

Supplementary Material – Online Appendix

A Classifications

A.1 Classifications of input-supplying countries by income status, export complexity, human capital abundance

In addition to the Rest of World, the forty input-supplying countries available in the World Input-Output Database (WIOD) are: Australia, Austria, Bulgaria, Belgium, Brazil, Canada, China, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Indonesia, India, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Latvia, Mexico, Malta, the Netherlands, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Turkey, Taiwan, United Kingdom, United States of America.

Classification of supplying countries by income level (benchmark): Relying on the World Bank’s Historical Country Classification By Income, I consider a supplying country as high-income (HI) if it belongs to the group of high-income countries according to its gross national income per capita for at least half of the years of the 1996–2005 period, or as lower-income (LMI) if it belongs to the group of upper-middle-, lower-middle- or low-income countries. The high-income group includes: Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Luxembourg, Malta, Netherlands, Portugal, Slovenia, Spain, Sweden, Taiwan, United Kingdom, and the United States of America. The lower-income group includes: Brazil, Bulgaria, China, Czech Republic, Estonia, Hungary, India, Indonesia, Latvia, Lithuania, Mexico, Poland, Romania, Russia, Slovakia, and Turkey.

Classification of supplying countries by export complexity: Relying on the ATLAS of Economic Complexity, I include a supplying country in the group of countries with relatively high (low) complexity of exports if its economic complexity index (ECI) is at least equal to (smaller than) the 75th percentile value of ECI, calculated across all supplying countries available by year. Under this classification, the group of countries with relatively high sophistication level of exports includes all countries of the high-income group under the benchmark classification except for Australia, Canada, Cyprus, Greece, Luxembourg, Malta, Netherlands, Portugal, Spain and Taiwan, which pertain to the group of countries with relatively low complexity of exports in all or most years of the sample. Also, Czech Republic, which pertains to

the lower-income group under the benchmark classification, is included in most years in the group of countries with relatively high complexity of exports.

Classification of supplying countries by human capital abundance: Relying on the Penn World Tables version 10.0, I consider a supplying country to be relatively abundant (scarce) in human capital if its human capital index is at least equal to (below) the 75th percentile value of the human capital index, calculated across all supplying countries available by year. Under this classification, the group of countries with relative human capital abundance comprises all high-income countries of the benchmark classification except for Cyprus, Greece, Italy, Malta, Portugal, Spain, and Taiwan. Also, Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Poland, Romania, Russia, and Slovakia pertain mostly or exclusively to this group, while they are considered as lower-income under the benchmark classification.

A.2 Classification of industrial automation technologies

Following [Acemoglu & Restrepo \(2021\)](#), I rely on the UN Comtrade database to retrieve information on imports and exports of ten different types of automation technologies. In particular, I consider the following automation technologies: industrial robots (ROBOTS), dedicated machinery, including industrial robots (DEDIC. MACH.), 3-D printing machines (3-D PRINT), automatic data processing machines (DATA PROC.), automatic conveyors (CONVEYORS), automatic regulating instruments (REGUL. INSTR.), electronic calculating machines (CALC. MACH.), automatic machine tools (MACH. TOOLS), automatic welding machines (WELD. MACH.), and automatic textile, knitting and weaving machines (TEXT. MACH.).

I identify these technologies by their HS 1996 codes. The list of codes per technology are as follows: industrial robots (847950), dedicated machinery, including industrial robots (847989), 3-D printing machines (847780), automatic data processing machines (8471, 847330), automatic conveyors (8428), automatic regulating instruments (9032), electronic calculating machines (8470, 847321), automatic machine tools (8456, 8457, 8468), automatic welding machines (8515), automatic textile, knitting and weaving machines (8444, 8445, 8446, 8447, 8448).

A.3 Classification of countries examined by employment protection legislation strictness and union density

Relying on the OECD indicators of employment protection legislation (EPL) strictness, I include a country in the group of countries with relatively high (low) EPL strictness if its EPL index in 1996 is at least equal to (smaller than) the unweighted cross-country median EPL value in the same year. The group of countries with relatively high EPL strictness comprises Austria, Finland, Germany, Italy, the Netherlands, and Spain, while the group of countries with relatively low EPL strictness comprises Australia, Denmark, Japan, the United Kingdom, and the United States of America.

Similarly, relying on the OECD union density database, I include a country in the group of countries with relatively high (low) union density if the value of the variable in 1996 is at least equal to (smaller than) the unweighted cross-country median union density in the same year. The group of countries with relatively high union density comprises Australia, Austria, Denmark, Finland, Italy, and the United Kingdom, while the group of countries with relatively low union density comprises Germany, Japan, the Netherlands, Spain, and the United States of America.

A.4 Concordance between ind6090 and NACE Rev. 1.1

Table A1: Concordance between ind6090 and NACE Rev. 1.1

ind6090	Industry (ind6090) Name	NACE Rev. 1.1
100	Meat products	15T16
101	Dairy products	15T16
102	Canned and preserved fruits and vegetables	15T16
110	Grain mill products	15T16
111	Bakery products	15T16
112	Sugar and confectionary products	15T16
120	Beverage industries	15T16
121	Misc. food preparations and kindred products	15T16
122	Not specified food industries	15T16
130	Tobacco manufactures	15T16
132	Knitting mills	17T19
140	Dyeing and finishing textiles, except wool and knit goods	17T19
141	Floor coverings, except hard surfaces	17T19
142	Yarn, thread, and fabric mills	17T19
146	Primary aluminum industries; Other primary metal industries	27T28
150	Misc. textile mill products	17T19
151	Apparel and accessories, except knit	17T19
152	Misc. fabricated textile products	17T19
160	Pulp, paper, and paperboard mills	21T22
161	Misc. paper and pulp products	21T22
162	Paperboard containers and boxes	21T22
166	Screw machine products; metal forgings and stampings; and Misc. fabricated metal products	27T28
171	Newspaper publishing and printing	21T22
172	Printing, publishing, and allied industries except newspapers	21T22
176	Engine and turbines; Construction and material handling machines; metalworking machinery; machinery, except electrical, n.e.c.; Not specified machinery	29
181	Drugs	24
186	Electronic computing equipment; Office and accounting machines	30T33
190	Paints, varnishes, and related products	24
200	Petroleum refining	23
201	Misc. petroleum and coal products	23
206	Household appliances; Radio, TV and Communications equipment; Electric machinery, equipment and supplies, n.e.c.; Not specified electrical machinery, equipment and supplies.	30T33
211	Other rubber products, and plastics footwear and belting + Tires & Inner tubes	25
212	Misc. plastic products	25
220	Leather tanning and finishing	17T19
221	Footwear, except rubber and plastic	17T19
222	Leather products, except footwear	17T19
230	Logging	20
231	Sawmills, planing mills, and millwork	20
236	Railroad locomotives and equipment; Cycles and Misc transportation equipment; Wood buildings and mobile homes	34T35
241	Misc. wood products	20
242	Furniture and fixtures	20
246	Scientific and controlling instruments; Optical and health service supplies	30T33
250	Glass and glass products	26
251	Cement, concrete, and gypsum, and plaster products	26
252	Structural clay products	26
261	Pottery and related products	26
262	Misc. nonmetallic mineral and stone products	26
270	Blast furnaces, steelworks, rolling and finishing mills	27T28
271	Iron and steel foundries	27T28
281	Cutlery, hand tools, and other hardware	27T28
282	Fabricated structural metal products	27T28
301	Not specified metal industries	27T28
311	Farm machinery and equipment	29
346	Plastics, synthetics, and resins; Soaps and cosmetics; Agricultural Chemicals; Industrial and miscellaneous chemicals.	24
351	Transportation equipment	34T35
360	Ship and boat building and repairing	34T35
362	Guided missiles, space vehicles, and parts, Ordnance, and Aircraft and parts	34T35
380	Photographic equipment and supplies	30T33
381	Watches, clocks, and clockwork operated devices	30T33
391	Misc. manufacturing industries and toys, amusement and sporting goods	36T37
392	Not specified manufacturing industries	36T37

ind6090	Industry (ind6090) Name	NACE Rev. 1.1
400	Railroads	60T63
401	Bus service and urban transit	60T63
402	Taxicab service	60T63
410	Trucking service	60T63
411	Warehousing and storage	60T63
412	U.S. Postal Service	64
420	Water transportation	60T63
421	Air transportation	60T63
422	Pipe lines, except natural gas	60T63
432	Services incidental to transportation	60T63
441	Telephone (wire and radio)	64
442	Telegraph and misc. communication services & Radio television and broadcasting	64
500	Motor vehicles and equipment wholesale	50
536	Electrical goods; Hardware, plumbing and heating supplies wholesale	51
541	Drugs, chemicals, and allied products wholesale	51
542	Apparel, fabrics, and notions wholesale	51
550	Groceries and related products wholesale	51
551	Farm products, raw materials wholesale	51
552	Petroleum products	23
566	Lumber and construction materials; Metals and minerals, except petroleum; Scrap and waste materials; Paper and paper products; Alcoholic beverages (all wholesale)	51
571	Not specified wholesale trade	51
580	Lumber and building material retailing	52
581	Hardware stores	52
592	Variety stores	52
602	Diary product stores	52
621	Gasoline service stations	52
626	Misc. general merchandise stores and Sewing, needlework, and piece good stores; Department stores and mail order houses; Vending machine operators; Direct selling establishments	52
630	Apparel and accessory stores, except shoe	52
631	Shoe stores	52
632	Furniture and home furnishings stores	52
636	Grocery Stores; Retail Bakeries; Food stores, n.e.c.	52
640	Household appliances, TV, and radio stores	52
642	Drug stores	52
646	Motor vehicle dealers; Auto and home supply stores; Misc. vehicle dealers and mobile home dealers	50
650	Liquor stores	52
660	Jewelry stores	52
672	Fuel and ice dealers	50
681	Retail florists	52
691	Not specified retail trade	52
696	Farm supplies & Retail nurseries and garden stores; Misc. retail stores; Sporting goods, bicycle and hobby stores; Book and stationery stores	52
706	Banking; Credit agencies, n.e.c.; Savings and Loan associations	J
710	Security, commodity brokerage, and investment companies	J
711	Insurance	J
712	Real estate; including real estate-insurance-law offices	70
721	Advertising	71T74
736	Misc. Personal services; Misc. Business services; Computer and data processing services; Detective and protective services; business services, n.e.c.;	71T74
756	Automotive repair shops; automotive services, except repair	50
766	Services to dwellings and other buildings; Misc. repair services; Electrical repair shops	52
771	Laundry, cleaning, and garment services	71T74
782	Shoe repair shops	52
841	Legal services	71T74
882	Engineering, architectural, and surveying services	71T74
890	Accounting, auditing, and bookkeeping services	71T74

Notes: I map ind6090 codes to NACE Rev. 1.1 codes manually based on the corresponding industry (ind6090) names.
Source: Author's concordance table based on Autor et al. (2003) and EU KLEMS.

B Calculation of descriptive statistics for the main and additional variables

B.1 Calculation of descriptive statistics for the main variables

As the variables for offshoring intensities and wage bill shares vary by country, industry and year, I produce statistics for these for the whole sample, by country, and by industry emulating the relevant methodologies implemented by [Graetz & Michaels \(2018\)](#). The description of all these methodologies can also be found in [Blanas \(2024\)](#) and [Blanas et al. \(2026b,a\)](#).

Calculation of mean levels for the whole sample by year I first average offshoring intensities and wage bill shares across industries within each country and year using as weights each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Then, I average across countries by year without using country weights.

Calculation of mean levels by country and year I average offshoring intensities and wage bill shares across industries within each country and year using as weights each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Calculation of mean levels by industry and year I average offshoring intensities and wage bill shares across countries within each industry and year without using country weights.

Calculation of mean percentage (point) changes between the start and end years for the whole sample First, I calculate the percentage (point) changes of offshoring intensities and wage bill shares between 1996 and 2005 by country-industry pair. In the second step, I average the percentage (point) changes across industries by country using as weights each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Then, I average across countries without using country weights.

Calculation of mean percentage (point) changes between the start and end years by country First, I calculate the percentage (point) changes of offshoring intensities and wage bill shares between 1996 and 2005 by country-industry pair. Then, I calculate the weighted averages of the percentage (point) changes across industries by country using as weights each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Calculation of mean percentage (point) changes between the start and end years by industry First, I calculate the percentage (point) changes of offshoring intensities and wage bill shares between 1996 and 2005 by country-industry pair. Then, I average the percentage (point) changes across countries by industry without using country weights.

Calculation of mean robot imports for the whole sample by year In contrast to

the offshoring intensities and wage bill shares, normalised imports of industrial robots vary by country and year. Hence, I calculate their mean levels for the whole sample by year as unweighted averages across countries by year.

B.2 Calculation of descriptive statistics for additional variables

Calculation of mean student enrollment rates by education level for the whole sample by year I calculate unweighted averages of gross rates of student enrollment in primary, secondary, and tertiary education across the countries examined by year. Note that gross rates exceeding 100% point to the enrollment of overage students in a certain education level because of repetition or late entry.

Calculation of mean years of completed secondary and tertiary education for the whole sample by year I calculate unweighted averages of years of completed secondary and tertiary education across countries in 1996, 2000, and 2005 for groups of individuals aged 15–24, 25–34, 35–44, 45–54, and 55–64.

Calculation of mean shares of individuals aged 15–29, 30–49, 50–64, and 50 and over in total population for the whole sample by year I calculate unweighted averages of the shares of individuals aged 15–29, 30–49, 50–64, and 50 and over in total population across the countries examined by year.

Calculation of task content measures by age group To create task content measures by age group, I implement the methodology of [Acemoglu & Autor \(2011\)](#). First, I retrieve information from [Autor & Dorn \(2013\)](#) on the offshorable, abstract, non-routine manual, and routine task content of 330 (occ1990d) occupations in 1980—a year that precedes the start year of my sample, and information from [Autor & Dorn \(2009\)](#) on the employment shares held by young (aged 16–29), middle-aged (30–54), and older workers (55–64) in these 330 occupations in 1990 and 2005.^{B1} Following [Autor & Dorn \(2013\)](#), I also calculate the routine task intensity (*RTI*) of each occupation as: $RTI = \ln routine - (\ln manual + \ln abstract)$. Using these two pieces of information, I then calculate the offshorable, abstract, non-routine manual, and routine task content, and RTI by age group as the weighted average of the respective occupation-specific measure across the 330 occupations using as weights the occupational employment shares of age groups in 1990 and 2005.

Decomposition of wage bill share changes To decompose the percentage point changes of

^{B1} [Autor & Dorn \(2013\)](#) calculate the offshorable task content of occupations as the unweighted average of two variables from the US O*NET, “Face-to-Face Contact” and “On-Site Job”, thereby capturing the degree to which occupations require direct interaction in physical presence or proximity to a specific work location. Then, they reverse the signs of the calculated averages, so that higher values indicate higher degrees of offshorability of occupations. To calculate the abstract, non-routine manual, and routine task content of occupations, the authors rely on the respective measures constructed by [Autor et al. \(2003\)](#) according to the fourth (1977) edition of the US Department of Labor’s Dictionary of Occupational Titles (DOT), namely: the non-routine cognitive analytical and non-routine cognitive interactive task content, the non-routine manual task content, and the routine cognitive and routine manual task content. For the calculation of employment shares by occupation and year, [Autor & Dorn \(2009\)](#) rely on information from the US Census IPUMS.

the wage bill shares of the three age groups between 1996 and 2005, I implement the methodology proposed by pertinent studies (e.g., [Berman et al., 1994](#)). First, I calculate the between-industry, within-industry, and interaction components by country-industry pair. Then, I sum each component over industries by country: $\sum_i \Delta Esh_{ci} Wsh_{ci,1996}^g$, $\sum_i Esh_{ci,1996} \Delta Wsh_{ci}^g$, and $\sum_i \Delta Esh_{ci} \Delta Esh_{ci}^g$, where Esh_{ci} is the share of industry i 's hours worked by persons engaged in country c 's hours worked by persons engaged, Δ denotes the percentage point change of a variable between 1996 and 2005, and $g \in G = \{15 - 29, 30 - 49, 50+\}$. After obtaining the country-specific statistics, I calculate the unweighted cross-country mean or median of each component to obtain statistics for the whole sample.

Note that the sum of the percentage point changes of the within-industry component across the three age groups per country and the respective sum for the interaction component are equal to one, confirming internal consistency. The small non-zero sum of the percentage point changes of the between-industry component across the three age groups per country is due to the fact that the analysis covers industries of the manufacturing and market service sectors only, while the actual wage bill share changes are likely to have occurred not only through shifts across industries of these two sectors, but also across industries of other economic sectors.

C Additional descriptive statistics

Table C1: Share of routine tasks in 1980 and 1990 by industry

Industry	Share of routine tasks (R)	
	1980	1990
15T16	0.604	0.587
17T19	0.802	0.821
20	0.560	0.584
21T22	0.654	0.617
23	0.490	0.474
24	0.576	0.526
25	0.708	0.699
26	0.591	0.649
27T28	0.688	0.741
29	0.781	0.780
30T33	0.710	0.587
34T35	0.753	0.695
36T37	0.831	0.674
50	0.436	0.422
51	0.354	0.324
52	0.457	0.452
60T63	0.292	0.322
64	0.576	0.533
70	0.375	0.318
71T74	0.497	0.477
J	0.564	0.480

Notes: Authors' calculations based on [Autor et al. \(2003\)](#).

