*	0.00	-1.43
	(1.24)	(1.60)	(1.28)	(0.97)	(1.22)
R^2	0.04	0.01	0.30	0.14	0.06
Weighted mean Δ	-2.03	2.57	-1.88	-1.45	0.30
Panel D: Within industry: Some College					
Share of automation patents in machinery	-11.94	-7.49	-4.92	-5.92	12.48*
	(8.04)	(7.31)	(6.01)	(5.72)	(6.56)
Δ Computer use 1984 - 1997	7.05	13.85	-14.68*	-14.11*	9.14
	(11.29)	(10.26)	(8.44)	(8.03)	(9.20)
Intercept	-1.10	0.31	0.38	2.21*	-2.74*
	(1.83)	(1.66)	(1.37)	(1.30)	(1.49)
R^2	0.04	0.04	0.06	0.07	0.07
Weighted mean Δ	-0.97	1.78	-2.17	-0.33	-0.43
Panel E: Within industry: College graduates					
Share of automation patents in machinery	-6.54	-7.28**	-11.58*	-7.70	17.00***
	(4.25)	(3.59)	(6.48)	(7.74)	(6.03)
Δ Computer use 1984 - 1997	14.44**	9.29*	-5.55	-7.69	11.14
	(6.00)	(5.06)	(9.14)	(10.91)	(8.50)
Intercept	-0.94	0.17	-1.22	-0.14	-5.35***
	(0.97)	(0.82)	(1.48)	(1.77)	(1.38)
R^2	0.01	0.09	0.06	0.03	0.14
Weighted mean Δ	0.69	0.99	-2.93	-1.86	-2.40
Panel F: Decomposition of automation effects into within and between education group					
Explained task Δ	0.73	1.38	-2.04	-1.31	0.96
Within educ groups (%)	-63.96	15.80	72.32	54.61	81.96
Between educ groups (%)	163.96	84.20	27.68	45.39	18.04

Formal set-up

- Consider a manufacturing good produced with

$$Y = \exp\left(\int_0^1 \ln y(i)\, di\right).$$

- In each subsector i, production is competitive with technology:

$$y_i = h_{1,i}^{1-\beta}\left(\gamma(i)\, l_i + \alpha(i)\,\kappa x_i^{\nu} h_{2,i}^{1-\nu}\right)^{\beta},$$

- where $\kappa x_i^{\nu} h^{1-\nu}$ is a composite of high-skill workers and machines ($\kappa \equiv \nu^{\nu}(1-\nu)^{1-\nu}$)
  - $\alpha(i) = 1$ for automated sectors, $\alpha(i) = 0$ for non-automated sectors.
  - Machines are produced with the manufacturing good (i.e. at cost 1), if they exist.
- Once a machine is invented, it is produced monopolistically by its inventor, who charges a price $p_x(i) \geq 1$.

Production and profits

- In an automated sector, the intermediate producer is indifferent between using machines and low-skill labor if

$$w_H^{\nu} p_x^{1-\nu} = w_L/\gamma(i).$$

- Monopolist makes a take-it-or-leave-it offer, so for an automated sector:
  - If $w_L/\gamma(i) < w_H^{\nu}$: the producer uses low-skill labor.
  - If$w_L/\gamma(i) > w_H^{\nu}$: the producer uses machines and the monopolist charges $p_x(i) = \left(\frac{w}{\gamma(i)}\right)^{\frac{1}{1-\nu}} w_H^{-\frac{\nu}{1-\nu}} > 1$.
- Profits collected by a machine producer are:

$$\pi_i^A = \max\left(1 - \left(\frac{w_L}{\gamma(i)}\right)^{-\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}, 0\right) \nu\beta Y.$$

Innovation

- Automation technology are introduced by machines producers.
  - Machine producer innovate with probability λ if she spends $\theta\lambda^2 Y/2$.
  - Machine producer solves:

$$\max \lambda\pi_i^A - \theta\frac{\lambda^2}{2}Y$$

$$\Longrightarrow \lambda = \frac{\nu\beta}{\theta}\max\left(1-\left(\frac{w_L}{\gamma(i)}\right)^{-\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}, 0\right)$$

- Therefore the number of automation innovations is equal to

$$Aut_{i,t} = \frac{\nu\beta}{\theta}\int_0^1 (1-\alpha(i))\max\left(\left(1-\left(\frac{w_L}{\gamma(i)}\right)^{-\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}\right), 0\right) di$$