Table C2: Offshoring intensities by country, 1996–2005

Panel A: Mean levels in 1996					
Country	OFF	OFF_HI	OFF_LMI	OFF_LMInC	OFF_CHN
Australia	0.036	0.025	0.004	0.002	0.002
Austria	0.087	0.070	0.008	0.007	0.000
Denmark	0.084	0.070	0.006	0.005	0.001
Finland	0.081	0.067	0.007	0.006	0.001
Germany	0.070	0.055	0.008	0.007	0.001
Italy	0.058	0.043	0.006	0.005	0.001
Japan	0.019	0.012	0.003	0.002	0.002
Netherlands	0.113	0.088	0.006	0.005	0.001
Spain	0.064	0.055	0.004	0.003	0.000
United Kingdom	0.079	0.063	0.006	0.004	0.001
United States	0.025	0.018	0.003	0.003	0.001
Unweighted mean	0.065	0.052	0.006	0.005	0.001
Panel B: Mean percentage changes in 1996–2005					
Country	OFF	OFF_HI	OFF_LMI	OFF_LMInC	OFF_CHN
Australia	12.77	-1.66	317.39	36.69	2302.02
Austria	59.39	42.22	179.85	168.09	2906
Denmark	297.08	303.19	2257.23	2398.48	1613.60
Finland	59.74	42.03	235.13	221.67	1400.66
Germany	63.05	35.36	188.12	163.22	4968.63
Italy	63.91	18.94	253.52	233.04	938.22
Japan	6.19	6.36	308.85	114.67	801.93
Netherlands	67.29	73.70	205.47	159.50	1792.67
Spain	61.42	58.03	298.79	305.94	2138.94
United Kingdom	52.46	37.97	99.56	86.01	136.37
United States	32.24	3.66	181.50	61.81	715.11
Unweighted mean	70.50	56.34	411.40	359.01	1792.19

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added; *OFF_LMInC*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added; *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added. Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

Table C3: Offshoring intensities by industry, 1996–2005

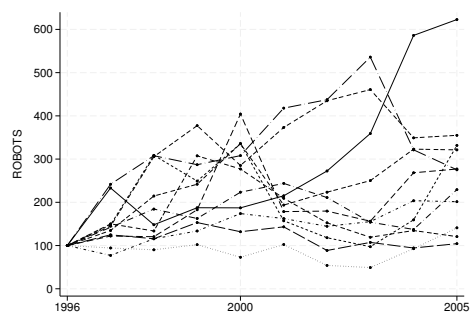
Panel A: Mean levels in 1996					
Industry	OFF	OFF_HI	OFF_LMI	OFF_LMI _{nC}	OFF_CHN
15T16	0.0556	0.0337	0.0080	0.0078	0.0002
17T19	0.2606	0.2027	0.0532	0.0354	0.0178
20	0.1501	0.1039	0.0232	0.0223	0.0009
21T22	0.1392	0.1194	0.0060	0.0057	0.0004
23	0.0860	0.0537	0.0106	0.0106	0.0000
24	0.2879	0.2258	0.0140	0.0126	0.0015
25	0.0587	0.0511	0.0052	0.0032	0.0020
26	0.0395	0.0340	0.0049	0.0043	0.0006
27T28	0.2611	0.1955	0.0270	0.0248	0.0022
29	0.1129	0.1014	0.0046	0.0039	0.0007
30T33	0.2780	0.2253	0.0145	0.0076	0.0069
34T35	0.2964	0.2851	0.0111	0.0101	0.0010
36T37	0.0247	0.0193	0.0025	0.0022	0.0002
50	0.0002	0.0001	0.0000	0.0000	0.0000
51	0.0036	0.0024	0.0012	0.0012	0.0000
52	0.0002	0.0001	0.0001	0.0001	0.0000
60T63	0.0217	0.0184	0.0033	0.0026	0.0007
64	0.0064	0.0052	0.0010	0.0008	0.0002
70	0.0007	0.0003	0.0001	0.0001	0.0000
71T74	0.0305	0.0194	0.0010	0.0009	0.0001
J	0.0175	0.0144	0.0013	0.0013	0.0000

Panel B: Mean percentage changes in 1996–2005					
Industry	OFF	OFF_HI	OFF_LMI	OFF_LMI _{nC}	OFF_CHN
15T16	11.23	-7.49	18.60	9.20	759.15
17T19	-2.36	-34.59	101.97	42.03	283.39
20	47.12	21.00	149.63	124.07	619.43
21T22	0.11	-6.72	84.60	73.53	164.41
23	483.66	312.74	654.60	634.31	5294.73
24	13.10	3.47	71.72	17.89	356.67
25	49.03	28.10	200.83	205.02	178.04
26	24.63	-0.05	52.62	20.32	339.45
27T28	39.15	19.28	121.11	82.29	321.37
29	34.54	15.46	254.28	192.14	562.68
30T33	1.28	-18.85	347.88	272.43	564.93
34T35	77.06	53.76	592.62	533.91	999.60
36T37	32.77	8.15	245.17	243.80	338.74
50	64.89	20.51	574.13	574.13	
51	12.29	-3.18	145.38	108.36	
52	76.18	38.89	530.37	492.80	
60T63	59.66	37.59	165.66	168.40	475.98
64	178.75	132.56	355.86	425.18	800.61
70	666.30	978.06	133.77	133.77	
71T74	92.51	80.56	1423.87	1220.57	6520.65
J	77.45	90.24	55.56	91.90	361.99

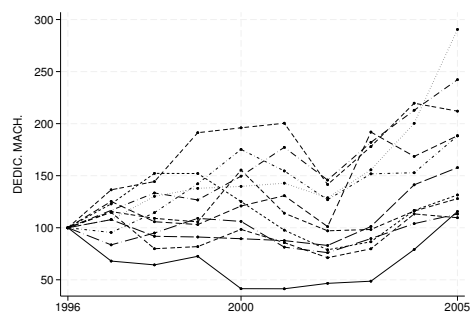
Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added; *OFF_LMI_{nC}*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added; *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added. Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

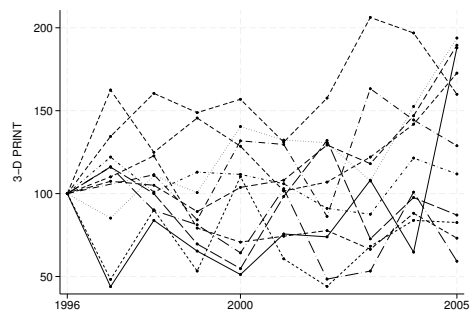
Figure C1: Imports of industrial robots and other automation technologies by country, 1996–2005



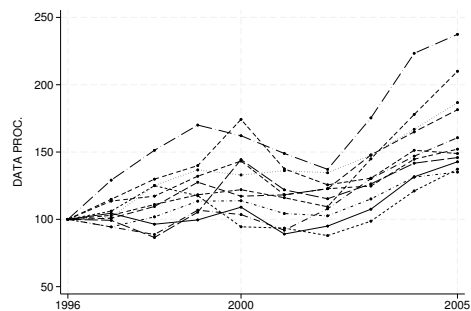
(a) Industrial robots



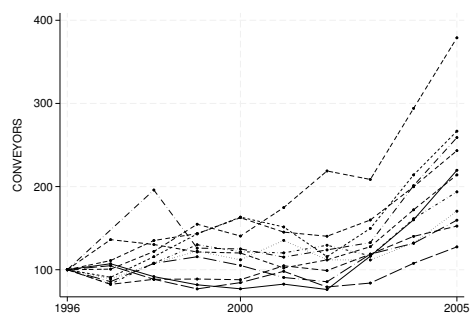
(b) Dedicated machinery



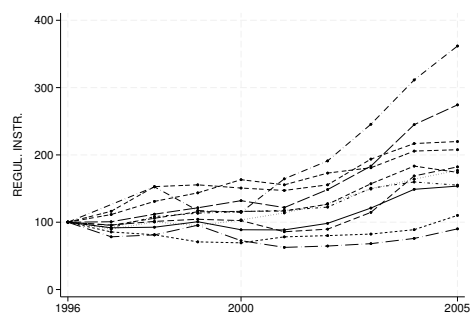
(c) 3-D printing machines



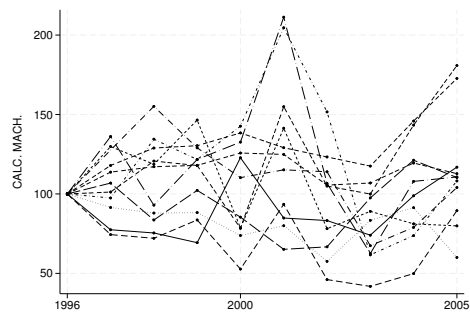
(d) Data processing machines



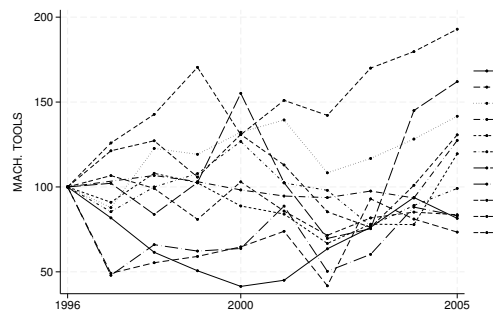
(e) Automatic conveyors



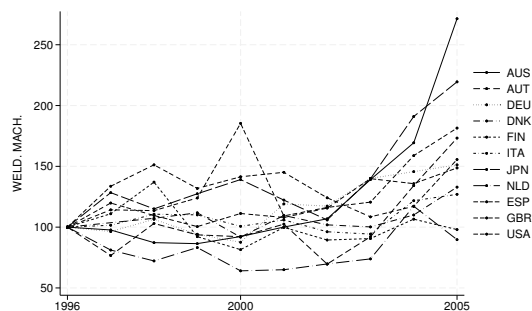
(f) Regulating instruments



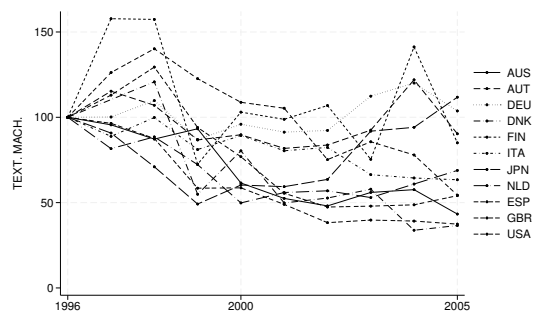
(g) Calculating machines



(h) Machine tools



(i) Welding machines



(j) Textile machines

Notes: Imports by the countries examined of industrial robots (Panel (a)), dedicated machinery (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), regulating instruments (Panel (f)), calculating machines (Panel (g)), automatic machine tools (Panel (h)), welding machines (Panel (i)), textiles machines (Panel (j)) from the world normalised by the corresponding values in 1996. Automation technologies are identified by their HS 1996 codes (see Appendix A.2).

Source: Author's calculations based on UN Comtrade.

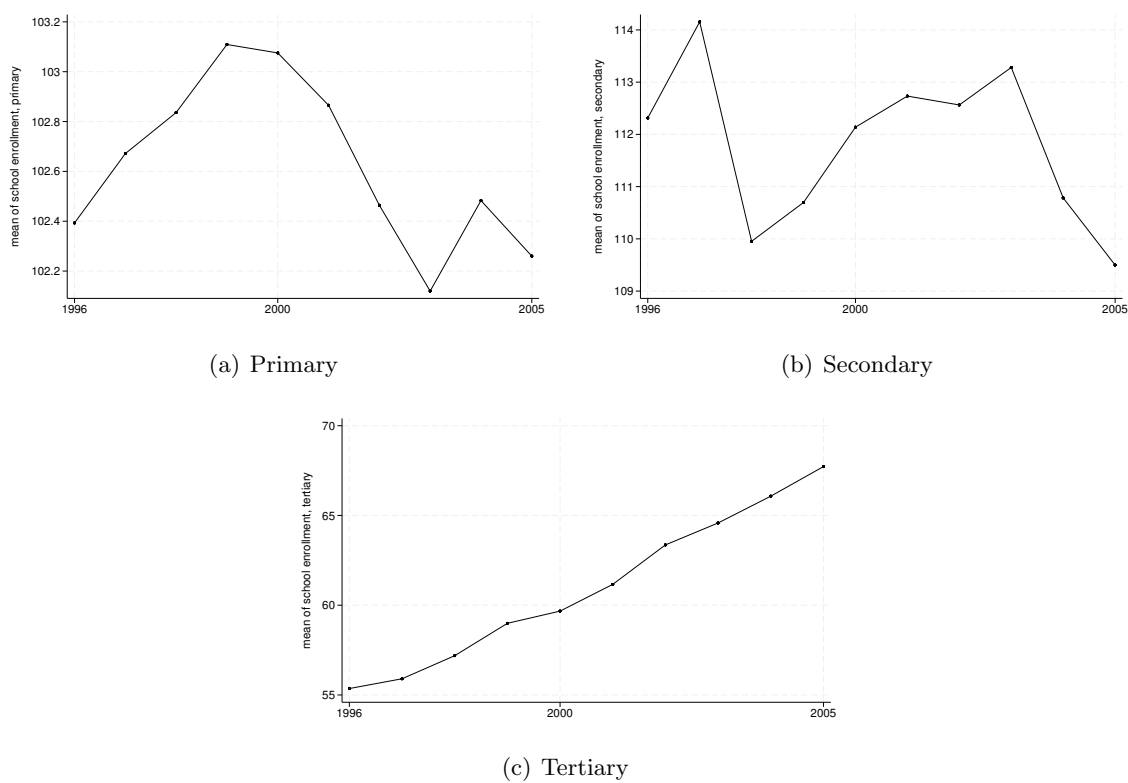
Table C4: Wage bill shares of age groups by country and by industry, 1996–2005

Panel A: By country						
Country	Mean level			Mean % ch.		
	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺
Australia	0.268	0.560	0.173	-14.92	-7.22	46.69
Austria	0.256	0.561	0.183	-19.61	6.66	9.47
Denmark	0.228	0.550	0.222	-31.32	7.43	13.58
Finland	0.153	0.639	0.208	-1.46	-11.98	39.26
Germany	0.162	0.622	0.216	-17.14	0.49	11.30
Italy	0.295	0.660	0.045	-10.41	5.11	-21
Japan	0.203	0.518	0.279	-25.66	0.96	16.29
Netherlands	0.231	0.589	0.180	-21.34	-1.32	30.37
Spain	0.202	0.565	0.233	-5.79	1.07	4.02
United Kingdom	0.244	0.554	0.202	-21.48	2.29	18.35
United States	0.294	0.575	0.132	-17.24	-1.70	45.66
Unweighted mean	0.230	0.581	0.188	-16.94	0.16	19.45
Panel B: By industry						
Industry	Mean level			Mean % ch.		
	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺
15T16	0.229	0.577	0.194	-20.40	0.97	19.98
17T19	0.236	0.567	0.197	-26.94	1.86	23.58
20	0.218	0.566	0.217	-20.43	0.80	18.65
21T22	0.206	0.582	0.211	-19.87	0.22	18.53
23	0.167	0.616	0.207	-18.64	0.65	20.16
24	0.188	0.605	0.207	-20.64	-0.15	19.68
25	0.211	0.584	0.205	-18.82	-0.38	18.13
26	0.195	0.588	0.217	-20.61	-0.10	17.33
27T28	0.209	0.582	0.209	-19.90	0.11	17.14
29	0.207	0.596	0.197	-20.65	0.23	21.92
30T33	0.224	0.600	0.175	-24.74	1.58	25.43
34T35	0.201	0.606	0.192	-21.64	-0.14	25.71
36T37	0.234	0.572	0.194	-23.12	1.58	20.07
50	0.265	0.556	0.178	-15.24	1.32	17.48
51	0.245	0.566	0.188	-15.38	0.75	16.44
52	0.294	0.529	0.176	-10.79	1.31	15.23
60T63	0.197	0.603	0.200	-21.01	-0.99	25.08
64	0.184	0.635	0.181	-6.93	-2.45	24.78
70	0.213	0.578	0.210	-14.72	-3.70	19.23
71T74	0.228	0.597	0.176	-13.72	-1.06	17.79
J	0.183	0.643	0.174	-13.31	-0.89	23.13

Notes: Wsh: Wage bill shares of young workers (aged 15–29), middle-aged workers (aged 30–49) and older workers (aged 50+). For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on EU KLEMS.

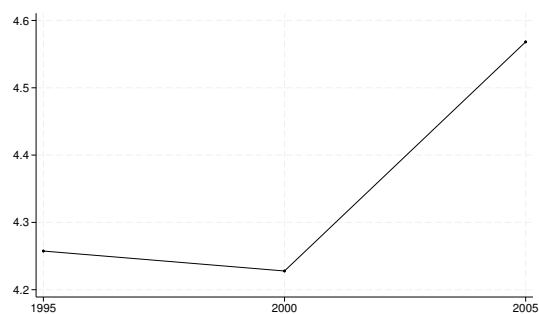
Figure C2: Student enrollment rates by education level



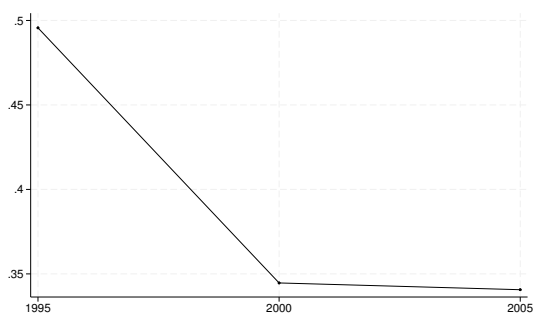
Notes: Unweighted means of the gross rates of student enrollment in primary (Panel (a)), secondary (Panel (b)), and tertiary (Panel (c)) education across countries by year.

Source: Author's calculations based on the World Bank's World Development Indicators.

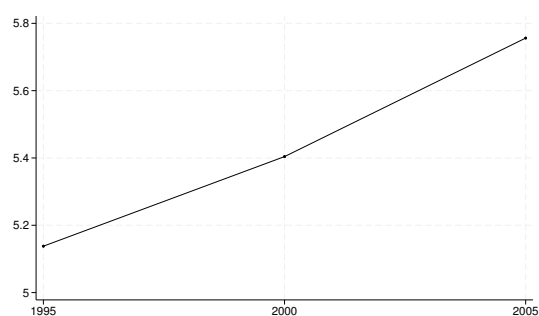
Figure C3: Years of completed secondary and tertiary education by age group



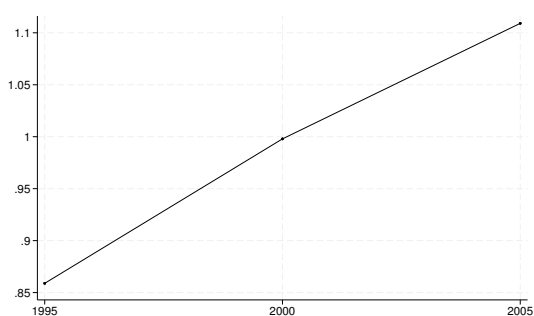
(a) Secondary, Aged 15–24



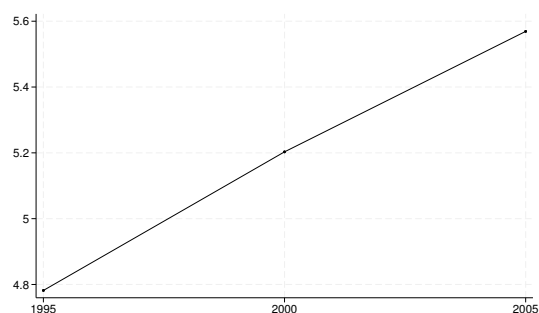
(b) Tertiary, Aged 15–24



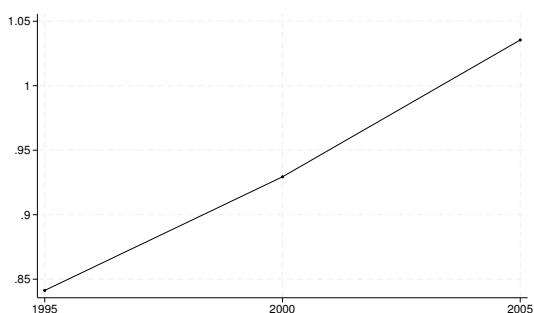
(c) Secondary, Aged 25–34



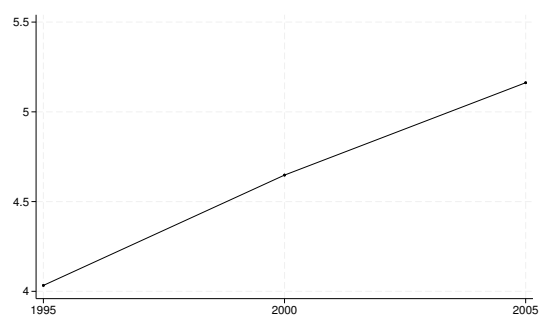
(d) Tertiary, Aged 25–34



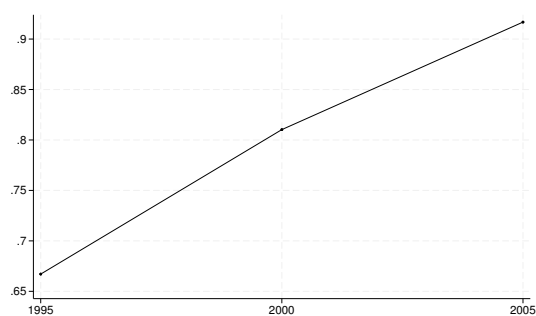
(e) Secondary, Aged 35–44



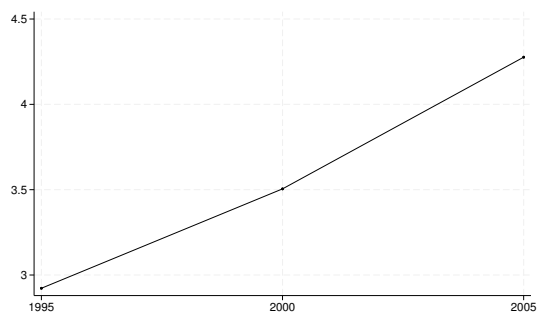
(f) Tertiary, Aged 35–44



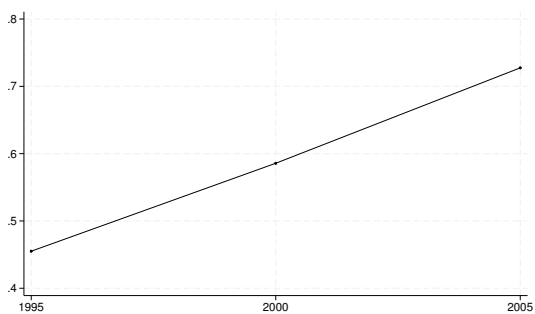
(g) Secondary, Aged 45–54



(h) Tertiary, Aged 45–54



(i) Secondary, Aged 55-64

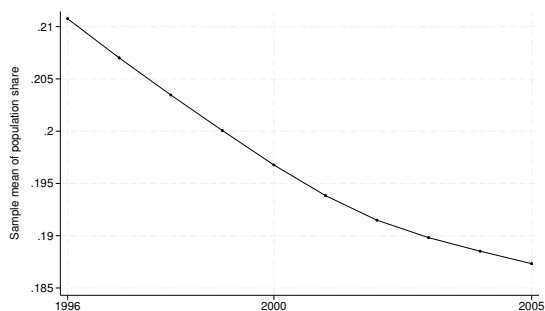


(j) Tertiary, Aged 55-64

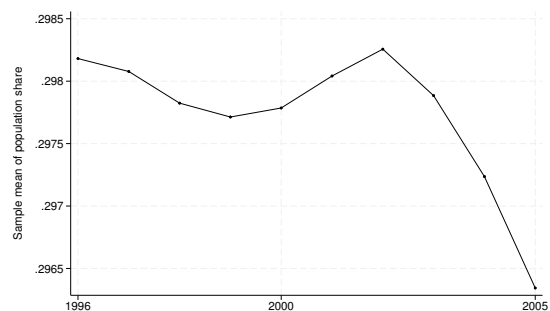
Notes: Unweighted means of the years of completed secondary and tertiary education of individuals aged 15-24 (Panels (a) and (b)), 25-34 (Panels (c) and (d)), 35-44 (Panels (e) and (f)), 45-54 (Panels (g) and (h)), and 55-64 (Panels (i) and (j)) across countries by year.

Source: Author's calculations based on Barro & Lee (2013).

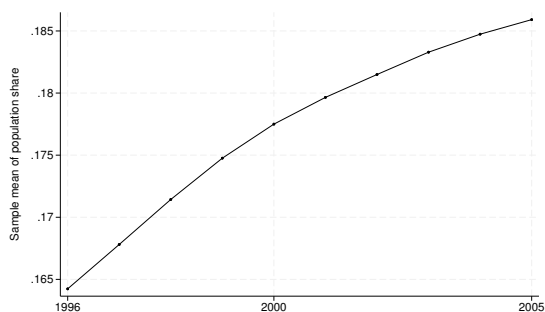
Figure C4: Shares of age groups in total population



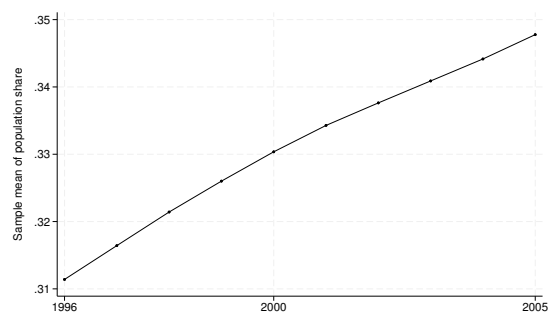
(a) Aged 15-29



(b) Aged 30-49



(c) Aged 50-64



(d) Aged 50+

Notes: Unweighted means of the shares of individuals aged 15-29 (Panel (a)), 30-49 (Panel (b)), 50-64 (Panel (c)), and 50+ (Panel (d)) in total population across countries by year.

Source: Author's calculations based on the OECD Demographics database.

Table C5: Employment, value added, and gross output shares of industries, 1996–2005

Panel A: Mean level 1996						
Industry	EMPsh	EMPEsh	HEMPsh	HEMPEsh	VAsh	GOsh
15T16	0.023	0.025	0.024	0.026	0.025	0.048
17T19	0.016	0.017	0.015	0.017	0.010	0.015
20	0.007	0.007	0.008	0.008	0.006	0.008
21T22	0.019	0.020	0.018	0.021	0.023	0.030
23	0.001	0.001	0.001	0.001	0.004	0.010
24	0.009	0.011	0.010	0.012	0.019	0.027
25	0.008	0.009	0.008	0.009	0.008	0.011
26	0.008	0.009	0.008	0.009	0.009	0.011
27T28	0.024	0.027	0.025	0.028	0.026	0.038
29	0.019	0.022	0.020	0.023	0.020	0.028
30T33	0.020	0.023	0.021	0.024	0.025	0.035
34T35	0.013	0.016	0.014	0.017	0.015	0.028
36T37	0.011	0.012	0.012	0.012	0.008	0.011
50	0.021	0.020	0.023	0.022	0.017	0.017
51	0.050	0.052	0.054	0.056	0.059	0.054
52	0.092	0.085	0.086	0.074	0.047	0.038
60T63	0.044	0.045	0.051	0.052	0.049	0.053
64	0.015	0.017	0.015	0.017	0.025	0.019
70	0.011	0.010	0.011	0.010	0.096	0.066
71T74	0.085	0.082	0.086	0.083	0.080	0.069
J	0.032	0.036	0.032	0.036	0.055	0.047
Panel B: Mean % ch. 1996–2005						
Industry	EMPsh	EMPEsh	HEMPsh	HEMPEsh	VAsh	GOsh
15T16	-14.172	-15.297	-14.330	-15.598	-11.940	-14.952
17T19	-46.792	-49.072	-46.445	-48.980	-42.180	-43.881
20	-15.132	-15.241	-15.349	-14.778	-13.905	-12.733
21T22	-20.759	-22.476	-19.576	-21.274	-10.773	-15.720
23	-24.670	-26.180	-25.740	-27.374	-42.694	-14.891
24	-15.530	-17.164	-16.243	-18.483	4.774	-4.194
25	-10.859	-11.963	-10.519	-11.659	-4.182	-4.798
26	-17.512	-18.778	-17.389	-18.843	-4.382	-8.541
27T28	-11.569	-12.931	-10.868	-11.999	-7.888	-8.368
29	-13.443	-14.934	-13.662	-15.157	-4.321	-4.144
30T33	-17.589	-19.119	-17.475	-19.198	41.945	19.853
34T35	-11.344	-13.036	-11.871	-13.410	3.301	9.047
36T37	-13.248	-14.412	-13.813	-14.438	-13.721	-10.999
50	-0.189	2.160	-1.011	2.834	6.285	5.045
51	-4.588	-5.433	-5.333	-5.797	6.328	3.466
52	-0.338	4.700	-2.031	3.947	0.652	-0.620
60T63	-0.487	0.325	-0.942	0.131	1.078	1.214
64	-6.927	-10.741	-6.607	-11.550	55.995	69.787
70	19.377	22.219	18.043	21.903	-3.257	-1.444
71T74	35.690	35.774	36.436	36.524	21.558	21.950
J	-7.001	-9.126	-5.727	-8.015	5.165	10.441

Notes: EMPsh, EMPEsh, HEMPsh, HEMPEsh, VAsh, GOsh denote, respectively, shares of an industry in economy-wide total number of persons engaged, total number of salaried employees, total hours worked by persons engaged, total hours worked by salaried employees, value added, and gross output.

Source: Authors' calculations based on EU KLEMS.

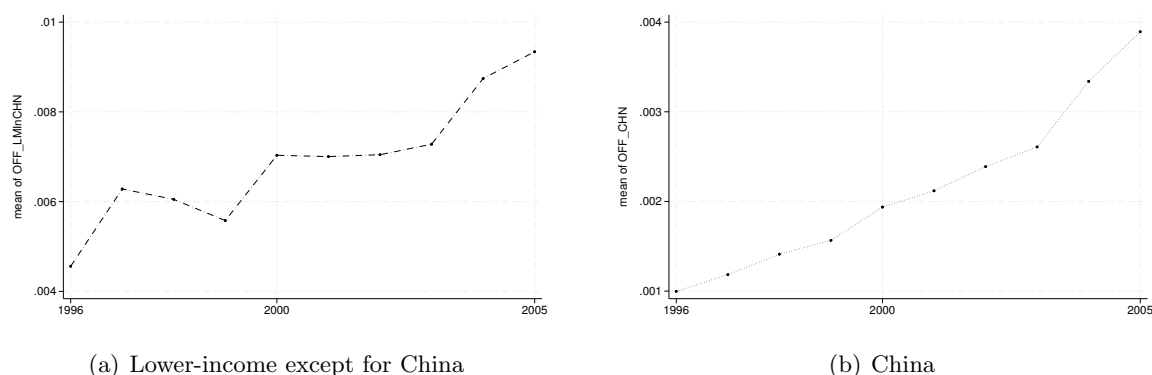
Table C6: Between- and within-industry percentage point changes of wage bill shares of age groups by country, 1996–2005

	ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}		ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}		ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}	
	Between Industries	Within Industries	Between Industries	Within Industries	Interaction	Between Industries	Within Industries	Interaction	Between Industries	Within Industries	Interaction	Between Industries	Within Industries	Interaction	Between Industries	Within Industries	Interaction	Between Industries
Australia	-0.019	-0.039	-0.028	-0.041	0.003	-0.037	0.037	-0.003	-0.011	0.080	-0.005	-0.013	0.015	-0.001	1	1	1	1
Austria	-0.018	-0.052	-0.037	0.037	0.004	-0.037	0.038	-0.002	-0.012	0.015	-0.001	-0.012	0.029	-0.001	1	1	1	1
Denmark	-0.010	-0.067	-0.031	0.038	0.003	-0.031	-0.077	0.001	-0.003	0.082	-0.001	-0.003	0.024	-0.001	1	1	1	1
Finland	-0.002	-0.005	-0.011	-0.077	0.000	-0.028	0.003	-0.000	-0.009	0.024	-0.001	-0.009	-0.008	-0.001	1	0	1	1
Germany	-0.007	-0.027	0.001	0.034	0.001	0.007	0.006	-0.001	0.000	-0.008	-0.000	-0.004	0.046	-0.001	1	1	1	1
Italy	0.002	-0.026	0.001	0.006	0.000	-0.006	-0.008	0.001	-0.007	0.053	-0.002	-0.004	0.053	-0.002	1	1	1	1
Japan	-0.002	-0.052	0.000	-0.025	0.001	-0.025	-0.005	0.000	0.000	0.008	-0.001	-0.007	0.008	-0.001	1	0	1	1
Netherlands	-0.010	-0.045	0.001	0.005	0.001	-0.001	0.013	0.001	0.006	0.037	-0.001	0.000	0.037	-0.001	1	1	1	1
Spain	-0.000	-0.014	0.001	0.017	-0.001	0.017	0.013	0.001	0.006	0.001	0.001	0.001	0.001	0.001	1	1	1	1
United Kingdom	0.007	-0.050	-0.001	-0.010	-0.000	0.008	-0.010	-0.000	0.001	0.060	0.001	0.001	0.060	0.001	1	1	1	1
United States	0.003	-0.050	-0.000	-0.013	-0.000	0.008	-0.010	-0.000	0.001	0.060	0.001	0.001	0.060	0.001	1	1	1	1
Unweighted mean	-0.005	-0.039	0.001	0.000	0.001	-0.013	0.000	-0.000	-0.005	0.039	-0.001	-0.005	0.039	-0.001	-	-	-	-
Unweighted median	-0.002	-0.045	0.001	0.005	0.000	-0.011	0.005	0.000	-0.004	0.037	-0.001	-0.004	0.037	-0.001	-	-	-	-

Notes: Wsh^{15-29} , Wsh^{30-49} and Wsh^{50+} denote shares of self-employed individuals, informal workers, and informal-sector workers, respectively. I first calculate the between-industry, within-industry, and interaction components by country-industry pair, and then, sum each component over industries by country: $\sum_i \Delta Wsh_{i,c}^{15-29}$, $\sum_i Wsh_{i,c}^{15-29} \Delta Wsh_{i,c}^{30-49}$, and $\sum_i Wsh_{i,c}^{15-29} Wsh_{i,c}^{30-49} \Delta Wsh_{i,c}^{50+}$, where $Wsh_{i,c}$ is the share of industry i 's total employment in country c 's aggregate employment. Δ signifies the percentage point change of a variable between 1996 and 2005, and $g \in \{15-29, 30-49, 50+\}$. The interaction component is calculated as $\sum_i Wsh_{i,c}^{15-29} Wsh_{i,c}^{30-49} \Delta Wsh_{i,c}^{50+}$. The within-industry component is calculated as $\sum_i Wsh_{i,c}^{15-29} Wsh_{i,c}^{30-49} \Delta Wsh_{i,c}^{50+}$. The interaction component is calculated as $\sum_i Wsh_{i,c}^{15-29} Wsh_{i,c}^{30-49} \Delta Wsh_{i,c}^{50+}$. Value one (zero) in the last three columns indicates that the within-industry component is larger (smaller) than the between-industry component for the three labour variables.

Source: Authors' calculations based on EU KLEMS.

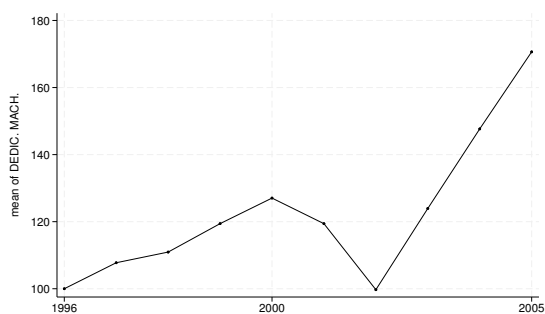
Figure C5: Intensities of offshoring to China and to other lower-income countries, 1996–2005



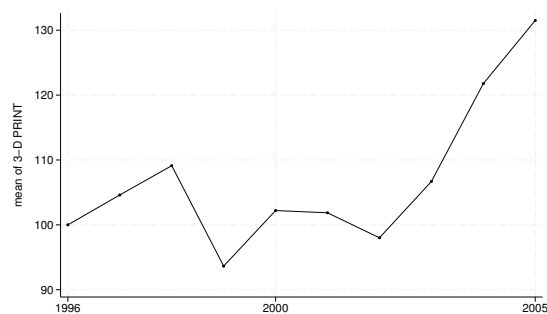
Notes: *OFF_LMinC* Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added (Panel (a)); *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added (Panel (b)). Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. Lower-income: offshoring destination countries are labeled as upper-middle-income, lower-middle-income or low-income for at least half of the years of the period examined. For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

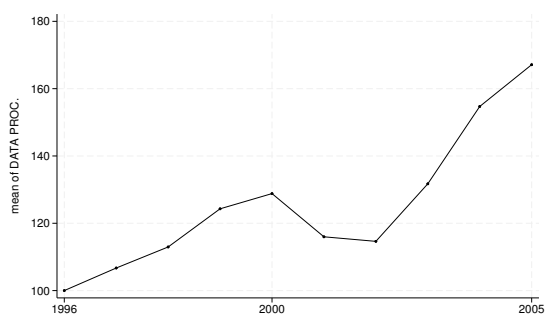
Figure C6: Cross-country mean of imports of additional automation technologies, 1996–2005



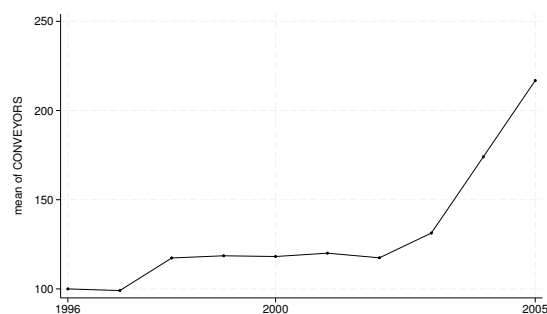
(a) Dedicated machinery



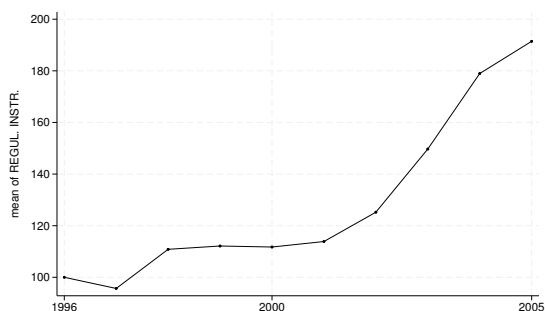
(b) 3-D printing machines



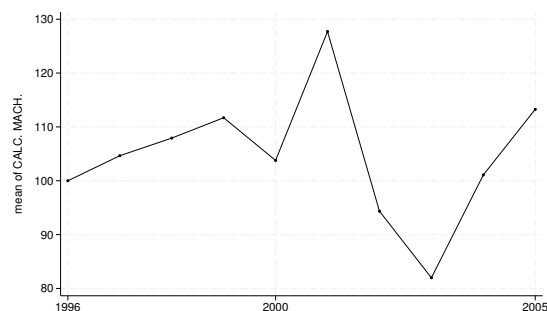
(c) Data processing machines



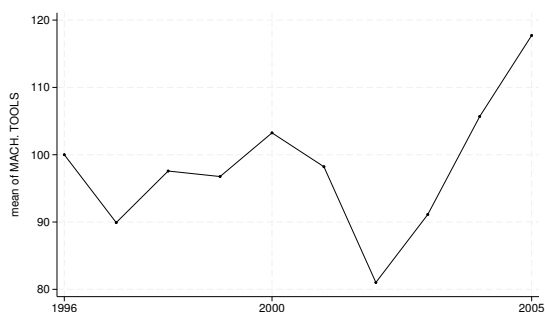
(d) Automatic conveyors



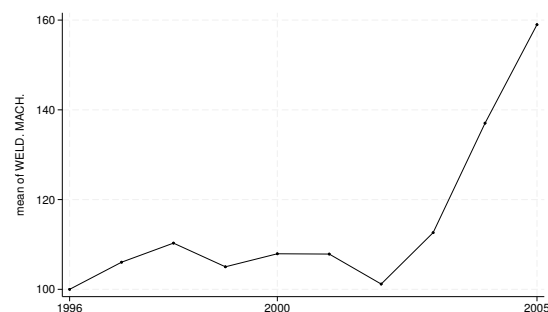
(e) Regulating instruments



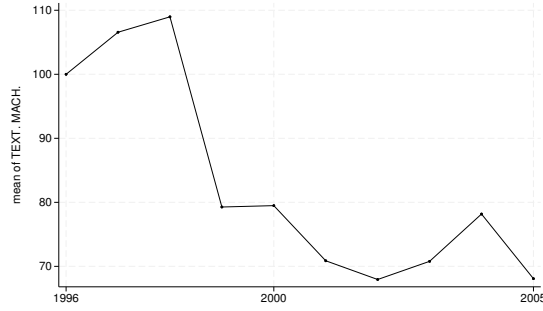
(f) Calculating machines



(g) Machine tools



(h) Welding machines

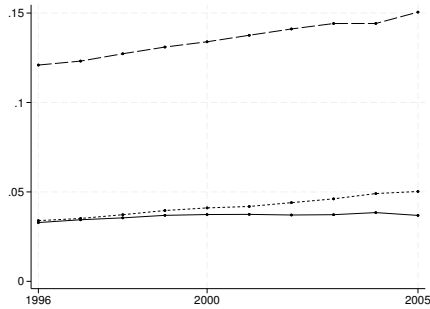


(i) Textile machines

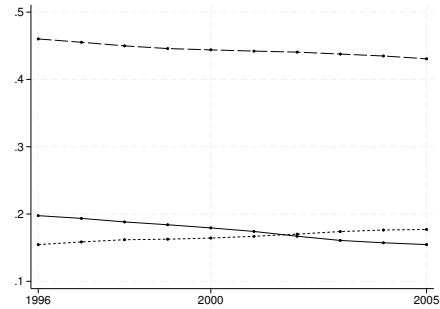
Notes: Imports of dedicated machinery (Panel (a)), 3-D printing machines (Panel (b)), data processing machines (Panel (c)), automatic conveyors (Panel (d)), regulating instruments (Panel (e)), calculating machines (Panel (f)), automatic machine tools (Panel (g)), welding machines (Panel (h)), textiles machines (Panel (i)) from the world normalised by the corresponding values in 1996. Automation technologies are identified by their HS 1996 codes (see Appendix A.2). For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on UN Comtrade.