  - which is increasing in w_L and decreasing in w_H. Back

Clustering at the country level

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.2000***	2.8254***	1.8160***	1.9058***	1.9992**	2.2954***	2.4627***	2.4266***	3.7365***
	(0.5464)	(0.7421)	(0.6310)	(0.6863)	(0.9001)	(0.5383)	(0.7170)	(0.8727)	(0.6582)
High-skill wage		-0.9210	-0.9009**	-0.9695***	-0.8698	-0.2971	-1.6180***	-1.6700**	-0.4838*
		(0.6234)	(0.3519)	(0.3701)	(0.7025)	(0.2972)	(0.4701)	(0.7968)	(0.2831)
Stock automation			-0.1275***	-0.1269***	-0.1270***	-0.1239***	-0.1441***	-0.1443***	-0.1504***
			(0.0336)	(0.0339)	(0.0335)	(0.0355)	(0.0358)	(0.0365)	(0.0389)
Stock other			0.6311***	0.6296***	0.6309***	0.6260***	0.6408***	0.6407***	0.6489***
			(0.0495)	(0.0506)	(0.0483)	(0.0518)	(0.0493)	(0.0492)	(0.0501)
GDP gap				0.0210***	0.0214**	0.0179**	0.0279***	0.0278***	0.0265***
				(0.0081)	(0.0088)	(0.0074)	(0.0091)	(0.0096)	(0.0076)
Labor productivity					-0.2551			0.1285	
					(1.0309)			(0.9693)	
GDP per capita						-1.5635*			-3.3618***
						(0.8207)			(0.8952)
Spillovers automation							0.5442***	0.5478***	0.8587***
							(0.1831)	(0.1931)	(0.1270)
Spillovers other							-0.3014	-0.3089	-0.5853***
							(0.2573)	(0.2395)	(0.1790)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the country-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

back

Baseline results (auto 90)

Dependent variable	Auto90								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.7307***	2.4414***	1.3357**	1.3715**	1.4738**	1.8797***	1.9059***	1.8309***	3.1623***
	(0.4953)	(0.6610)	(0.6363)	(0.6610)	(0.6778)	(0.7051)	(0.6883)	(0.7008)	(0.7486)
High-skill wage		-1.0613*	-0.7746	-0.8019	-0.6844	0.0911	-1.4074**	-1.5340**	-0.0865
		(0.5844)	(0.5311)	(0.5480)	(0.6068)	(0.5491)	(0.6296)	(0.6850)	(0.6114)
Stock automation			-0.0347	-0.0345	-0.0348	-0.0328	-0.0475	-0.0479	-0.0538
			(0.0405)	(0.0405)	(0.0404)	(0.0406)	(0.0403)	(0.0403)	(0.0403)
Stock other			0.5682***	0.5676***	0.5690***	0.5611***	0.5773***	0.5770***	0.5814***
			(0.0496)	(0.0497)	(0.0495)	(0.0495)	(0.0508)	(0.0508)	(0.0504)
GDP gap				0.0081	0.0085	0.0038	0.0152	0.0151	0.0127
				(0.0137)	(0.0134)	(0.0135)	(0.0133)	(0.0133)	(0.0132)
Labor productivity					-0.2904			0.2911	
					(0.7011)			(0.7224)	
GDP per capita						-2.0568***			-3.5341***
						(0.7380)			(0.7721)
Spillovers automation							0.8903**	0.9102**	1.2870***
							(0.4162)	(0.4190)	(0.4170)
Spillovers other							-0.6079**	-0.6342**	-1.0159***
							(0.3050)	(0.3140)	(0.3174)
Fixed Effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	73545	73545	73545	73545	73545	73545	73545	73545	73545
Firms	4903	4903	4903	4903	4903	4903	4903	4903	4903

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

back

Multinational firms

back

Dependent Variable	Auto95					
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic weight	all (< 100%)	< 90%	< 80%	< 70%	< 60%	< 50%
Low-skill wage	3.7365***	2.9038***	3.3297***	2.7702***	1.9337	1.3778
	(0.9116)	(0.8996)	(0.9205)	(1.0572)	(1.3472)	(1.7334)
High-skill wage	-0.4838	0.2145	-0.0103	-0.2181	-0.6551	0.7987
	(0.7650)	(0.7540)	(0.7638)	(0.8887)	(1.0793)	(1.2537)
GDP gap	0.0265*	0.0140	0.0088	0.0128	-0.0077	-0.0149
	(0.0156)	(0.0164)	(0.0190)	(0.0231)	(0.0297)	(0.0340)
GDP per capita	-3.3618***	-2.7080***	-2.8505***	-2.2268**	-1.5900	-2.0282
	(0.8917)	(0.8760)	(0.9555)	(1.0344)	(2.0772)	(2.8055)
Stock automation	-0.1504***	-0.1855***	-0.2384***	-0.2264***	-0.1973***	-0.2069***
	(0.0510)	(0.0541)	(0.0573)	(0.0625)	(0.0661)	(0.0659)
Stock other	0.6489***	0.6832***	0.7513***	0.7276***	0.7270***	0.7597***
	(0.0595)	(0.0633)	(0.0649)	(0.0671)	(0.0745)	(0.0821)
Spillovers automation	0.8587***	0.7931**	1.0109***	1.2503***	1.0217***	1.1416***
	(0.3213)	(0.3183)	(0.3309)	(0.3567)	(0.3540)	(0.3833)
Spillovers other	-0.5853**	-0.6162***	-0.8172***	-0.9773***	-0.8854***	-1.0279***
	(0.2303)	(0.2285)	(0.2393)	(0.2525)	(0.2638)	(0.2930)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	47640	44190	40485	35865	30690
Firms	3341	3176	2946	2699	2391	2046