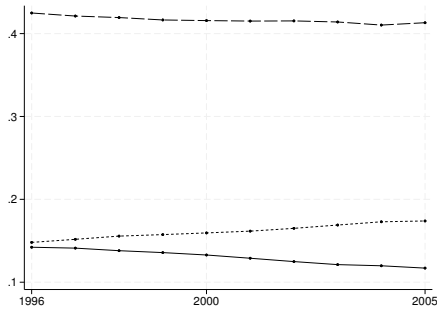
Figure C7: Wage bill shares by age-education or age-gender group, 1996–2005



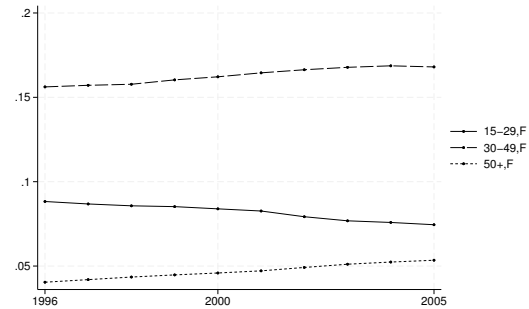
(a) High-educated by age



(b) Lower-educated by age



(c) Male by age



(d) Female by age

Notes: Wage bill shares of young (aged 15–29), middle-aged (aged 30–49) and older (aged 50+) workers with high education level (HS) or lower-education level (LS) in Panels (a) and (b), respectively. Wage bill shares of young (aged 15–29), middle-aged (aged 30–49) and older (aged 50+) male (M) or female (F) workers in Panels (c) and (d), respectively. For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on EU KLEMS.

Table C7: Hours worked shares of age groups by country and by industry, 1996–2005

Panel A: By country						
Country	Mean level			Mean % ch.		
	Hsh ^{15–29}	Hsh ^{30–49}	Hsh ⁵⁰⁺	Hsh ^{15–29}	Hsh ^{30–49}	Hsh ⁵⁰⁺
Australia	0.342	0.505	0.153	-9.68	-9.67	53.34
Austria	0.297	0.541	0.162	-18.07	7.34	11.63
Denmark	0.310	0.474	0.216	-21.32	5.97	15.02
Finland	0.230	0.591	0.180	6.41	-15.46	44.56
Germany	0.231	0.567	0.203	-15.80	0.10	17.37
Italy	0.287	0.617	0.096	-3.58	3.07	-9.77
Japan	0.287	0.463	0.249	-25.17	5.59	18.84
Netherlands	0.317	0.540	0.143	-19.94	0.17	39.94
Spain	0.287	0.524	0.189	-5.63	4.29	0.93
United Kingdom	0.326	0.479	0.195	-16.22	1.22	22.02
United States	0.378	0.508	0.114	-12.95	0.55	40.05
Unweighted mean	0.299	0.528	0.173	-12.90	0.29	23.08
Panel B: By industry						
Industry	Mean level			Mean % ch.		
	Hsh ^{15–29}	Hsh ^{30–49}	Hsh ⁵⁰⁺	Hsh ^{15–29}	Hsh ^{30–49}	Hsh ⁵⁰⁺
15T16	0.296	0.527	0.177	-17.11	1.90	24.04
17T19	0.293	0.525	0.182	-22.97	2.43	29.23
20	0.268	0.527	0.206	-16.45	1.24	20.62
21T22	0.280	0.534	0.186	-17.30	1.93	21.59
23	0.230	0.579	0.181	-16.28	1.26	21.74
24	0.257	0.561	0.182	-17.41	1.57	20.30
25	0.277	0.542	0.182	-15.77	0.86	19.57
26	0.254	0.548	0.198	-17.22	1.06	18.73
27T28	0.269	0.541	0.190	-16.96	1.48	19.19
29	0.272	0.553	0.175	-17.95	1.37	25.34
30T33	0.296	0.550	0.154	-21.75	3.64	28.63
34T35	0.265	0.563	0.172	-17.94	1.03	28.54
36T37	0.290	0.529	0.181	-20.27	2.72	24.75
50	0.346	0.494	0.160	-10.22	0.16	19.64
51	0.329	0.502	0.168	-10.52	0.47	18.16
52	0.362	0.470	0.167	-5.30	-0.26	14.70
60T63	0.251	0.561	0.188	-17.28	-1.12	28.13
64	0.250	0.581	0.170	3.06	-4.72	21.12
70	0.272	0.521	0.206	-11.80	-2.84	24.26
71T74	0.304	0.534	0.162	-11.50	-0.38	26.41
J	0.260	0.586	0.154	-7.87	-0.88	31.43

Notes: Hsh: Shares of hours worked by young (aged 15–29), middle-aged (aged 30–49) and older (aged 50+) persons engaged. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on EU KLEMS.

Table C8: Number of hours worked by age group by country and by industry, 1996–2005

Panel A: By country						
Country	Mean level			Mean % ch.		
	1996			1996–2005		
	H ^{15–29}	H ^{30–49}	H ⁵⁰⁺	H ^{15–29}	H ^{30–49}	H ⁵⁰⁺
Australia	2.4e+08	3.4e+08	1.0e+08	3.29	3.47	77.25
Austria	7.0e+07	1.3e+08	3.7e+07	-13.57	13.96	18.94
Denmark	4.6e+07	6.8e+07	3.1e+07	-13.46	13.69	22.96
Finland	2.7e+07	6.7e+07	2.0e+07	27.07	0.17	71.45
Germany	5.0e+08	1.2e+09	4.2e+08	-15.86	-0.24	17.56
Italy	2.9e+08	6.2e+08	1.0e+08	12.23	18.06	2.90
Japan	1.7e+09	2.5e+09	1.2e+09	-34.54	-7.43	3.06
Netherlands	1.9e+08	3.1e+08	7.8e+07	-12.40	8.09	51.81
Spain	2.4e+08	4.2e+08	1.5e+08	26.37	41.02	34.63
United Kingdom	7.1e+08	1.1e+09	4.4e+08	-8.95	7.50	30.65
United States	4.7e+09	5.7e+09	1.3e+09	-9.70	3.74	45.51
Unweighted mean	7.9e+08	1.1e+09	3.6e+08	-3.59	9.28	34.25
Panel B: By industry						
Industry	Mean level			Mean % ch.		
	1996			1996–2005		
	H ^{15–29}	H ^{30–49}	H ⁵⁰⁺	H ^{15–29}	H ^{30–49}	H ⁵⁰⁺
15T16	2.9e+08	5.0e+08	1.9e+08	-22.80	-5.61	14.61
17T19	2.3e+08	3.7e+08	1.3e+08	-56.31	-41.89	-26.36
20	8.7e+07	1.4e+08	5.7e+07	-19.62	-3.97	17.07
21T22	2.7e+08	4.5e+08	1.5e+08	-27.39	-11.61	4.62
23	1.2e+07	3.1e+07	8.2e+06	-32.92	-19.00	-1.92
24	1.3e+08	2.6e+08	7.6e+07	-25.80	-8.75	6.90
25	1.4e+08	2.4e+08	7.9e+07	-17.75	-2.37	15.54
26	9.0e+07	1.8e+08	6.9e+07	-24.36	-9.37	7.34
27T28	3.2e+08	6.0e+08	2.2e+08	-17.61	-1.66	15.53
29	2.6e+08	5.1e+08	1.7e+08	-20.88	-5.16	15.08
30T33	3.9e+08	6.9e+08	1.9e+08	-30.12	-8.14	15.00
34T35	2.3e+08	4.6e+08	1.4e+08	-21.40	-4.75	21.10
36T37	1.3e+08	2.2e+08	7.7e+07	-22.66	-3.08	21.56
50	3.0e+08	4.0e+08	1.1e+08	2.19	13.34	34.74
51	8.3e+08	1.2e+09	4.0e+08	-5.49	5.21	22.02
52	1.5e+09	1.7e+09	5.9e+08	10.21	14.54	31.88
60T63	5.5e+08	1.1e+09	3.9e+08	-7.58	9.93	41.08
64	1.7e+08	3.3e+08	7.8e+07	1.01	-7.50	18.36
70	1.1e+08	2.3e+08	1.2e+08	19.69	35.50	71.30
71T74	1.4e+09	2.0e+09	5.9e+08	34.16	49.29	88.29
J	6.0e+08	9.1e+08	2.3e+08	-7.87	0.54	34.13

Notes: H: Number of hours worked by young (aged 15–29), middle-aged (aged 30–49) and older (aged 50+) persons engaged. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on EU KLEMS.

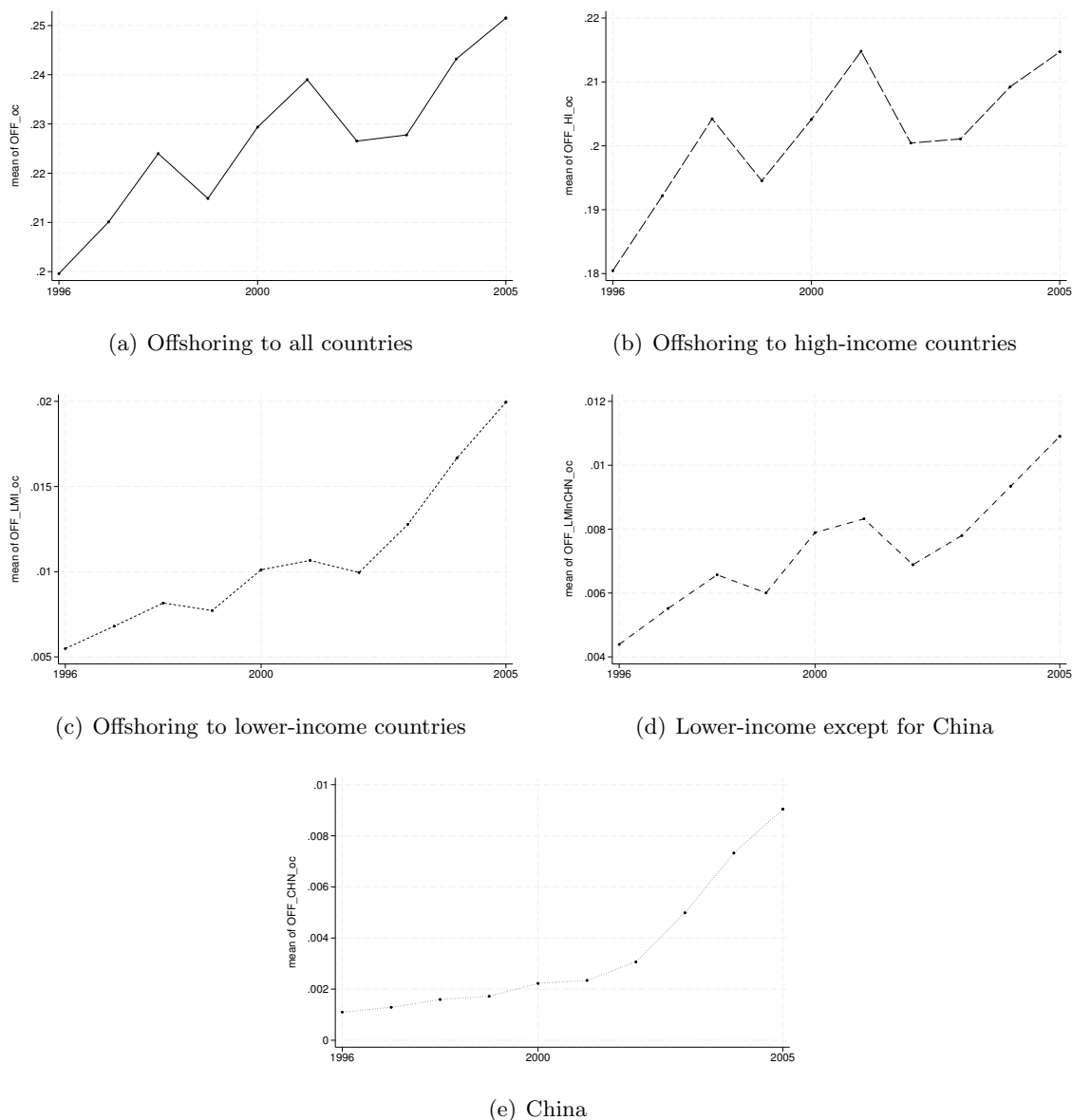
Table C9: Persons engaged and salaried employees by country and by industry, 1996–2005

Panel A: By country								
Country	Mean level 1996				Mean % ch. 1996–2005			
	EMP	EMPE	HEMP	HEMPE	EMP	EMPE	HEMP	HEMPE
Australia	4.5e+05	3.9e+05	7.9e+08	6.8e+08	12.86	15.83	12.28	14.61
Austria	1.5e+05	1.3e+05	2.7e+08	2.3e+08	10.28	9.47	7.72	6.13
Denmark	1.1e+05	1.0e+05	1.6e+08	1.4e+08	2.54	4.24	5.38	7.77
Finland	7.7e+04	6.7e+04	1.4e+08	1.1e+08	16.90	20.02	13.38	18.82
Germany	1.7e+06	1.5e+06	2.5e+09	2.1e+09	5.86	5.37	0.24	-0.19
Italy	9.9e+05	5.9e+05	2.0e+09	1.0e+09	11.44	19.33	6.88	15.07
Japan	3.6e+06	3.0e+06	6.7e+09	5.4e+09	-7.56	-5.79	-14.51	-12.80
Netherlands	4.8e+05	4.2e+05	7.1e+08	5.9e+08	10.49	12.53	4.47	8.23
Spain	5.9e+05	4.3e+05	1.1e+09	8.1e+08	36.02	44.04	27.01	34.65
United Kingdom	1.5e+06	1.3e+06	2.6e+09	2.2e+09	6.09	7.00	4.48	7.13
United States	7.6e+06	6.9e+06	1.3e+10	1.2e+10	3.59	5.28	1.61	3.43
Unweighted mean	1.6e+06	1.3e+06	2.7e+09	2.3e+09	9.86	12.48	6.27	9.35
Panel B: By industry								
Industry	Mean level 1996				Mean % ch. 1996–2005			
	EMP	EMPE	HEMP	HEMPE	EMP	EMPE	HEMP	HEMPE
15T16	5.7e+05	5.3e+05	1.1e+09	9.8e+08	-4.46	-3.94	-7.80	-7.25
17T19	4.8e+05	4.2e+05	8.5e+08	7.3e+08	-40.18	-41.55	-41.83	-43.34
20	1.8e+05	1.5e+05	3.4e+08	2.8e+08	-4.37	-2.56	-7.52	-4.75
21T22	5.2e+05	4.9e+05	9.4e+08	8.7e+08	-11.28	-11.52	-13.10	-13.15
23	2.6e+04	2.6e+04	5.2e+07	5.1e+07	-15.84	-15.97	-19.86	-19.87
24	2.6e+05	2.6e+05	4.8e+08	4.7e+08	-5.96	-6.02	-9.72	-10.30
25	2.6e+05	2.5e+05	4.8e+08	4.6e+08	-0.63	-0.04	-3.64	-2.93
26	2.0e+05	1.8e+05	3.7e+08	3.4e+08	-7.37	-6.96	-10.23	-9.87
27T28	6.7e+05	6.2e+05	1.2e+09	1.1e+09	-0.73	-0.28	-3.37	-2.51
29	5.3e+05	5.1e+05	9.9e+08	9.5e+08	-3.01	-2.75	-6.61	-6.22
30T33	7.1e+05	6.9e+05	1.3e+09	1.3e+09	-8.27	-8.28	-11.03	-11.05
34T35	4.5e+05	4.5e+05	8.4e+08	8.3e+08	-1.60	-1.77	-5.57	-5.46
36T37	2.8e+05	2.4e+05	5.1e+08	4.3e+08	-2.25	-1.54	-5.99	-4.51
50	5.4e+05	4.5e+05	1.0e+09	8.1e+08	11.21	15.93	6.77	13.26
51	1.5e+06	1.4e+06	2.8e+09	2.5e+09	6.80	7.94	2.86	4.61
52	3.1e+06	2.5e+06	5.0e+09	3.8e+09	11.20	19.46	6.21	15.38
60T63	1.2e+06	1.0e+06	2.4e+09	2.1e+09	11.23	14.51	7.22	10.99
64	3.5e+05	3.4e+05	6.0e+08	5.8e+08	3.93	1.18	0.99	-2.62
70	3.6e+05	2.8e+05	6.1e+08	4.7e+08	35.62	42.39	29.60	37.57
71T74	2.7e+06	2.3e+06	4.8e+09	3.9e+09	50.67	53.69	46.95	50.22
J	1.1e+06	1.0e+06	1.9e+09	1.7e+09	3.43	2.96	1.66	1.26

Notes: EMP: Number of persons engaged; EMPE: Number of salaried employees; HEMP: Number of hours worked by persons engaged; HEMPE: Number of hours worked by salaried employees. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on EU KLEMS.