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Column (1) contains all firms, (2) restricts attention to firm with a domestic weight below 90%, (3) below 80%, (4) below 70%, (5) below 60%, (6) below 50%. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Weighted CY fe

back

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.8108	2.3860*	2.2889*	2.0881*	2.6237**	2.9819**	2.1664*	2.6391**	2.9695**
	(1.1242)	(1.2486)	(1.3755)	(1.1178)	(1.2557)	(1.3805)	(1.1418)	(1.2624)	(1.3847)
High-skill wage	-2.7802**	-2.0793*	-2.5647**	-2.7271**	-2.1941*	-2.3615**	-2.9054**	-2.4236*	-2.5943**
	(1.1391)	(1.2117)	(1.1867)	(1.1229)	(1.2359)	(1.1984)	(1.1471)	(1.2481)	(1.2101)
GDP gap	0.0053	-0.0020	0.0021	0.0086	0.0037	0.0046	0.0075	0.0028	0.0039
	(0.0436)	(0.0444)	(0.0445)	(0.0440)	(0.0448)	(0.0445)	(0.0441)	(0.0449)	(0.0447)
Labor productivity		-1.2255			-0.9968			-0.9151	
		(0.9351)			(0.9758)			(0.9585)	
GDP per capita			-0.7515			-1.3618			-1.2168
			(1.2918)			(1.3924)			(1.3560)
Stock automation	-0.1531***	-0.1525***	-0.1531***	-0.1518***	-0.1514***	-0.1523***	-0.1519***	-0.1515***	-0.1525***
	(0.0523)	(0.0521)	(0.0522)	(0.0522)	(0.0520)	(0.0521)	(0.0522)	(0.0520)	(0.0520)
Stock other	0.6433***	0.6417***	0.6429***	0.6420***	0.6407***	0.6412***	0.6422***	0.6409***	0.6415***
	(0.0605)	(0.0603)	(0.0603)	(0.0607)	(0.0606)	(0.0603)	(0.0607)	(0.0606)	(0.0603)
Spillovers automation	1.1705***	1.2209***	1.2079***	1.0883**	1.1219***	1.1442***	1.1121***	1.1484***	1.1663***
	(0.4154)	(0.4139)	(0.4199)	(0.4241)	(0.4227)	(0.4283)	(0.4191)	(0.4183)	(0.4241)
Spillovers other	-0.9536***	-0.9457***	-0.9736***	-0.9431***	-0.9441***	-0.9801***	-0.9379***	-0.9386***	-0.9719***
	(0.3302)	(0.3305)	(0.3319)	(0.3315)	(0.3310)	(0.3333)	(0.3315)	(0.3315)	(0.3335)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50085	50085	50085	50085	50085	50085	50085	50085	50085
Firms	3339	3339	3339	3339	3339	3339	3339	3339	3339

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm and country-year fixed effects. Country-year fixed effects are interacting with the countries' weights. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Auto90 CY fe back

Dependent variable	Auto90								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.3896*	1.4107	2.2798**	2.6344**	3.1221**	3.2536**	2.7215**	3.1094**	3.2428**
	(0.8386)	(0.8937)	(1.0390)	(1.1574)	(1.3170)	(1.3955)	(1.1927)	(1.3384)	(1.4122)
High-skill wage	-1.5576*	-1.5109	-1.0014	-3.0164**	-2.3531*	-2.6864**	-3.1666**	-2.6147*	-2.8915**
	(0.8304)	(0.9212)	(0.8793)	(1.2101)	(1.3149)	(1.2787)	(1.2485)	(1.3342)	(1.2984)
GDP gap	0.0387	0.0387	0.0405	-0.0044	-0.0060	-0.0042	-0.0053	-0.0070	-0.0053
	(0.0270)	(0.0270)	(0.0269)	(0.0361)	(0.0361)	(0.0360)	(0.0361)	(0.0362)	(0.0361)
Labor productivity		-0.1045			-1.0847			-0.8988	
		(1.1919)			(1.2059)			(1.1768)	
GDP per capita			-2.1599			-1.0595			-0.8978
			(1.4800)			(1.4139)			(1.3541)
Stock automation	-0.0537	-0.0536	-0.0556	-0.0572	-0.0576	-0.0577	-0.0577	-0.0580	-0.0581
	(0.0405)	(0.0406)	(0.0404)	(0.0405)	(0.0405)	(0.0405)	(0.0405)	(0.0404)	(0.0405)
Stock other	0.5846***	0.5847***	0.5845***	0.5802***	0.5794***	0.5792***	0.5802***	0.5796***	0.5795***
	(0.0510)	(0.0509)	(0.0508)	(0.0508)	(0.0507)	(0.0506)	(0.0508)	(0.0507)	(0.0506)
Spillovers automation	1.7794***	1.7789***	1.7682***	1.7676***	1.7438***	1.7562***	1.7652***	1.7459***	1.7563***
	(0.5417)	(0.5421)	(0.5434)	(0.5367)	(0.5388)	(0.5381)	(0.5357)	(0.5388)	(0.5370)
Spillovers other	-1.5492***	-1.5469***	-1.5563***	-1.5439***	-1.5316***	-1.5527***	-1.5350***	-1.5238***	-1.5431***
	(0.4359)	(0.4375)	(0.4366)	(0.4321)	(0.4320)	(0.4315)	(0.4305)	(0.4314)	(0.4298)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	73485	73485	73485	73485	73485	73485	73485	73485	73485
Firms	4899	4899	4899	4899	4899	4899	4899	4899	4899

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Correlation matrix

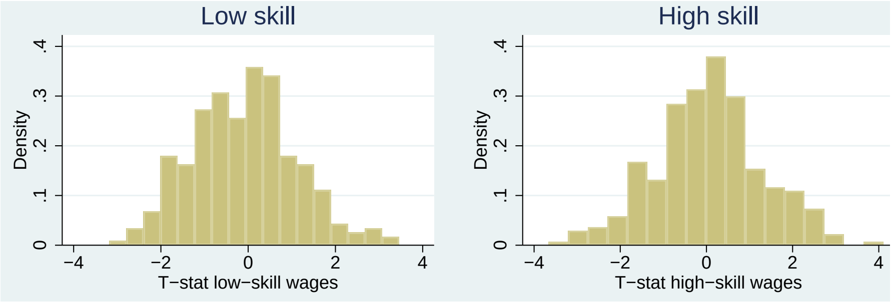
	Low-skill wage	Middle-skill wage	High-skill wage	GDP gap	GDP per capita	Labor productivity
Low-skill wage	1	.	.	.	.	.
Middle-skill wage	0.9401	1	.	.	.	.
High-skill wage	0.6009	0.7469	1		.	.
GDP gap	-0.0660	-0.0239	0.0482	1		.
GDP per capita	0.6972	0.7974	0.7277	-0.0117	1	.
Labor productivity	0.6678	0.7340	0.7724	0.1980	0.6519	1

Note: Correlation of residuals for the auto95 sample controlling for year and firm fixed effects.

back

Monte Carlo simulations for low-skill wages

- Run Monte Carlo simulations where we reallocate innovation across firms. Report t-stats on wage coefficients for baseline regression with GDP per capita. Back



1/skill premium and placebo

Dependent variable	Machinery					
	Domestic + Foreign				Foreign	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill / High-skill wage	0.2310	0.1733	0.1669	0.2370	-0.5869	-0.5817
	(0.6330)	(0.6275)	(0.8357)	(0.8471)	(1.2623)	(1.2637)
GDP gap	-0.0309***	-0.0316***	-0.0066	-0.0070	0.0170	0.0138
	(0.0105)	(0.0105)	(0.0187)	(0.0187)	(0.0348)	(0.0323)
GDP per capita		-1.3201**		-0.9322		-0.1680
		(0.5270)		(0.8127)		(0.6333)
Stock own	0.0865**	0.0871**	0.0961**	0.0950**	0.0965**	0.0962**
	(0.0408)	(0.0406)	(0.0405)	(0.0404)	(0.0408)	(0.0406)
Stock other	0.4796***	0.4766***	0.4852***	0.4852***	0.4875***	0.4864***
	(0.0464)	(0.0464)	(0.0459)	(0.0458)	(0.0450)	(0.0449)
Spillovers own	2.6743***	2.3165***	1.1452***	1.0975**	1.1430***	1.1370***
	(0.4073)	(0.4400)	(0.4423)	(0.4402)	(0.4405)	(0.4400)
Spillovers other	-2.3977***	-1.9672***	-1.2693**	-1.1955**	-1.2786**	-1.2721**
	(0.5072)	(0.5527)	(0.5058)	(0.5035)	(0.5002)	(0.4977)
Fixed effects	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY
Observations	115575	115575	115515	115515	115515	115515
Firms	7705	7705	7701	7701	7701	7701

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(2) include firm fixed effects and year dummies. Columns (3)-(6) include firm and country-year fixed effects. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Columns (5)-(6) use the log difference between foreign low-skill wages interacted with the share of foreign low-skill wages in total low-skill wages at the beginning of the sample and foreign high-skill wages similarly interacted; GDP gap and GDP per capita are also their interacted foreign components. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