Figure C8: Offshoring intensities, 1996–2005, group of other high-income countries



Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added (Panel (a)); *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added (Panel (b)); *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added (Panel (c)); *OFF_LMIInC* Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added (Panel (d)); *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added (Panel (e)). Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

Table C10: Offshoring intensities by country, 1996–2005, group of other high-income countries

Panel A: Mean levels in 1996					
Country	OFF	OFF_HI	OFF_LMI	OFF_LMInC	OFF_CHN
Belgium	0.221	0.197	0.010	0.009	0.001
France	0.069	0.060	0.004	0.003	0.001
Ireland	0.215	0.174	0.007	0.005	0.002
Luxembourg	0.392	0.383	0.004	0.002	0.001
Sweden	0.100	0.088	0.003	0.003	0.000
Unweighted mean	0.200	0.180	0.005	0.004	0.001
Panel B: Mean percentage changes in 1996–2005					
Country	OFF	OFF_HI	OFF_LMI	OFF_LMInC	OFF_CHN
Belgium	26.91	19.10	229.51	170.74	1921.55
France	29.22	11.14	132.43	113.22	280.08
Ireland	174.54	167.67	403.08	303.93	2640.01
Luxembourg	68.04	39.85	594.33	341.71	2189.66
Sweden	25.44	7.67	325.23	253.95	2093.36
Unweighted mean	64.83	49.09	336.92	236.71	1824.93

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added; *OFF_LMInC*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added; *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added. Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

Table C11: Offshoring intensities by industry, 1996–2005, group of other high-income countries

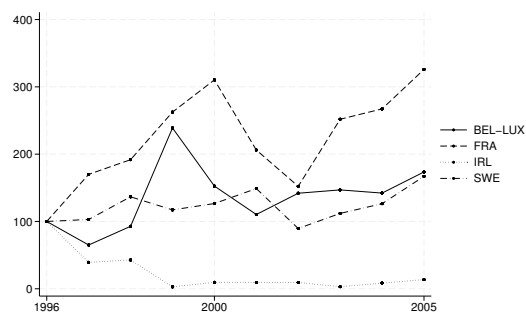
Panel A: Mean levels in 1996					
Industry	OFF	OFF_HI	OFF_LMI	OFF_LMI _{nC}	OFF_CHN
15T16	0.1001	0.0847	0.0065	0.0063	0.0002
17T19	0.3359	0.2979	0.0341	0.0277	0.0064
20	0.3058	0.2617	0.0205	0.0199	0.0006
21T22	0.3116	0.2956	0.0045	0.0043	0.0002
23	0.1880	0.1519	0.0100	0.0098	0.0002
24	0.4164	0.3718	0.0083	0.0074	0.0009
25	0.0906	0.0845	0.0036	0.0022	0.0015
26	0.0956	0.0900	0.0046	0.0041	0.0004
27T28	0.7652	0.6995	0.0234	0.0219	0.0015
29	0.2659	0.2544	0.0049	0.0044	0.0005
30T33	0.4965	0.3836	0.0144	0.0068	0.0076
34T35	0.5684	0.5613	0.0070	0.0067	0.0003
36T37	0.0681	0.0454	0.0088	0.0082	0.0006
50	0.0001	0.0001	0.0000	0.0000	0.0000
51	0.0071	0.0060	0.0009	0.0009	0.0000
52	0.0008	0.0006	0.0001	0.0001	0.0000
60T63	0.0473	0.0449	0.0024	0.0021	0.0003
64	0.0150	0.0138	0.0008	0.0007	0.0001
70	0.0005	0.0004	0.0000	0.0000	0.0000
71T74	0.0955	0.0844	0.0014	0.0012	0.0001
J	0.2616	0.2562	0.0052	0.0034	0.0018

Panel B: Mean percentage changes in 1996–2005					
Industry	OFF	OFF_HI	OFF_LMI	OFF_LMI _{nC}	OFF_CHN
15T16	13.08	7.52	-8.07	-11.19	159.30
17T19	1.44	-17.88	612.67	876.96	338.24
20	44.25	25.37	152.65	129.71	1017.57
21T22	-0.13	-8.10	175.45	203.25	160.44
23	71.09	43.78	159.73	166.70	2306.19
24	16.78	9.50	155.69	143.45	272.29
25	42.22	32.33	312.64	327.09	456.67
26	43.74	27.98	125.85	136.41	618.05
27T28	6.48	0.20	140.90	128.18	335.60
29	-0.30	-9.35	262.64	233.17	641.94
30T33	44.68	32.54	1034.37	688.61	1744.30
34T35	-4.99	-12.30	581.34	535.06	9308.71
36T37	70.21	49.77	315.01	310.96	429.99
50	108.36	103.48	168.04	168.04	
51	141.01	126.03	237.54	199.74	
52	92.56	66.33	212.67	212.19	
60T63	8.07	-1.43	185.78	157.34	391.92
64	420.06	372.49	1150.00	822.51	2994.98
70	71.02	134.98	-19.58	-19.58	
71T74	80.93	50.33	814.88	339.45	6253.99
J	11.05	4.53	39.97	85.76	-12.96

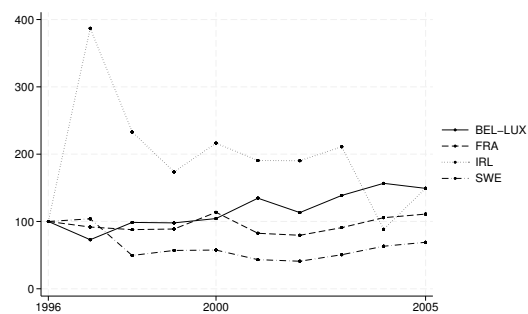
Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added; *OFF_LMI_{nC}*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries except for China to real gross value added; *OFF_CHN*: Ratio of real imports of a country-industry pair from the same industry of China to real gross value added. Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on WIOD, the World Bank's Historical Country Classification By Income, and EU KLEMS.

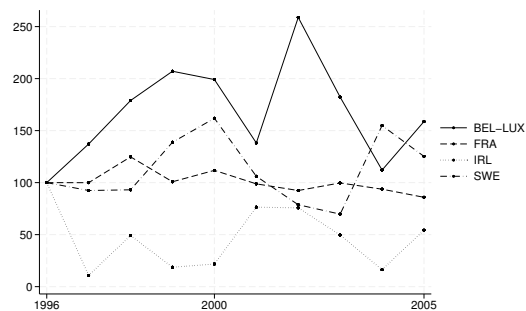
Figure C9: Imports of industrial robots and other automation technologies by country, 1996–2005, group of other high-income countries



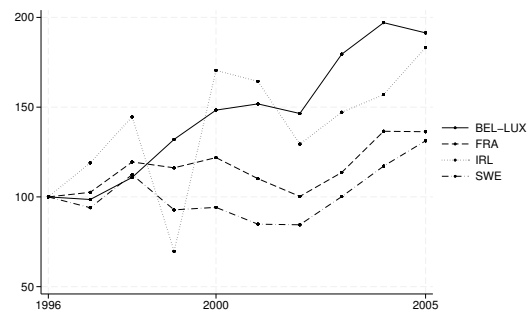
(a) Industrial robots



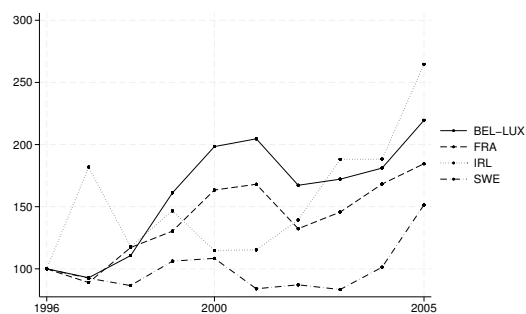
(b) Dedicated machinery



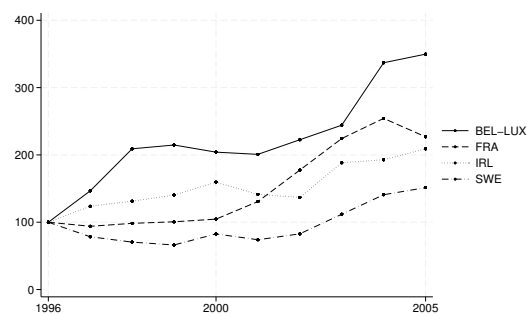
(c) 3-D printing machines



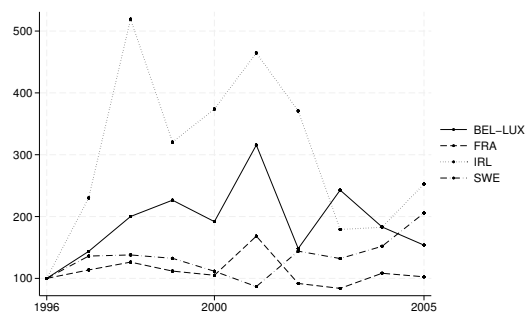
(d) Data processing machines



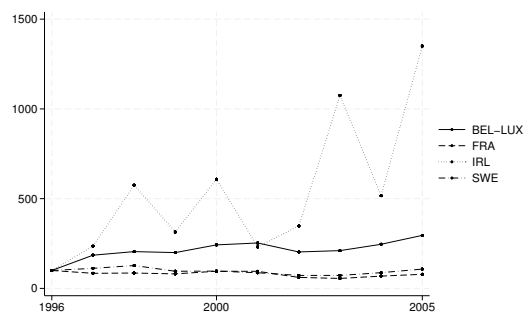
(e) Automatic conveyors



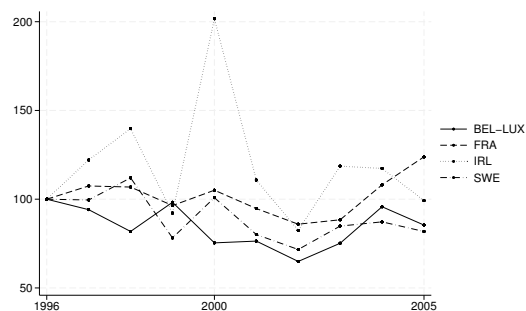
(f) Regulating instruments



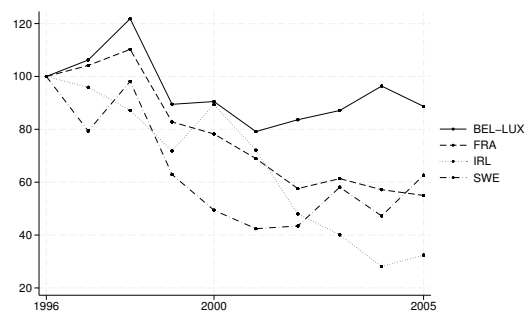
(g) Calculating machines



(h) Machine tools



(i) Welding machines

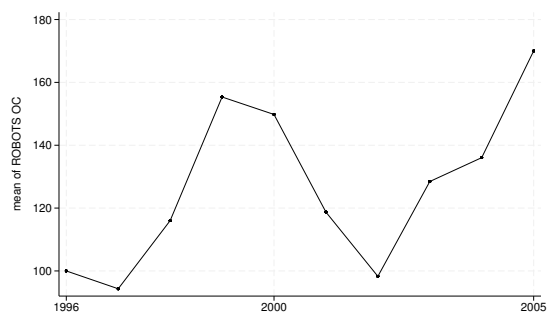


(j) Textile machines

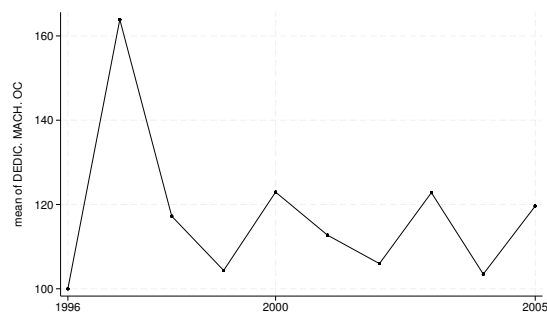
Notes: Imports by other high-income countries of industrial robots (Panel (a)), dedicated machinery (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), regulating instruments (Panel (f)), calculating machines (Panel (g)), automatic machine tools (Panel (h)), welding machines (Panel (i)), textiles machines (Panel (j)) from the world normalised by the corresponding values in 1996. Automation technologies are identified by their HS 1996 codes (see Appendix A.2).

Source: Author's calculations based on UN Comtrade.

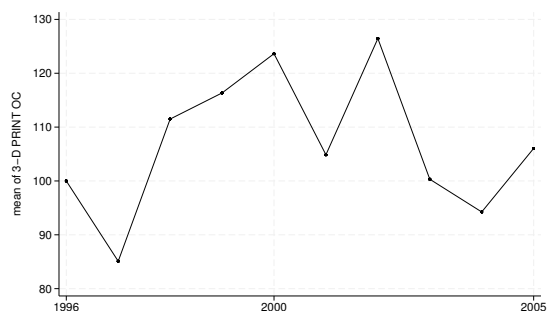
Figure C10: Cross-country mean of imports of industrial robots and other automation technologies, 1996–2005, group of other high-income countries



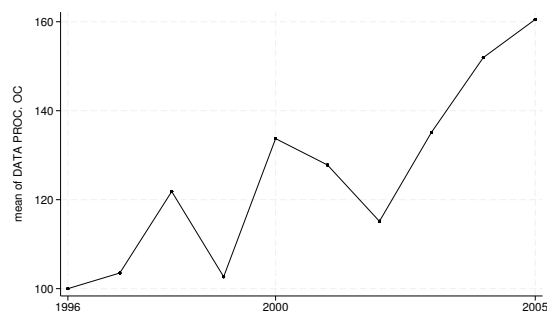
(a) Industrial robots



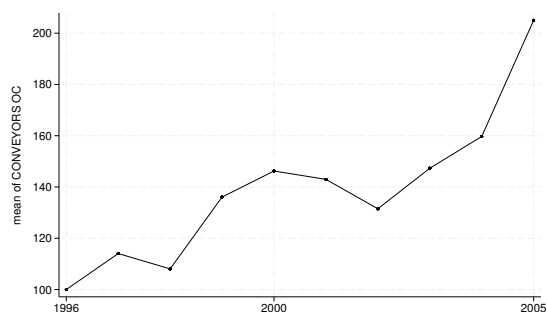
(b) Dedicated machinery



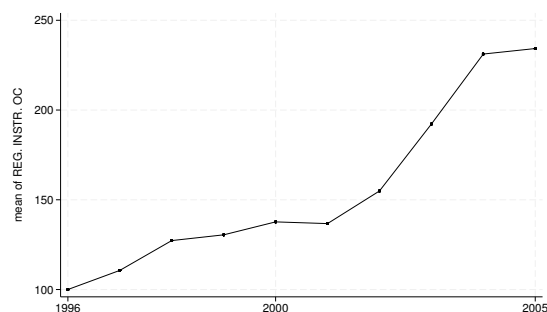
(c) 3-D printing machines



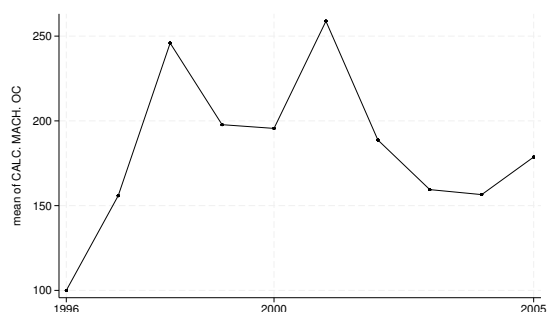
(d) Data processing machines



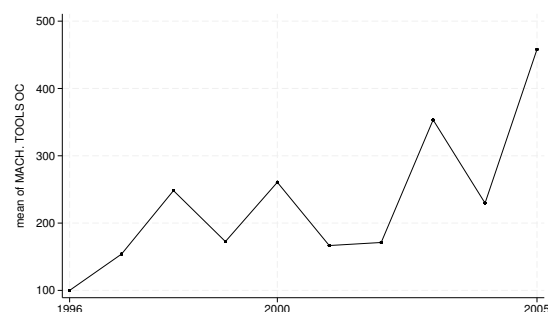
(e) Automatic conveyors



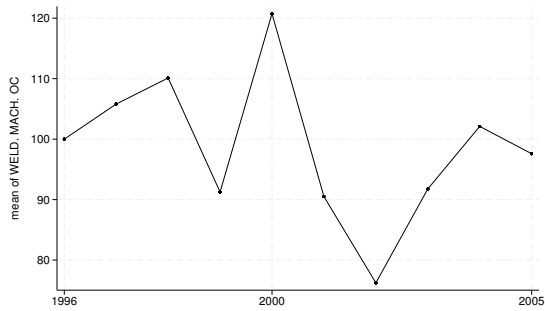
(f) Regulating instruments



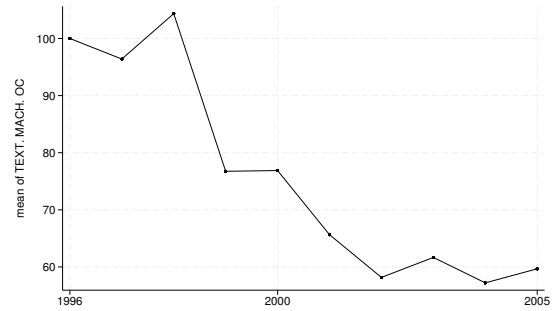
(g) Calculating machines



(h) Machine tools



(i) Welding machines



(j) Textile machines

Notes: Imports by other high-income countries of industrial robots (Panel (a)), dedicated machinery (Panel (b)), 3-D printing machines (Panel (c)), data processing machines (Panel (d)), automatic conveyors (Panel (e)), regulating instruments (Panel (f)), calculating machines (Panel (g)), automatic machine tools (Panel (h)), welding machines (Panel (i)), textiles machines (Panel (j)) from the world normalised by the corresponding values in 1996. Automation technologies are identified by their HS 1996 codes (see Appendix A.2). For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on UN Comtrade.

D Additional econometric results

Table D1: Offshoring and wage bill shares by age, OLS and 2SLS

Panel A: OLS						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.016* [0.009]	-0.0082 [0.009]	-0.0055 [0.006]	0.017** [0.007]	-0.0091 [0.009]	-0.0061 [0.006]
K	-0.0033 [0.003]	0.0038 [0.003]	0.0014 [0.001]	-0.0022 [0.003]	0.0028 [0.003]	0.0012 [0.001]
OFF	0.052 [0.03]	-0.067** [0.03]	0.028* [0.01]			
OFF_HI				0.11*** [0.04]	-0.10*** [0.04]	0.0044 [0.02]
OFF_LMI				-0.23*** [0.09]	0.071 [0.08]	0.16*** [0.06]
Observations	231	231	229	231	231	229
R^2	0.445	0.660	0.698	0.472	0.662	0.704
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.000805	0.0664	0.0163
Panel B: 2SLS, IV-OFF-OC						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.015* [0.008]	-0.0080 [0.009]	-0.0060 [0.006]	0.018*** [0.007]	-0.0094 [0.009]	-0.0064 [0.006]
K	-0.0049 [0.003]	0.0049* [0.003]	0.0014 [0.001]	-0.0020 [0.003]	0.0029 [0.003]	0.0011 [0.001]
OFF	0.12* [0.06]	-0.12* [0.06]	-0.00052 [0.04]			
OFF_HI				0.15** [0.07]	-0.14* [0.08]	-0.0082 [0.05]
OFF_LMI				-0.40*** [0.1]	0.14 [0.1]	0.26*** [0.07]
Observations	231	231	229	231	231	229
R^2	0.0409	0.0307	0.0120	0.0925	0.0430	0.0289
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.000135	0.0510	0.00840
Kleibergen-Paap rk LM	13.71	13.71	13.41	13.50	13.50	13.57
Kleibergen-Paap rk LM (p-value)	0.000213	0.000213	0.000250	0.000238	0.000238	0.000229
Kleibergen-Paap Wald rk F	17.77	17.77	17.20	10.40	10.40	10.35
Stock-Yogo critical value	16.38	16.38	16.38	7.03	7.03	7.03
Lewis-Mertens test statistic	16.24	16.24	15.84	9.559	9.559	9.728
Lewis-Mertens critical value	14.23	14.21	14.20	24.86	24.87	24.25
Wald χ^2	3.442	3.491	0.000191	15.33	4.327	12.48
Wald χ^2 (p-value)	0.0635	0.0617	0.989	0.000469	0.115	0.00195
AR χ^2	3.672	3.328	0.000191	8.767	3.311	12.25
AR χ^2 (p-value)	0.0553	0.0681	0.989	0.0125	0.191	0.00218
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC		

Notes: OLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6) of Panel B. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D2: Industrial robots and wage bill shares by age, OLS and 2SLS

Panel A: OLS			
	(1)	(2)	(3)
Dep var: Wsh	15-29	30-49	50+
ln Y	0.011 [0.009]	-0.0084 [0.01]	-0.00029 [0.006]
K	-0.0026 [0.003]	0.0021 [0.003]	0.0024** [0.001]
ROBOTS * R 1990	-0.014** [0.005]	0.00051 [0.005]	0.014*** [0.004]
Observations	231	231	229
R^2	0.454	0.652	0.711
Panel B: 2SLS, IV–AUT–OC			
	(1)	(2)	(3)
Dep var: Wsh	15-29	30-49	50+
ln Y	0.0092 [0.009]	-0.0058 [0.01]	-0.0011 [0.006]
K	-0.0027 [0.003]	0.0024 [0.003]	0.0023* [0.001]
ROBOTS * R 1990	-0.018** [0.007]	0.0073 [0.008]	0.012* [0.006]
Observations	231	231	229
R^2	0.0801	0.0138	0.0585
Kleibergen-Paap rk LM	56.14	56.14	53.09
Kleibergen-Paap rk LM (p-value)	6.75e-14	6.75e-14	3.18e-13
Kleibergen-Paap Wald rk F	134.3	134.3	128.7
Stock-Yogo critical value	16.38	16.38	16.38
Lewis-Mertens test statistic	49.43	49.43	49.10
Lewis-Mertens critical value	14.21	14.28	14.26
Wald χ^2	6.093	0.862	3.615
Wald χ^2 (p-value)	0.0136	0.353	0.0572
AR χ^2	5.567	0.861	3.331
AR χ^2 (p-value)	0.0183	0.353	0.0680
Hansen J	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A
IV strategy	ln Y, K: no IV ROBOTS: IV–AUT–OC		

Notes: OLS estimations of specifications in long differences in columns (1)–(3) of Panel A and 2SLS estimations of specifications in long differences in columns (1)–(3) of Panel B. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D3: Lewis-Mertens weak identification test per key endogenous regressor in Table 3

	(1)	(2)	(3)	(4)	(5)	(6)
	15-29	30-49	50+	15-29	30-49	50+
Lewis-Mertens test statistic (OFF)	10.72	10.72	11.27			
Lewis-Mertens critical value (OFF)	14.20	14.42	14.55			
Lewis-Mertens test statistic (OFF_HI)				17.63	17.63	18.67
Lewis-Mertens critical value (OFF_HI)				14.20	14.30	14.35
Lewis-Mertens test statistic (OFF_LMI)				27.35	27.35	29.01
Lewis-Mertens critical value (OFF_LMI)				14.23	14.74	14.93
Lewis-Mertens test statistic (ROBOTS * R 1990)	22.33	22.33	26.39	25.82	25.82	27.50
Lewis-Mertens critical value (ROBOTS * R 1990)	14.25	14.45	14.37	14.22	14.31	14.28

Notes: The Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D4: Offshoring, industrial robots, and wage bill shares by age, 2SLS, clustered standard errors by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.0044 [0.009]	-0.0016 [0.010]	-0.0011 [0.006]	0.015** [0.006]	-0.0073 [0.009]	-0.0051 [0.006]
K	-0.0069* [0.004]	0.0061** [0.003]	0.0024* [0.001]	-0.0025 [0.003]	0.0033 [0.002]	0.0014 [0.001]
OFF	0.16 [0.09]	-0.14** [0.06]	-0.018 [0.04]			
OFF_HI				0.16*** [0.03]	-0.14*** [0.04]	-0.012 [0.03]
OFF_LMI				-0.33*** [0.07]	0.091 [0.08]	0.23** [0.09]
ROBOTS * R 1990	-0.029** [0.01]	0.017* [0.009]	0.013 [0.009]	-0.0073 [0.007]	0.0053 [0.009]	0.0032 [0.009]
Observations	231	231	229	231	231	229
R^2	0.0408	0.000604	0.0518	0.111	0.0379	0.0452
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00000247	0.00403	0.0246
Clustered to robust s.e. ratio (OFF)	1.407	0.904	1.050			
Clustered to robust s.e. ratio (OFF_HI)				0.398	0.487	0.639
Clustered to robust s.e. ratio (OFF_LMI)				0.596	0.613	1.012
Clustered to robust s.e. ratio (ROBOTS * R 1990)	1.194	0.959	1.261	0.904	0.966	1.163
WREC bootstrap t-stat (OFF)	1.677	-2.250	-0.442			
WREC bootstrap p-value (OFF)	0.363	0.153	0.684			
WREC bootstrap t-stat (OFF_HI)				5.465	-3.872	-0.380
WREC bootstrap p-value (OFF_HI)				0.00370	0.0298	0.723
WREC bootstrap t-stat (OFF_LMI)				-4.580	1.187	2.436
WREC bootstrap p-value (OFF_LMI)				0.00980	0.364	0.0452
WREC bootstrap t-stat (ROBOTS * R 1990)	-2.695	1.878	1.473	-1.031	0.616	0.343
WREC bootstrap p-value (ROBOTS * R 1990)	0.126	0.165	0.259	0.381	0.566	0.784
Kleibergen-Paap rk LM	4.483	4.483	4.583	3.090	3.090	3.225
Kleibergen-Paap rk LM (p-value)	0.0342	0.0342	0.0323	0.0788	0.0788	0.0725
Kleibergen-Paap Wald rk F	8.553	8.553	7.474	15.05	15.05	16.62
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	8.818	8.818	8.419	20.30	20.30	22.11
Lewis-Mertens critical value	28.47	28.81	31.97	47.53	47.79	51.41
Wald χ^2	7.262	5.951	2.190	90.54	24.40	13.50
Wald χ^2 (p-value)	0.0265	0.0510	0.334	1.68e-19	0.0000206	0.00368
AR χ^2	4.117	3.628	1.999	4.306	5.170	3.823
AR χ^2 (p-value)	0.128	0.163	0.368	0.230	0.160	0.281
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC ROBOTS: IV-AUT-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC ROBOTS: IV-AUT-OC		

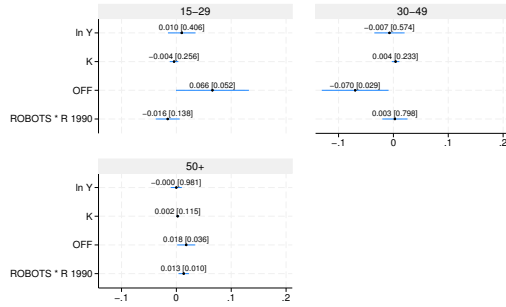
Notes: 2SLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6). The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights. The Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D5: Offshoring, industrial robots, and wage bill shares by age, OLS, clustered standard errors by industry

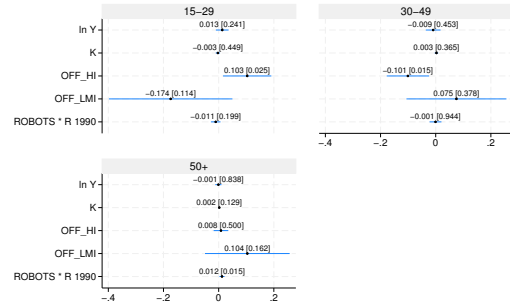
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.0098 [0.009]	-0.0072 [0.010]	-0.00011 [0.005]	0.013** [0.006]	-0.0093 [0.008]	-0.0010 [0.005]
K	-0.0042 [0.003]	0.0039 [0.003]	0.0024** [0.0009]	-0.0028 [0.003]	0.0027 [0.003]	0.0022** [0.0009]
OFF	0.066* [0.04]	-0.070** [0.03]	0.018 [0.01]			
OFF_HI				0.10** [0.04]	-0.10** [0.04]	0.0083 [0.01]
OFF_LMI				-0.17*** [0.04]	0.075* [0.04]	0.10*** [0.03]
ROBOTS * R 1990	-0.016*** [0.005]	0.0027 [0.004]	0.013** [0.005]	-0.011** [0.004]	-0.00070 [0.003]	0.012** [0.004]
Observations	231	231	229	231	231	229
R^2	0.470	0.661	0.712	0.482	0.662	0.714
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.0000267	0.000892	0.0156
Clustered to robust s.e. ratio (OFF)	1.034	1.058	0.771			
Clustered to robust s.e. ratio (OFF_HI)				1.014	0.949	0.665
Clustered to robust s.e. ratio (OFF_LMI)				0.490	0.443	0.579
Clustered to robust s.e. ratio (ROBOTS * R 1990)	0.953	0.755	1.188	0.815	0.632	1.090
WREC bootstrap t-stat (OFF)	1.839	-2.148	1.683			
WREC bootstrap p-value (OFF)	0.103	0.126	0.174			
WREC bootstrap t-stat (OFF_HI)				2.532	-2.784	0.791
WREC bootstrap p-value (OFF_HI)				0.0730	0.0918	0.338
WREC bootstrap t-stat (OFF_LMI)				-4.363	2.002	3.239
WREC bootstrap p-value (OFF_LMI)				0.0452	0.134	0.0549
WREC bootstrap t-stat (ROBOTS * R 1990)	-2.977	0.701	2.782	-2.697	-0.225	2.726
WREC bootstrap p-value (ROBOTS * R 1990)	0.0230	0.524	0.0304	0.0295	0.826	0.0273

Notes: OLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6). The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights.

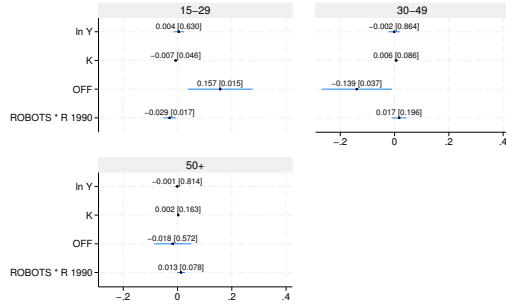
Figure D1: Offshoring, industrial robots, and wage bill shares by age, clustered standard errors



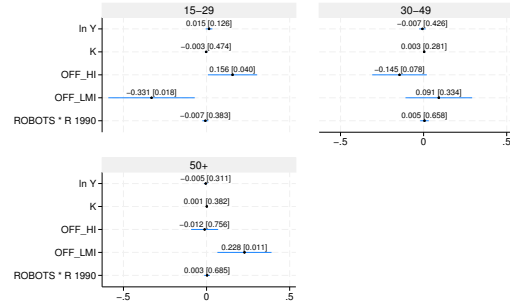
(a) OFF, OLS, by country



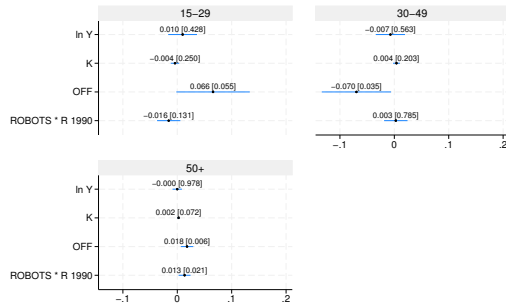
(b) OFF_HI & OFF_LMI, OLS, by country



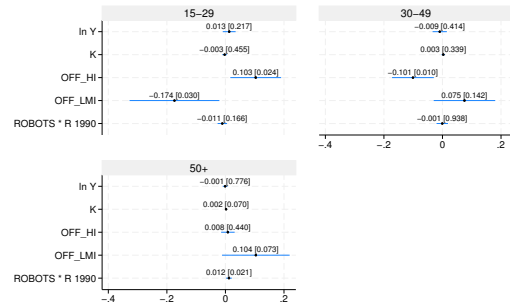
(c) OFF, IV-OFF-OC & IV-AUT-OC, by country



(d) OFF_HI & OFF_LMI, V-OFF-OC & IV-AUT-OC, by country



(e) OFF, OLS, by country and by industry



(f) OFF_HI & OFF_LMI, OLS, by country and by industry

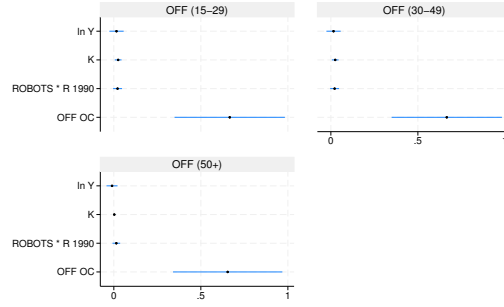
Notes: OLS and 2SLS estimations of specifications in long differences with standard errors clustered by country in Panels (a)–(b) and Panels (c)–(d), respectively. OLS estimations with two-way clustered standard errors by country and industry in Panel (e). The equations in all panels include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Table D6: Offshoring, industrial robots, and wage bill shares by age, 2SLS, [Borusyak et al. \(2022\)](#) exposure-robust inference

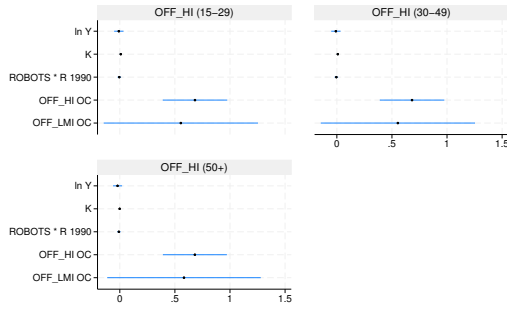
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
OFF	0.16*	-0.14**	-0.018			
	[0.09]	[0.06]	[0.04]			
OFF_HI				0.16***	-0.14***	-0.012
				[0.03]	[0.03]	[0.03]
OFF_LMI				-0.33***	0.091	0.23**
				[0.07]	[0.07]	[0.09]
ROBOTS * R 1990	-0.029***	0.017**	0.013	-0.0073	0.0053	0.0032
	[0.010]	[0.008]	[0.009]	[0.007]	[0.008]	[0.009]
Observations	21	21	21	21	21	21
R^2	0.0997	0.0237	0.0959	0.613	0.213	0.288
Kleibergen-Paap rk LM	3.628	3.628	3.503	2.839	2.839	2.936
Kleibergen-Paap rk LM (p-value)	0.0568	0.0568	0.0612	0.0920	0.0920	0.0866
Kleibergen-Paap Wald rk F	7.353	7.353	6.406	12.56	12.56	14.19
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	12.56	12.56	11.61	26.05	26.05	27.51
Lewis-Mertens critical value	53.29	53.94	56.02	87.18	87.53	91.23
Wald χ^2	9.009	7.527	1.983	106.6	28.15	14.40
Wald χ^2 (p-value)	0.0111	0.0232	0.371	5.96e-23	0.00000337	0.00241
AR χ^2	4.402	4.352	1.772	5.169	7.451	4.167
AR χ^2 (p-value)	0.111	0.113	0.412	0.160	0.0588	0.244
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A

Notes: 2SLS estimations in columns (1)–(3) and (4)–(6) after the aggregation of the sample at the industry-level based on the [Borusyak et al. \(2022\)](#) method. The equations are weighted by the effective number of shifts produced by the same method. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

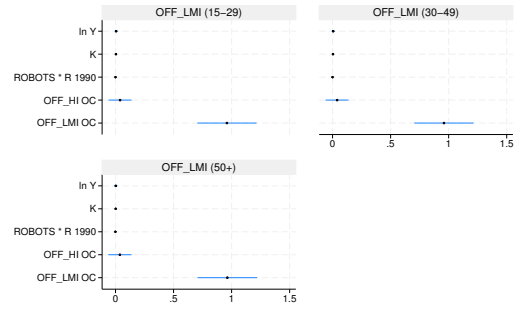
Figure D2: First stages of 2SLS estimations in Table 4



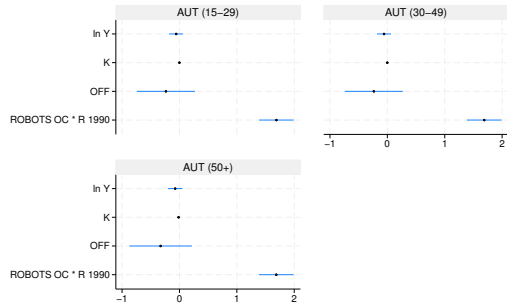
(a) OFF, IV-OFF-OC



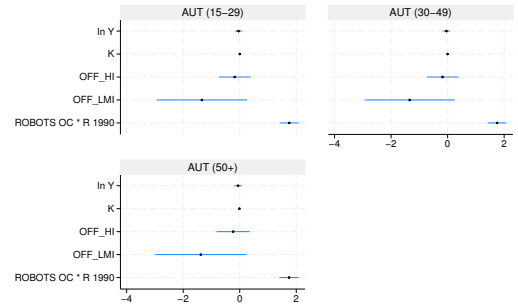
(b) OFF_HI, IV-OFF-OC



(c) OFF_LMI, IV-OFF-OC



(d) ROBOTS, IV-AUT-OC



(e) ROBOTS, IV-AUT-OC

Notes: Panel (a) and Panels (b)–(c) display the first-stage results of 2SLS estimations in columns (1)–(3) and columns (4)–(6), respectively, of Panel A of Table 4. Panels (d) and (e) display the first-stage results of 2SLS estimations in columns (1)–(3) and columns (4)–(6), respectively, of Panel B of Table 4.