back

Timing Back

Dependent variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lags (Leads)	-5	-4	-3	-2	-1	0	1	2
	Panel A: baseline							
Low-skill wage	2.4892***	3.1465***	3.3830***	3.7365***	3.3440***	3.0233***	3.2320***	2.5366***
	(0.9175)	(0.8858)	(0.8750)	(0.9116)	(0.8936)	(0.9104)	(0.9183)	(0.8982)
High-skill wage	0.9347	0.1035	-0.2368	-0.4838	-0.8886	-1.7253**	-1.6841**	-1.6868*
	(0.8260)	(0.7801)	(0.7565)	(0.7650)	(0.7645)	(0.8349)	(0.8300)	(0.8912)
GDP per capita	-2.7077**	-2.6067***	-2.9108***	-3.3618***	-3.2312***	-2.5012**	-2.7849**	-2.5574*
	(1.0927)	(0.9184)	(0.8558)	(0.8917)	(0.9855)	(1.1452)	(1.2627)	(1.4724)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	47565	48240	49395	50115	50670	51315	52470	53940
Firms	3171	3216	3293	3341	3378	3421	3498	3596
	Panel B: country-year fixed effects							
Low-skill wage	1.0489	1.6500	2.1535*	3.0411**	2.8868**	2.0860	1.8020	0.3302
	(1.5051)	(1.3450)	(1.2019)	(1.2232)	(1.2274)	(1.2729)	(1.2749)	(1.2557)
High-skill wage	0.0284	-1.0556	-1.4233	-1.7526	-1.5110	-2.0731*	-1.8181*	-1.5345
	(1.1186)	(1.1073)	(1.1018)	(1.1046)	(1.0873)	(1.1229)	(1.0894)	(1.0889)
GDP per capita	-0.9674	-1.1475	-1.6233	-2.8260	-3.1942	-1.9300	-1.4501	-0.4721
	(2.0060)	(1.8890)	(1.8120)	(2.0242)	(2.0544)	(2.0595)	(1.9272)	(1.8742)
	Panel C: country-year fixed effects and foreign variables							
Low-skill wage	1.8642	2.9249*	3.1771**	3.7989**	3.3156**	1.9156	1.9842	0.0399
	(1.6482)	(1.5679)	(1.5734)	(1.6370)	(1.6605)	(1.6756)	(1.7913)	(1.8767)
High-skill wage	1.4684	-1.1048	-2.7589*	-3.3526**	-2.9976**	-3.0576**	-2.5558*	-2.1341
	(1.7706)	(1.4707)	(1.4794)	(1.3633)	(1.3875)	(1.4395)	(1.3960)	(1.4394)
GDP per capita	-2.4369	-1.4358	-0.5750	-0.5289	-0.1492	1.0430	0.7528	1.8798
	(1.7216)	(1.7172)	(1.8799)	(1.9347)	(1.9087)	(1.8682)	(1.8246)	(1.8961)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	47565	48240	49365	50070	50595	51255	52410	53895
Firms	3171	3216	3291	3338	3373	3417	3494	3593

Note: Marginal effects; Standard errors in parentheses. Each panel represents a different regression. All regressions contain controls for GDP gap, stocks and spillovers, for which we do not report the coefficient. The independent variables (wages, GDP and GDP gap) are lagged by the number of periods indicated in lag, except for the stock variables which are always lagged by 2 periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Panel A regressions contain firm and year fixed effects. Panel B and C regressions contain firm and country-year fixed effects. In Panel C regressions, wages are replaced with foreign wages interacted with the share of foreign wages in total wages at the beginning of the sample, and similarly for the other macro variables. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Subcomponents

Dependent Variable	AutoX95	Auto80	Automat* 90	Automat* 80	Robot 90	Robot 80	CNC 90	CNC 80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	3.3630***	2.6821***	3.5169***	2.7574***	1.8204	3.2420***	-2.2039	-1.1100
	(0.9754)	(0.6677)	(1.2207)	(1.0092)	(1.6276)	(1.2362)	(2.1666)	(1.7553)
High-skill wage	0.1429	0.4858	-0.1368	0.0721	1.1749	-0.7976	2.7072	1.5419
	(0.8206)	(0.5592)	(0.9414)	(0.7547)	(1.6237)	(1.2595)	(2.0778)	(1.4857)
GDP gap	0.0356*	0.0018	0.0037	-0.0087	0.0290	0.0382	0.0296	0.0208
	(0.0183)	(0.0121)	(0.0218)	(0.0176)	(0.0370)	(0.0270)	(0.0415)	(0.0305)
GDP per capita	-3.5802***	-3.5251***	-3.2686***	-3.0322***	-3.8276*	-2.1214	0.8667	0.3249
	(1.0445)	(0.7236)	(0.9354)	(0.8876)	(1.9969)	(1.6989)	(2.9560)	(2.3555)
Stock own	-0.1449**	0.0234	-0.1228**	-0.0900*	-0.3156***	-0.1349*	-0.3031**	-0.2883***
	(0.0571)	(0.0369)	(0.0606)	(0.0526)	(0.1000)	(0.0792)	(0.1527)	(0.1002)
Stock other	0.6507***	0.5240***	0.6757***	0.6341***	0.8272***	0.6349***	0.5648***	0.6129***
	(0.0640)	(0.0455)	(0.0877)	(0.0737)	(0.1297)	(0.0983)	(0.1300)	(0.0952)
Spillovers own	1.0370***	1.1951**	0.6897	0.7882*	0.4072	0.2669	0.6402*	0.4261
	(0.3992)	(0.5109)	(0.4362)	(0.4751)	(0.5038)	(0.3193)	(0.3645)	(0.2750)
Spillovers other	-0.9125***	-0.9592**	-0.6828***	-0.6597*	-0.2324	-0.2693	-1.3296**	-0.5943
	(0.3007)	(0.4427)	(0.2642)	(0.3484)	(0.3267)	(0.2696)	(0.5171)	(0.3998)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	48600	97635	34170	50220	17670	24645	8970	15000
Firms	3240	6509	2278	3348	1178	1643	598	1000

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Stocks and spillovers are calculated with respect to the dependent variable. All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Alternatives to biadic as quality control