Table D7: Offshoring, industrial robots, and wage bill shares by age, stacked differences, OLS and 2SLS

Panel A: OLS						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.013 [0.009]	-0.0097 [0.008]	-0.0043 [0.005]	0.014* [0.008]	-0.010 [0.008]	-0.0044 [0.005]
K	-0.0030 [0.003]	0.0018 [0.002]	0.00091 [0.001]	-0.0027 [0.003]	0.00097 [0.002]	0.00076 [0.001]
OFF	0.053** [0.02]	-0.050 [0.04]	-0.0035 [0.02]			
OFF_HI				0.087*** [0.03]	-0.072 [0.04]	-0.014 [0.03]
OFF_LMI				-0.19*** [0.07]	0.063 [0.07]	0.12** [0.05]
ROBOTS * R 1990	0.00043 [0.003]	-0.0029 [0.002]	0.0024 [0.002]	0.0021 [0.003]	-0.0037 [0.002]	0.0016 [0.002]
Observations	460	462	458	460	462	458
R^2	0.460	0.604	0.640	0.475	0.606	0.643
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.000304	0.119	0.0333
Panel B: 2SLS, IV-OFF-OC and IV-AUT-OC						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.011 [0.008]	-0.0067 [0.008]	-0.0035 [0.005]	0.014* [0.008]	-0.011 [0.009]	-0.0048 [0.006]
K	-0.0036 [0.003]	0.0036* [0.002]	0.00091 [0.001]	-0.0023 [0.003]	0.00082 [0.002]	0.00043 [0.001]
OFF	0.11* [0.06]	-0.12* [0.06]	0.011 [0.03]			
OFF_HI				0.073 [0.06]	-0.10* [0.06]	0.034 [0.04]
OFF_LMI				-0.41*** [0.1]	0.18 [0.1]	0.23*** [0.08]
ROBOTS * R 1990	-0.011* [0.006]	0.0049 [0.006]	0.0059 [0.005]	0.0036 [0.006]	-0.0042 [0.006]	0.00017 [0.005]
Observations	460	462	458	460	462	458
R^2	0.00586	-0.00733	0.000627	0.0474	0.0203	-0.00631
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.000180	0.0248	0.0257
Kleibergen-Paap rk LM	17.06	15.66	17.09	18.10	17.22	18.17
Kleibergen-Paap rk LM (p-value)	0.0000362	0.0000759	0.0000357	0.0000210	0.0000333	0.0000202
Kleibergen-Paap Wald rk F	10.81	10.21	10.82	7.511	7.098	7.536
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	5.545	4.030	5.536	1.384	0.839	1.381
Lewis-Mertens critical value	33.29	31.19	33.31	37.54	37.41	37.70
Wald χ^2	4.355	4.115	3.063	15.26	7.279	13.50
Wald χ^2 (p-value)	0.113	0.128	0.216	0.00161	0.0635	0.00367
AR χ^2	3.756	3.860	3.094	13.36	6.933	12.06
AR χ^2 (p-value)	0.153	0.145	0.213	0.00392	0.0741	0.00719
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
ln Y, K: no IV						
IV strategy	OFF: IV-OFF-OC			OFF_HI, OFF_LMI: IV-OFF-OC		
	ROBOTS: IV-AUT-OC			ROBOTS: IV-AUT-OC		

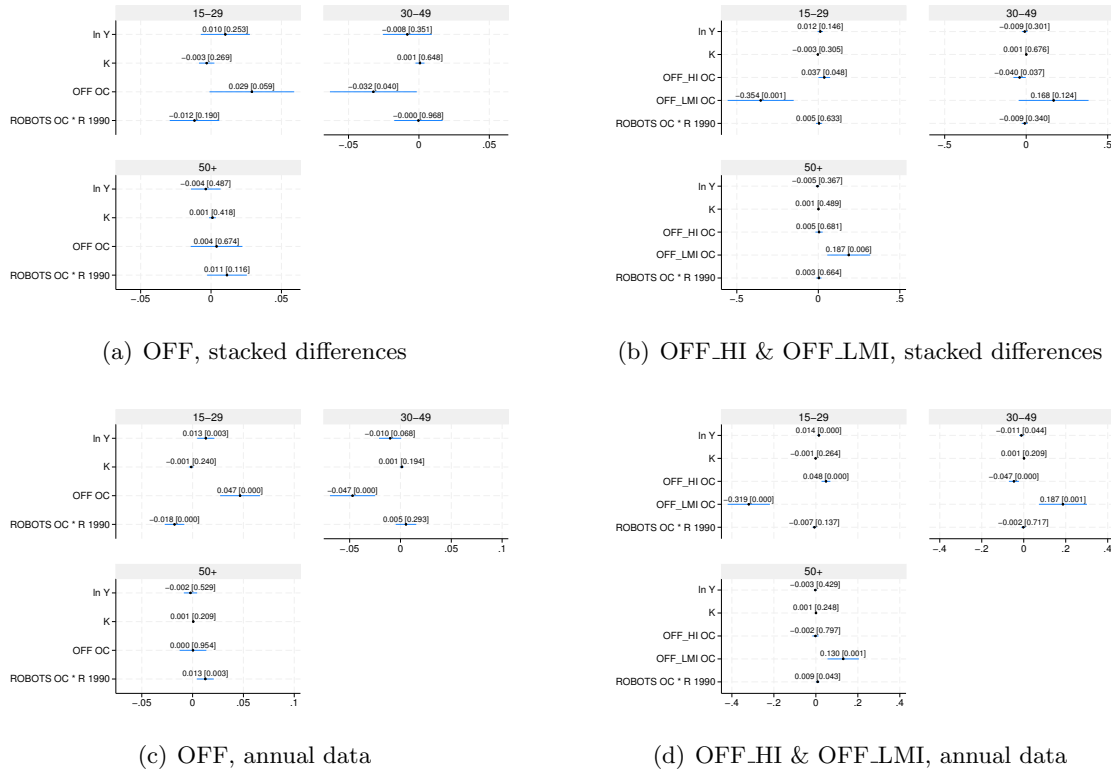
Notes: OLS estimations of the specifications in stacked differences in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of the specifications in stacked differences in columns (1)–(3) and (4)–(6) of Panel B. The equations include country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D8: Offshoring, industrial robots, and wage bill shares by age, annual data, OLS and 2SLS

Panel A: OLS						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.014*** [0.004]	-0.012** [0.006]	-0.0017 [0.003]	0.015*** [0.004]	-0.013** [0.005]	-0.0020 [0.003]
K	-0.0024** [0.001]	0.0021** [0.001]	0.00073 [0.0005]	-0.0015 [0.001]	0.0015 [0.001]	0.00061 [0.0005]
OFF	0.056*** [0.01]	-0.048*** [0.01]	-0.0064 [0.007]			
OFF_HI				0.094*** [0.01]	-0.073*** [0.02]	-0.020** [0.009]
OFF_LMI				-0.19*** [0.04]	0.11*** [0.04]	0.078*** [0.03]
ROBOTS * R 1990	-0.0017 [0.002]	-0.0030 [0.002]	0.0047*** [0.002]	0.000088 [0.002]	-0.0043** [0.002]	0.0042** [0.002]
Observations	2287	2289	2280	2287	2289	2280
R^2	0.983	0.967	0.987	0.983	0.968	0.987
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				1.23e-12	0.0000144	0.000850
Panel B: 2SLS, IV-OFF-OC and IV-AUT-OC						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.010** [0.004]	-0.0093* [0.006]	-0.00014 [0.004]	0.015*** [0.004]	-0.013** [0.006]	-0.0011 [0.004]
K	-0.0040*** [0.001]	0.0037*** [0.001]	0.00090 [0.0006]	-0.0013 [0.001]	0.0014 [0.001]	0.00057 [0.0006]
OFF	0.13*** [0.03]	-0.12*** [0.03]	-0.0058 [0.02]			
OFF_HI				0.11*** [0.03]	-0.10*** [0.03]	-0.0087 [0.02]
OFF_LMI				-0.37*** [0.06]	0.25*** [0.07]	0.12** [0.05]
ROBOTS * R 1990	-0.020*** [0.005]	0.0093* [0.005]	0.011*** [0.004]	-0.0042 [0.004]	-0.0031 [0.005]	0.0076* [0.004]
Observations	2287	2289	2280	2287	2289	2280
R^2	-0.0399	-0.0147	-0.00178	0.0581	0.0235	0.00606
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				8.81e-14	0.00000380	0.0128
Kleibergen-Paap rk LM	92.45	92.28	93.94	140.2	140.0	142.8
Kleibergen-Paap rk LM (p-value)	6.90e-22	7.54e-22	3.26e-22	2.37e-32	2.63e-32	6.59e-33
Kleibergen-Paap Wald rk F	48.71	48.63	49.39	52.42	52.37	53.17
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	118.6	118.4	121.1	88.54	88.54	89.08
Lewis-Mertens critical value	32.46	32.42	32.81	42.52	42.51	42.69
Wald χ^2	30.76	17.48	8.281	67.09	25.96	19.13
Wald χ^2 (p-value)	0.000000209	0.000160	0.0159	1.79e-14	0.00000972	0.000258
AR χ^2	24.58	15.47	8.171	42.12	20.44	17.54
AR χ^2 (p-value)	0.00000459	0.000438	0.0168	3.77e-09	0.000138	0.000548
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
ln Y, K: no IV						
IV strategy			ln Y, K: no IV			
			OFF: IV-OFF-OC			
			ROBOTS: IV-AUT-OC			
			OFF_HI, OFF_LMI: IV-OFF-OC			
			ROBOTS: IV-AUT-OC			

Notes: OLS estimations of the specifications on annual data in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of the specifications on annual data in columns (1)–(3) and (4)–(6) of Panel B. The equations include country-industry and country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Figure D3: Offshoring, industrial robots, and wage bill shares by age, stacked differences or annual data, reduced-form, IV–OFF–OC and IV–AUT–OC



Notes: OLS estimations of reduced-form specifications in stacked differences and on annual data with robust standard errors in Panels (a)–(b) and Panels (c)–(d), respectively. The equations in Panels (a)–(b) include country-year fixed effects and the equations in Panels (c)–(d) include country-industry and country-year fixed effects. The equations in all panels are weighted by each industry’s share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Table D9: Offshoring, industrial robots, and wage bill shares by age, stacked differences, 2SLS, clustered standard errors by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.011 [0.009]	-0.0067 [0.008]	-0.0035 [0.005]	0.014* [0.007]	-0.011 [0.007]	-0.0048 [0.005]
K	-0.0036 [0.003]	0.0036** [0.001]	0.00091 [0.0008]	-0.0023 [0.003]	0.00082 [0.002]	0.00043 [0.0009]
OFF	0.11** [0.04]	-0.12*** [0.03]	0.011 [0.02]			
OFF_HI				0.073 [0.05]	-0.10** [0.04]	0.034 [0.03]
OFF_LMI				-0.41*** [0.09]	0.18*** [0.06]	0.23** [0.10]
ROBOTS * R 1990	-0.011 [0.007]	0.0049 [0.006]	0.0059 [0.007]	0.0036 [0.006]	-0.0042 [0.006]	0.00017 [0.006]
Observations	460	462	458	460	462	458
R^2	0.00586	-0.00733	0.000627	0.0474	0.0203	-0.00631
H_0 : $\beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00000666	0.0000116	0.0436
Clustered to robust s.e. ratio (OFF)	0.691	0.515	0.656			
Clustered to robust s.e. ratio (OFF_HI)				0.760	0.633	0.698
Clustered to robust s.e. ratio (OFF_LMI)				0.637	0.469	1.214
Clustered to robust s.e. ratio (ROBOTS * R 1990)	1.168	1.034	1.441	0.978	1.096	1.292
WREC bootstrap t-stat (OFF)	2.768	-3.776	0.474			
WREC bootstrap p-value (OFF)	0.250	0.0447	0.572			
WREC bootstrap t-stat (OFF_HI)				1.543	-2.667	1.240
WREC bootstrap p-value (OFF_HI)				0.0523	0.0372	0.449
WREC bootstrap t-stat (OFF_LMI)				-4.781	2.960	2.325
WREC bootstrap p-value (OFF_LMI)				0.00180	0.0625	0.0824
WREC bootstrap t-stat (ROBOTS * R 1990)	-1.517	0.760	0.888	0.623	-0.667	0.0268
WREC bootstrap p-value (ROBOTS * R 1990)	0.247	0.485	0.444	0.563	0.566	0.983
Kleibergen-Paap rk LM	2.872	2.766	2.880	4.785	4.737	4.821
Kleibergen-Paap rk LM (p-value)	0.0901	0.0963	0.0897	0.0287	0.0295	0.0281
Kleibergen-Paap Wald rk F	11.95	11.70	11.92	8.763	8.120	8.741
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	2.532	1.938	2.527	0.534	0.326	0.533
Lewis-Mertens critical value	56.28	43.78	43.77	83.42	82.38	81.56
Wald χ^2	7.917	14.93	3.547	48.33	39.18	9.602
Wald χ^2 (p-value)	0.0191	0.000573	0.170	1.81e-10	1.59e-08	0.0223
AR χ^2	1.666	2.788	2.461	3.065	3.056	3.796
AR χ^2 (p-value)	0.435	0.248	0.292	0.382	0.383	0.284
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC ROBOTS: IV-AUT-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC ROBOTS: IV-AUT-OC		

Notes: 2SLS estimations of the specifications in stacked differences in columns (1)–(3) and (4)–(6). The equations include country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights. The Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table D10: Offshoring, industrial robots, and wage bill shares by age, stacked differences, OLS, clustered standard errors by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.013 [0.01]	-0.0097 [0.009]	-0.0043 [0.005]	0.014 [0.008]	-0.010 [0.008]	-0.0044 [0.004]
K	-0.0030 [0.003]	0.0018 [0.002]	0.00091 [0.0008]	-0.0027 [0.003]	0.00097 [0.002]	0.00076 [0.0008]
OFF	0.053** [0.02]	-0.050 [0.03]	-0.0035 [0.03]			
OFF_HI				0.087*** [0.03]	-0.072* [0.04]	-0.014 [0.04]
OFF_LMI				-0.19*** [0.03]	0.063* [0.04]	0.12*** [0.04]
ROBOTS * R 1990	0.00043 [0.004]	-0.0029 [0.004]	0.0024 [0.003]	0.0021 [0.004]	-0.0037 [0.004]	0.0016 [0.003]
Observations	460	462	458	460	462	458
R^2	0.460	0.604	0.640	0.475	0.606	0.643
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00000256	0.0269	0.0930
Clustered to robust s.e. ratio (OFF)	0.895	0.923	1.328			
Clustered to robust s.e. ratio (OFF_HI)				0.988	0.900	1.434
Clustered to robust s.e. ratio (OFF_LMI)				0.434	0.525	0.815
Clustered to robust s.e. ratio (ROBOTS * R 1990)	1.629	1.562	1.313	1.624	1.532	1.298
WREC bootstrap t-stat (OFF)	2.644	-1.535	-0.119			
WREC bootstrap p-value (OFF)	0.0783	0.279	0.969			
WREC bootstrap t-stat (OFF_HI)				3.441	-1.811	-0.351
WREC bootstrap p-value (OFF_HI)				0.0452	0.256	0.856
WREC bootstrap t-stat (OFF_LMI)				-6.654	1.725	2.856
WREC bootstrap p-value (OFF_LMI)				0.00430	0.214	0.0400
WREC bootstrap t-stat (ROBOTS * R 1990)	0.0964	-0.739	0.812	0.497	-1.003	0.561
WREC bootstrap p-value (ROBOTS * R 1990)	0.924	0.566	0.457	0.606	0.440	0.609

Notes: OLS estimations of the specifications in stacked differences in columns (1)–(3) and (4)–(6). The equations include country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights.

Table D11: Offshoring, industrial robots, and wage bill shares by age, annual data, 2SLS, clustered standard errors by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.010 [0.007]	-0.0093 [0.008]	-0.00014 [0.004]	0.015*** [0.004]	-0.013* [0.006]	-0.0011 [0.004]
K	-0.0040 [0.002]	0.0037* [0.002]	0.00090 [0.0007]	-0.0013 [0.002]	0.0014 [0.002]	0.00057 [0.0008]
OFF	0.13* [0.07]	-0.12** [0.06]	-0.0058 [0.02]			
OFF_HI				0.11*** [0.02]	-0.10*** [0.02]	-0.0087 [0.02]
OFF_LMI				-0.37*** [0.04]	0.25*** [0.07]	0.12 [0.07]
ROBOTS * R 1990	-0.020** [0.007]	0.0093 [0.007]	0.011* [0.006]	-0.0042 [0.005]	-0.0031 [0.006]	0.0076 [0.005]
Observations	2287	2289	2280	2287	2289	2280
R^2	-0.0399	-0.0147	-0.00178	0.0581	0.0235	0.00606
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				8.53e-08	0.000259	0.157
Clustered to robust s.e. ratio (OFF)	2.803	2.100	1.165			
Clustered to robust s.e. ratio (OFF_HI)				1.002	0.673	1.229
Clustered to robust s.e. ratio (OFF_LMI)				0.767	1.132	1.582
Clustered to robust s.e. ratio (ROBOTS * R 1990)	1.563	1.542	1.473	1.198	1.360	1.234
WREC bootstrap t-stat (OFF)	1.795	-1.986	-0.277			
WREC bootstrap p-value (OFF)	0.426	0.335	0.787			
WREC bootstrap t-stat (OFF_HI)				4.423	-5.439	-0.393
WREC bootstrap p-value (OFF_HI)				0.0132	0.0102	0.710
WREC bootstrap t-stat (OFF_LMI)				-7.960	3.131	1.591
WREC bootstrap p-value (OFF_LMI)				0.000900	0.0920	0.0517
WREC bootstrap t-stat (ROBOTS * R 1990)	-2.639	1.210	1.883	-0.803	-0.470	1.464
WREC bootstrap p-value (ROBOTS * R 1990)	0.0322	0.260	0.130	0.445	0.660	0.222
Kleibergen-Paap rk LM	5.151	5.140	5.240	8.868	8.845	9.140
Kleibergen-Paap rk LM (p-value)	0.0232	0.0234	0.0221	0.00290	0.00294	0.00250
Kleibergen-Paap Wald rk F	9.327	9.300	9.519	33.14	32.79	37.13
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	13.63	13.62	13.74	21.30	21.31	21.70
Lewis-Mertens critical value	130.4	126.5	125.8	157.4	155.1	154.4
Wald χ^2	7.298	4.118	3.583	85.35	50.02	5.525
Wald χ^2 (p-value)	0.0260	0.128	0.167	2.18e-18	7.89e-11	0.137
AR χ^2	3.025	2.251	2.825	3.448	2.709	3.172
AR χ^2 (p-value)	0.220	0.324	0.244	0.328	0.439	0.366
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
	ln Y, K: no IV			ln Y, K: no IV		
IV strategy	OFF: IV-OFF-OC			OFF_HI, OFF_LMI: IV-OFF-OC		
	ROBOTS: IV-AUT-OC			ROBOTS: IV-AUT-OC		

Notes: 2SLS estimations of the specifications in on annual data in columns (1)–(3) and (4)–(6). The equations include country-industry and country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights. The Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance. The Lewis-Mertens test statistics and critical values have exceptionally been produced based on the Stata code developed by Zhou (2026), as that developed by Lewis & Mertens (2026) is computationally infeasible for these specifications due to the high number of fixed effects and clustered standard errors.