Dependent Variable	Auto95			
	Biadic (US, JP, EU)		Triadic	
	(1)	(2)	(3)	(4)
Low-skill wage	2.2776**	3.6377***	3.1886**	4.8171***
	(1.0383)	(1.1449)	(1.4150)	(1.5950)
High-skill wage	-1.3409	-0.0925	-2.3417*	-0.9527
	(0.9663)	(0.9133)	(1.3640)	(1.3336)
GDP gap	0.0397**	0.0382**	0.0178	0.0158
	(0.0191)	(0.0192)	(0.0289)	(0.0290)
GDP per capita		-3.5710***		-4.0592**
		(1.0090)		(1.6804)
Stock automation	-0.1683***	-0.1740***	-0.3665***	-0.3722***
	(0.0597)	(0.0598)	(0.0772)	(0.0771)
Stock other	0.6342***	0.6433***	0.6500***	0.6560***
	(0.0662)	(0.0652)	(0.0875)	(0.0870)
Spillovers automation	0.3839	0.7402*	0.7925	0.9280*
	(0.4014)	(0.4057)	(0.5469)	(0.5550)
Spillovers other	-0.5402**	-0.8222***	-0.3499	-0.7226
	(0.2587)	(0.2685)	(0.4685)	(0.5312)
Observations	40410	40410	26310	26310
Firms	2694	2694	1754	1754

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Columns (1)-(2) consider biadic patents in at least two countries among US, JP, EU. Columns (3)-(4) consider triadic patents. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Middle-skill wages

Dependent Variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	4.7035***		3.8985***	5.1140***		4.2760***	4.4204***		4.1503***
	(1.4991)		(1.3667)	(1.5892)		(1.4222)	(1.5087)		(1.3903)
Middle-skill wage	-3.9194**	2.3617**	-2.2614	-4.2997**	2.4746**	-2.5516	-1.1345	4.2681***	-0.6235
	(1.6096)	(1.0085)	(1.6773)	(1.6815)	(1.0411)	(1.6819)	(1.5678)	(1.1856)	(1.7027)
High-skill wage		-1.7189*	-0.9608		-1.8154*	-1.0225		-1.1170	-0.3643
		(0.9218)	(0.8867)		(0.9485)	(0.8960)		(0.9053)	(0.8589)
GDP gap				0.0288*	0.0216	0.0304*	0.0265*	0.0186	0.0271*
				(0.0153)	(0.0151)	(0.0157)	(0.0151)	(0.0150)	(0.0156)
GDP per capita							-3.4017***	-3.3267***	-3.2856***
							(0.9643)	(0.9865)	(0.9138)
Stock automation	-0.1454***	-0.1404***	-0.1457***	-0.1460***	-0.1405***	-0.1464***	-0.1509***	-0.1448***	-0.1509***
	(0.0508)	(0.0508)	(0.0509)	(0.0509)	(0.0509)	(0.0510)	(0.0511)	(0.0510)	(0.0511)
Stock other	0.6458***	0.6394***	0.6436***	0.6456***	0.6389***	0.6433***	0.6503***	0.6450***	0.6494***
	(0.0598)	(0.0598)	(0.0600)	(0.0599)	(0.0600)	(0.0601)	(0.0593)	(0.0594)	(0.0595)
Spillovers automation	0.4733	0.4518	0.5330*	0.5007*	0.4692	0.5657*	0.8454***	0.7663**	0.8569***
	(0.2891)	(0.3140)	(0.3097)	(0.2885)	(0.3143)	(0.3105)	(0.3114)	(0.3245)	(0.3220)
Spillovers other	-0.3173	-0.1874	-0.3100	-0.3478	-0.2013	-0.3416	-0.5992***	-0.4552**	-0.5887**
	(0.2254)	(0.2208)	(0.2265)	(0.2247)	(0.2197)	(0.2257)	(0.2302)	(0.2264)	(0.2301)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables include a dummy for no stock and no spillover. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Nickell's bias

Dependent Variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.3903***	3.8111***	2.1515***	2.2756***	2.0925**	3.3064***	2.3955**	2.5926**
	(0.8004)	(0.8733)	(0.7991)	(0.8300)	(0.9778)	(1.1699)	(0.9713)	(1.1376)
High-skill wage	-1.5544**	-0.2518	-0.9069	-0.2523	-2.4648**	-1.6999	-2.5627***	-2.2586**
	(0.7840)	(0.7392)	(0.6129)	(0.8284)	(0.9779)	(1.0525)	(0.9338)	(1.0549)
GDP gap	0.0276*	0.0256	0.0266	0.0241	0.0653*	0.0679**	0.0752**	0.0773**
	(0.0159)	(0.0157)	(0.0191)	(0.0189)	(0.0343)	(0.0343)	(0.0353)	(0.0354)
GDP per capita		-3.8282***		-1.4329		-2.9746		-0.6334
		(0.8762)		(1.3087)		(1.9049)		(1.8229)
Stock automation			1.1938***	1.1803***			1.1912***	1.1861***
			(0.0244)	(0.0240)			(0.0243)	(0.0236)
Stock other	0.5101***	0.5148***	0.0895***	0.0891***	0.5230***	0.5219***	0.0869***	0.0873***
	(0.0454)	(0.0437)	(0.0120)	(0.0119)	(0.0439)	(0.0434)	(0.0120)	(0.0118)
Spillovers automation	0.3519	0.7057**	0.0098	-0.0228	1.3383***	1.3247***	-0.0667	-0.0442
	(0.2949)	(0.3032)	(0.0746)	(0.0724)	(0.4669)	(0.4699)	(0.0784)	(0.0776)
Spillovers other	-0.0735	-0.3940*	0.0219	0.0692	-1.0318***	-1.0459***	0.1163	0.0930
	(0.2127)	(0.2153)	(0.0782)	(0.0779)	(0.3544)	(0.3541)	(0.0827)	(0.0824)
Fixed effects	F + Y	F + Y	BGVR + Y	BGVR + Y	F + CY	F + CY	BGVR + CY	BGVR + CY
Observations	50115	50115	50115	50115	50070	50070	50070	50070
Firms	3341	3341	3341	3341	3338	3338	3338	3338

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG) in columns (1), (2), (5) and (6). In columns (3), (4), (7) and (8), estimation is done by Poisson regressions where the firm fixed effects are replaced by the pre-sample mean, following Blundell, Griffith and Van Reenen (1999, BGVR). Columns (1) to (4) include year fixed effects and columns (5) to (8) country-year fixed effects. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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Deflators

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Dependent Variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	3.7365***	2.4627***	3.9223***	2.7140***	3.4104***	3.2654***	3.7675**	2.5337***
	(0.9116)	(0.8351)	(0.9351)	(0.8686)	(0.9896)	(0.8400)	(1.5237)	(0.8874)
High-skill wage	-0.4838	-1.6180**	-0.6187	-1.7475**	-0.8389	-1.5307*	-0.1621	-0.6657
	(0.7650)	(0.8033)	(0.7646)	(0.7943)	(0.8541)	(0.8034)	(0.9158)	(0.8844)
GDP gap	0.0265*	0.0279*	0.0271*	0.0285*	0.0304*	0.0197	0.0448**	0.0287*
	(0.0156)	(0.0158)	(0.0157)	(0.0158)	(0.0160)	(0.0144)	(0.0178)	(0.0152)
GDP per capita	-3.3618***		-3.3402***		-4.2436***	-2.1549***	-3.0981***	-2.2709**
	(0.8917)		(0.9144)		(1.0551)	(0.7233)	(1.2015)	(0.9264)
Stock automation	-0.1504***	-0.1441***	-0.1510***	-0.1439***	-0.1522***	-0.1524***	-0.1470***	-0.1477***
	(0.0510)	(0.0509)	(0.0511)	(0.0510)	(0.0514)	(0.0511)	(0.0514)	(0.0511)
Stock other	0.6489***	0.6408***	0.6458***	0.6392***	0.6498***	0.6448***	0.6533***	0.6503***
	(0.0595)	(0.0600)	(0.0595)	(0.0600)	(0.0593)	(0.0598)	(0.0595)	(0.0594)
Spillovers automation	0.8587***	0.5442*	0.8775***	0.5795*	1.1422***	0.9717***	0.9116***	0.8723**
	(0.3213)	(0.3135)	(0.3120)	(0.3073)	(0.3714)	(0.3421)	(0.3533)	(0.3498)
Spillovers other	-0.5853**	-0.3014	-0.5912***	-0.3314	-0.7249***	-0.6025**	-0.5122**	-0.4704*
	(0.2303)	(0.2248)	(0.2290)	(0.2259)	(0.2361)	(0.2407)	(0.2564)	(0.2602)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables include a dummy for no stock and no spillover. Columns (1) and (2) consider manifacturing wages and GDP per capita deflated by manifacturing PPI (USD 1995), (3) and (4) consider manifacturing wages and GDP per capita deflated by manifacturing PPI (USD 2005), (5) considers manifacturing wages and GDP per capita deflated by local GDP deflator (USD 1995), (6) considers manifacturing wages and GDP per capita deflated by US manifacturing PPI (USD every year), (7) consider total wages and GDP per capita deflated by manifacturing PPI (USD 1995), (8) considers total wages and GDP per capita deflated by US manifacturing PPI (USD every year). Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Weights

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Dependent Variable	Auto95							
	1985-1994		1970-1989		GDP^0		GDP^1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.4739***	3.7419***	1.8155*	3.0953***	1.8685**	3.1229***	2.8690***	3.8862***
	(0.8691)	(0.9387)	(0.9480)	(0.9991)	(0.7776)	(0.8903)	(0.8855)	(0.8988)
High-skill wage	-1.7055**	-0.2061	-0.8990	0.0754	-1.3791*	-0.5817	-1.6609**	-0.0664
	(0.8288)	(0.8641)	(0.8354)	(0.7733)	(0.8226)	(0.7850)	(0.7114)	(0.7221)
GDP gap	0.0226	0.0188	0.0140	0.0134	0.0276*	0.0288*	0.0265*	0.0214
	(0.0163)	(0.0162)	(0.0164)	(0.0163)	(0.0154)	(0.0153)	(0.0158)	(0.0156)
GDP per capita		-3.9086***		-3.1164***		-2.8432***		-3.6086***
		(1.1661)		(0.9376)		(0.8687)		(0.8483)
Stock automation	-0.1337**	-0.1426***	-0.1194**	-0.1256**	-0.1436***	-0.1486***	-0.1429***	-0.1489***
	(0.0524)	(0.0527)	(0.0602)	(0.0606)	(0.0509)	(0.0511)	(0.0511)	(0.0509)
Stock other	0.6539***	0.6553***	0.6900***	0.6959***	0.6414***	0.6471***	0.6385***	0.6467***
	(0.0639)	(0.0630)	(0.0769)	(0.0761)	(0.0600)	(0.0594)	(0.0598)	(0.0593)
Spillovers automation	0.5655*	0.8970***	0.2618	0.5929*	0.4091	0.7351**	0.8056**	1.0189***
	(0.3154)	(0.3273)	(0.3206)	(0.3210)	(0.3093)	(0.3256)	(0.3340)	(0.3271)
Spillovers other	-0.3401	-0.6299***	-0.3772	-0.6481***	-0.1913	-0.4962**	-0.4680**	-0.6526***
	(0.2303)	(0.2376)	(0.2435)	(0.2379)	(0.2311)	(0.2397)	(0.2265)	(0.2267)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	45735	45735	35955	35955	50115	50115	50115	50115
Firms	3049	3049	2397	2397	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). In columns (1) and (2) firms' country weights for the macroeconomic variables are computed over the period 1985-1994; and over the period 1970-1989 for columns (3) and (4). Columns (5) to (8) use the baseline pre-sample period of 1970-1994, but columns (5) and (6) do not adjust for GDP in the computation of the weights and columns (7) and (8) use GDP instead of $GDP^{0.35}$ to adjust for countries' size in the computation of the weights. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

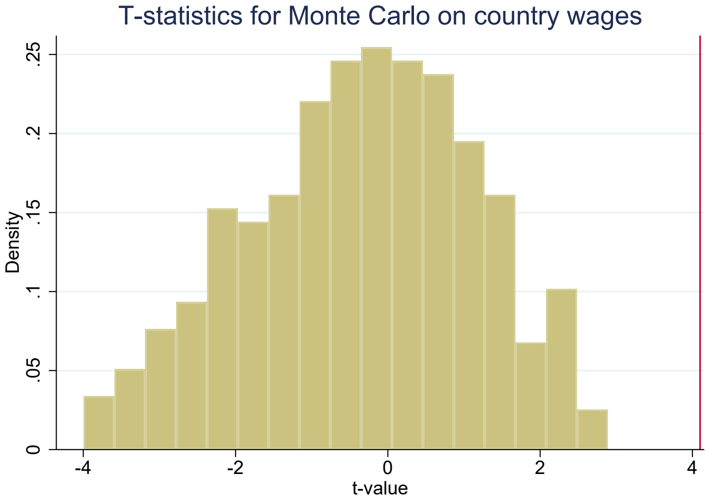
Recent literature on Bartik / shift-share

- Goldsmith Pinkham, Sorkin and Swift (2018) on consistency:
  - Bartik instrument is equal to (time-interacted) country-weights as instruments in firm-regression
  - Here plausible that firm's weights are uncorrelated with future country trends.
- Borusyak, Hull and Jaravel (2018)
  - Firm weights just need to be uncorrelated with wage growth in countries (though all countries x year must be small)
  - Country-year fixed effects help here
- Adão, Kolesár and Morales (2018) on standard errors
  - Very much about within labor-market area labor market clearing
  - Our setting: Concern that standard errors might be correlated within firms with exposure to same export markets.
  - Suggestions for corrected standard errors

Monte Carlo simulations for low-skill wages

Back

- Run Monte Carlo simulations where we reallocate country macro variables. Report t-stat on low-skill wage coefficient for baseline regression with GDP per capita.



Time trend in automation Back

Dependent variables	Auto 95 and other + low auto				Auto95 and low auto	Auto95 and other and low auto
	(1)	(2)	(3)	(4)	(5)	(6)
time trend*dummy auto95*German exposure	0.6309**	0.6245***	0.7726*	0.0929**	0.6486***	0.6523***
	(0.2502)	(0.2296)	(0.3957)	(0.0366)	(0.2464)	(0.2322)
time trend*dummy auto95*post_2003*German exposure	-1.2330***	-1.2322***	-1.3229**	-0.1810**	-1.2500***	-1.2826***
	(0.4473)	(0.4291)	(0.5273)	(0.0766)	(0.4605)	(0.4300)
dummy auto95*post_2003*German exposure			-0.7289			
			(1.0856)			
time trend*dummy low auto*German exposure						0.0081
						(0.1278)
time trend*dummy low auto*post_2003*German exposure						-0.0386
						(0.1835)
year dummy*German exposure	Y	Y	Y	Y	Y	Y
firm innovation stocks * innovation types	N	Y	Y	Y	Y	Y
firm *innovation types fixed effects	Y	Y	Y	Y	Y	Y
country * year * innovation types fixed effects	Y	Y	Y	Y	Y	Y

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm innovation types fixed effects, country year innovation types fixed effects and controls for the year dummy times the measure of German exposure. German exposure is measured by the German weights in all regressions except for column (4) where it is replaced by a dummy signaling that the firm is in the top quartile of Germany exposed firms. Innovation types are auto95 and (other + low auto) in columns (1) to (4), auto 95 and low auto in column (5) and auto 95, other and low auto in column (6). All regressions with stock variables include a dummy for no stock. Standard errors are clustered at the firm-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$