Table D12: Offshoring, industrial robots, and wage bill shares by age, annual data, OLS, clustered standard errors by industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.014 [0.009]	-0.012 [0.008]	-0.0017 [0.005]	0.015** [0.006]	-0.013* [0.007]	-0.0020 [0.004]
K	-0.0024 [0.002]	0.0021 [0.002]	0.00073 [0.0007]	-0.0015 [0.002]	0.0015 [0.002]	0.00061 [0.0007]
OFF	0.056** [0.02]	-0.048** [0.02]	-0.0064 [0.009]			
OFF_HI				0.094*** [0.03]	-0.073*** [0.02]	-0.020 [0.01]
OFF_LMI				-0.19*** [0.03]	0.11*** [0.04]	0.078* [0.04]
ROBOTS * R 1990	-0.0017 [0.003]	-0.0030 [0.003]	0.0047*** [0.001]	0.000088 [0.002]	-0.0043 [0.003]	0.0042*** [0.001]
Observations	2287	2289	2280	2287	2289	2280
R^2	0.983	0.967	0.987	0.983	0.968	0.987
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.000000847	0.00101	0.0524
Clustered to robust s.e. ratio (OFF)	2.077	1.592	1.217			
Clustered to robust s.e. ratio (OFF_HI)				1.963	1.352	1.522
Clustered to robust s.e. ratio (OFF_LMI)				0.747	1.109	1.503
Clustered to robust s.e. ratio (ROBOTS * R 1990)	1.570	1.474	0.933	1.404	1.358	0.813
WREC bootstrap t-stat (OFF)	2.177	-2.361	-0.704			
WREC bootstrap p-value (OFF)	0.0819	0.0983	0.492			
WREC bootstrap t-stat (OFF_HI)				3.362	-3.430	-1.459
WREC bootstrap p-value (OFF_HI)				0.0365	0.0590	0.164
WREC bootstrap t-stat (OFF_LMI)				-7.139	2.768	1.933
WREC bootstrap p-value (OFF_LMI)				0.00520	0.127	0.112
WREC bootstrap t-stat (ROBOTS * R 1990)	-0.541	-1.021	3.032	0.0344	-1.595	3.148
WREC bootstrap p-value (ROBOTS * R 1990)	0.649	0.367	0.000900	0.976	0.202	0.00200

Notes: OLS estimations of the specifications in on annual data in columns (1)–(3) and (4)–(6). The equations include country-industry and country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on clustered standard errors by industry. "Clustered to robust s.e. ratio" is the ratio of clustered standard errors of this table to the respective non-clustered robust standard errors of Table 3. The wild restricted efficient (WREC) bootstrap method is implemented at 95% confidence level with 9,999 repetitions and Rademacher weights.

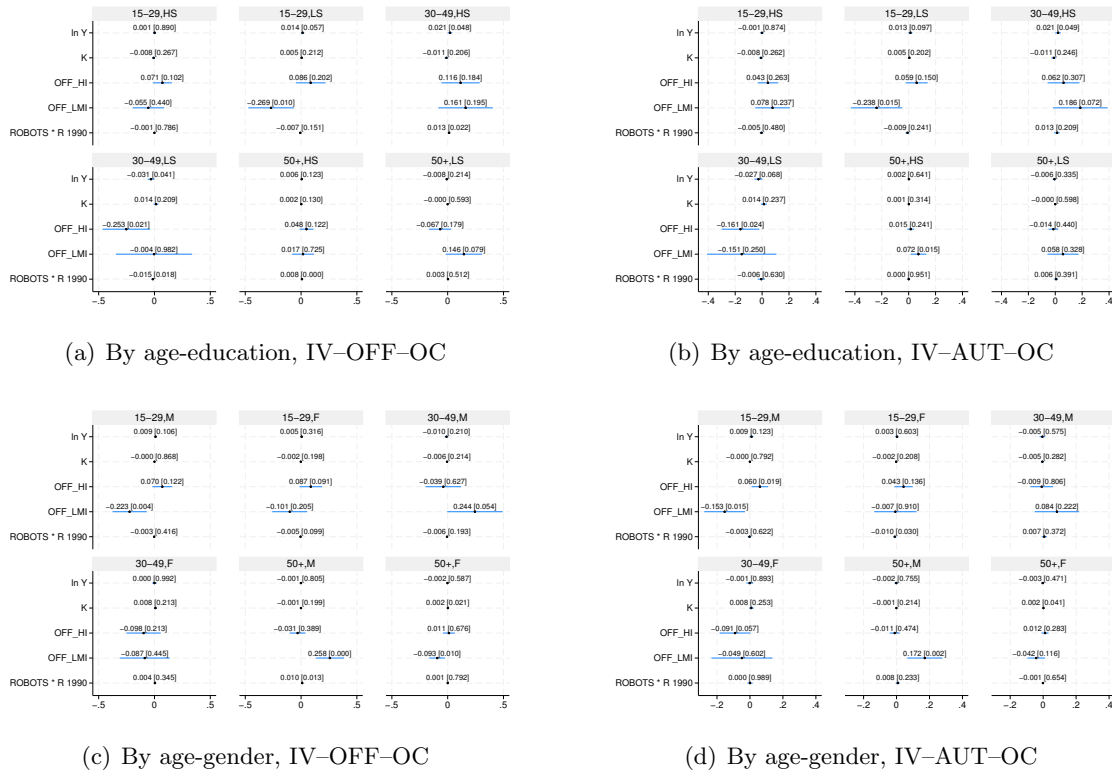
Table D13: Offshoring, industrial robots, and wage bill shares by age, stacked differences or annual data, 2SLS, [Borushyak et al. \(2022\)](#) exposure-robust inference

Panel A: Stacked differences						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
OFF	0.11 [0.08]	-0.12** [0.05]	0.011 [0.04]			
OFF_HI				0.073 [0.05]	-0.10*** [0.04]	0.034 [0.03]
OFF_LMI				-0.41*** [0.1]	0.18** [0.08]	0.23** [0.09]
ROBOTS * R 1990	-0.011 [0.007]	0.0049 [0.006]	0.0059 [0.006]	0.0036 [0.006]	-0.0042 [0.006]	0.00017 [0.006]
Observations	42	42	42	42	42	42
R ²	-0.0491	-0.0203	0.0197	0.253	0.161	0.122
Kleibergen-Paap rk LM	4.038	3.906	4.043	7.695	7.804	7.744
Kleibergen-Paap rk LM (p-value)	0.0445	0.0481	0.0444	0.00554	0.00521	0.00539
Kleibergen-Paap Wald rk F	14.07	13.37	14.06	5.984	5.512	5.921
Stock-Yogo weak critical values	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	12.26	10.97	12.27	8.849	8.268	8.813
Lewis-Mertens critical value	42.02	34.53	35.53	53.00	52.46	52.45
Wald χ^2	2.486	5.482	1.713	25.14	21.60	9.274
Wald χ^2 (p-value)	0.288	0.0645	0.425	0.0000144	0.0000790	0.0259
AR χ^2	1.415	1.998	1.628	5.406	3.644	4.487
AR χ^2 (p-value)	0.493	0.368	0.443	0.144	0.303	0.213
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC ROBOTS: IV-AUT-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC ROBOTS: IV-AUT-OC		

Panel B: Annual data						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
OFF	0.13*** [0.04]	-0.12*** [0.04]	-0.0058 [0.02]			
OFF_HI				0.11*** [0.02]	-0.10*** [0.02]	-0.0087 [0.02]
OFF_LMI				-0.37*** [0.04]	0.25*** [0.05]	0.12*** [0.04]
ROBOTS * R 1990	-0.020*** [0.005]	0.0093* [0.005]	0.011** [0.005]	-0.0042 [0.004]	-0.0031 [0.005]	0.0076* [0.005]
Observations	210	210	210	210	210	210
R ²	-0.0158	-0.0519	0.0364	0.372	0.126	0.0779
Kleibergen-Paap rk LM	19.73	19.73	19.74	32.55	32.50	33.73
Kleibergen-Paap rk LM (p-value)	0.00000893	0.00000893	0.00000889	1.16e-08	1.19e-08	6.32e-09
Kleibergen-Paap Wald rk F	21.57	21.55	21.81	26.74	26.67	27.81
Stock-Yogo weak critical values	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	10.37	10.38	10.37	6.474	6.477	6.481
Lewis-Mertens critical value	24.91	24.34	24.75	41.89	41.88	41.96
Wald χ^2	20.24	12.25	5.881	139.5	48.13	18.06
Wald χ^2 (p-value)	0.0000402	0.00219	0.0528	4.86e-30	2.00e-10	0.000427
AR χ^2	12.09	9.621	5.501	15.33	10.21	10.25
AR χ^2 (p-value)	0.00236	0.00814	0.0639	0.00155	0.0168	0.0166
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC ROBOTS: IV-AUT-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC ROBOTS: IV-AUT-OC		

Notes: 2SLS estimations with year fixed effects in columns (1)–(3) and (4)–(6) of Panels A and B after the aggregation of the sample at the industry-year-level based on the [Borushyak et al. \(2022\)](#) method. The equations are weighted by the effective number of shifts produced by the same method. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Figure D4: Offshoring, industrial robots, and wage bill shares by age-education or age-gender, IV-OFF-OC or IV-AUT-OC



Notes: 2SLS estimations of specifications in long differences with robust standard errors in all panels. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

E Robustness

In this Appendix, I make a full description of the rationale for each robustness exercise and the corresponding results.

Offshoring to lower-income countries other than China One concern regarding the main effects of offshoring to lower-income countries is that they might have been driven by China, given its extraordinary capacity to attract offshoring and empirical evidence on adverse effects of Chinese import competition on the labour markets of developed countries, especially the US (Hanson, 2012; Autor et al., 2013, 2016, 2021; Autor et al., 2014). To address this legitimate concern, I first document that the remarkable rise in the intensity of offshoring to lower-income countries was driven by both China and other lower-income countries, but China's contribution was much larger (see relevant statistics for the whole sample in Panels (a) and (b) of Figure C5 and bottom of Panels A and B of Table C2 and statistics by country in Table C2 and by industry in Table C3). While the intensity of offshoring to China, *OFF_CHN*, was initially smaller than the intensity of offshoring to other lower-income countries, *OFF_LMInC* (0.1% Vs roughly 0.5%), its average growth rate was almost four times as high over the period examined (1,792% Vs 359%).^{E1}

With these useful statistics in mind, I then estimate by OLS and 2SLS the wage bill share specifications using the intensities of offshoring to high-income countries and to lower-income countries other than China or to China as the two key regressors (Panels (a)–(b) and (c)–(d), respectively, of Figure E1). The OLS and 2SLS estimates of the intensity of offshoring to high-income countries and robot adoption remain largely unchanged. Although the OLS estimates of the intensity of offshoring to lower-income countries other than China are statistically insignificant, the 2SLS estimates suggest that this type of offshoring activity decreased the wage bill share of young workers and increased the wage bill share of the oldest. Both effects are consistent with those identified in the main analysis. The intensity of offshoring to China exerted very similar effects and the OLS estimates of this key regressor accord with its 2SLS estimates.^{E2}

^{E1}In line with the aforementioned trends, the pair-wise correlations of the sample mean growth rate of the intensity of offshoring to high-income countries with the sample mean growth rates of the intensities of offshoring to all available lower-income countries, to all lower-income countries except for China, and to China are quite high (55.2%, 61.5%, and 44%, respectively), but the correlation between the sample mean growth rates of the intensities of offshoring to lower-income countries other than China and to China is much higher (95.2%). On top of that, the latter correlation becomes stronger in almost every year, while this is less evident for the first three correlations. The corresponding correlations when the variables vary by country-industry-year cell are larger in the first two cases (63.7% and 67.5%) and smaller in the latter two cases (23.9%, and 40.8%). The relevant scatterplots showing correlations are available upon request. In addition, the patterns and trends of the intensities of offshoring to China and to lower-income countries other than China constructed for the five high-income countries that serve as instruments bear a very close resemblance to the variables corresponding to the countries of the main sample (Panels (d) and (e) of Figure C8 and Panels A and B of Tables C10 and C11).

^{E2}Incorporating in the specifications jointly the intensities of offshoring to China and to other lower-income countries does not change the OLS estimates of the intensity of offshoring to high-income countries and robot adoption, but yields insignificant estimates of the other two key regressors. Also, the 2SLS estimates of all four key regressors are statistically insignificant (results available upon request). These changes may be suggestive

Construction of offshoring intensities based on alternative classifications of input-supplying countries Another concern regarding the main effects of offshoring to high- and lower-income countries is whether they are sensitive to the methodology implemented for the classification of input-supplying countries by income status. As alternatives to the benchmark methodology, I consider their income status in 1996 (*HI2*, *LMI2*) according to the World Bank’s Historical Country Classification By Income, or their OECD membership status by 1996 (*OECD*, *NOECD*). The country compositions of the two groups under these alternative income classifications are almost identical to those under the benchmark classification and are available upon request.^{E3}

In addition, I distinguish input-supplying countries by their export complexity or human capital abundance. Using data on countries’ economic complexity indices (ECI) from the ATLAS of Economic Complexity database, I include an input-supplying country in the group of countries with relatively high complexity of exports (*HECI*) if its ECI is at least equal to the 75th percentile value of ECI, calculated across all input-supplying countries available by year. Conversely, I include an input-supplying country in the group of countries with relatively low complexity (*LECI*) if its ECI is below that threshold. Similarly, using data on countries’ human capital indices from the Penn World Tables version 10.0, I consider an input-supplying country as human capital abundant (*HHC*) if its human capital index is at least equal to the 75th percentile value of the human capital index, calculated across all input-supplying countries available by year, and as human capital scarce (*LHC*) if its human capital index is below this threshold.^{E4}

The patterns and trends of offshoring intensities constructed based on the alternative classifications are very similar to those obtained for the benchmark measures (figures and tables available upon request). Also, estimating the specifications with offshoring intensity variables based on the two alternative country income classifications, the classification by export complexity, or the classification by human capital abundance barely changes the results (Panels (a)–(b), (c)–(d), (e)–(f), and (g)–(h), respectively, of Figure E2).

Elimination of Japan and Germany from the sample Given data limitations on robot stocks, using country-level imports is a good alternative and quite common in the related

of the presence of multi-collinearity in these specifications.

^{E3}The benchmark classification taking advantage of information for all years in the sample is not very dissimilar conceptually from the two alternative classifications taking advantage of information for the initial year only. The principal reason is that sourcing strategies of firms represent mostly relationship-specific investments, implying that a radical revision of these would be very costly, not least in a relatively short time frame such as the one that I consider in the analysis. This stickiness is likely to hold true even in the presence of continuously rising labour costs and income per capita in supplying countries, as well as during temporary economic downturns in these countries, which may lead to the (temporary) downgrade of their income status while leaving their production base largely unscathed. This was particularly evident in the global trade collapse in 2009, following the credit crunch of 2007–2009, and during COVID-19.

^{E4}There are non-negligible differences in the compositions of groups that are formed based on these two classifications and the main and alternative income classifications (Appendix A.1). Be that as it may, the correlations of offshoring intensity variables based on these two alternative classifications with the corresponding offshoring intensity variables based on the main and alternative income classifications are very high, ranging between 80% and 99%.

literature. One possible concern over this approach, however, is that a few countries in my sample—most notably, Japan and Germany—are top global developers and exporters of robotic technology (Acemoglu & Restrepo, 2020, 2021). Therefore, I ensure that the exclusion of these countries from the sample yields very similar OLS and 2SLS estimates of robot adoption in qualitative and quantitative terms, while the estimates of the other regressors also remain largely unchanged (Panels (a)–(b) and (c)–(d) of Figure E3).^{E5}

Iterative elimination of a different country from the sample In relation to the previous exercise, countries differ along various dimensions (e.g., labour market institutions) that may impact directly or indirectly (e.g., through offshoring and automation) wage bill shares. Although I always control in the long-differenced specifications for unobserved cross-country heterogeneity using country fixed effects, I perform an additional check in which I remove iteratively a different country from the sample. Reassuringly, results are not sensitive to the removal of any of the countries examined. Given their very large volume, these results are available upon request.

Distinction of countries by the strictness of employment protection legislation In yet another pertinent exercise, I check the robustness of the main effects to OLS and 2SLS estimations of the main specifications on separate samples of countries with relatively high and relatively low strictness of employment protection legislation (EPL). To do this exercise, I use relevant data from the OECD and classify the countries into two groups based on whether their EPL in the initial sample year (1996) is at least equal to or smaller than the unweighted cross-country median of EPL in the same year (see description of the data source and methodology in Appendix A.3). The OLS and 2SLS estimates obtained on the sample of countries with relatively high EPL strictness are very similar to the main ones (Panels (a), (c), (e), (g), (i), (k), (m), and (o) of Figure E4) and, despite some loss of significance and rare occurrences of sign reversals of coefficient estimates of aggregate offshoring intensity, this is also the case for the effects identified on the sample of countries with relatively low EPL strictness (Panels (b), (d), (f), (h), (j), (l), (n), and (p) of the same figure). Repeating the exercise while distinguishing countries by their union density also yields results on separate samples that are similar to the main ones (results available upon request). Although these findings should not be deemed as downplaying the critical role of institutions in general and labour market institutions in particular, they are very important in the sense that they demonstrate that something fundamental and structural has been at play regarding globalisation, automation, and the labour market situation of different age groups of workers in advanced economies. This echoes cross-country studies providing evidence on job polarisation as a structural, rather than simply country-specific, phenomenon (e.g., Goos et al., 2014; Michaels et al., 2014; Autor, 2014; Blanas, 2024).

Computation of Rotemberg weights and iterative elimination of a different industry from the sample In a similar vein, I emulate related studies in checking whether

^{E5}The main results are also robust to the elimination from the sample of Italy—another top developer and exporter of robotic technology—along with Japan and Germany (results available upon request).

the main results are driven by certain industries (e.g., [Acemoglu & Restrepo, 2020](#)). For instance, the automotive, electronics, chemicals, and metal industries have been the fastest robot-adopting industries since the 1990s and 2000s ([Graetz & Michaels, 2018](#); [Acemoglu & Restrepo, 2020](#)), while Panels A and B of Table C3 reveal that the same industries had the highest, or among the highest, initial intensities of offshoring to high- and lower-income countries and growth rates of these variables over 1996–2005. In line with these facts, Rotemberg weights for the top five industries by key regressor, shown in Table E1, suggest that the transport equipment, electrical and optical equipment, basic metals and fabricated metal products, along with a few other industries (i.e., textiles, wood, refined petroleum products, other machinery and equipment, rubber and plastics) are among those that contribute the most to the identification of the estimates of the aggregate offshoring intensity (Panel A), the intensities of offshoring to high- and lower-income countries (Panels B and C), and robot adoption (Panel D). However, it is also noteworthy that the contributions of the top 1 or 2 industries to the identification of the estimates of offshoring intensities are much larger than those for robot adoption. Another interesting observation from the overall rankings of industries, which are available upon request, is that only a small number of industries have negative weights for the aggregate offshoring intensity (NACE 25, 26, 29, 71T74, J), the intensity of offshoring to high-income countries (NACE 24, 25, 26, 29), and the intensity offshoring to lower-income countries (NACE 24, 36T37), while there is no industry with negative weights for robot adoption.^{E6}

By iteratively eliminating a different industry from the sample, I find clear evidence that 19 out of the 21 industries do not drive the main results, while the evidence is mixed from the removal of the transport equipment or electrical and optical equipment industry. Figures E5 and E6 display these results, while the remaining ones are available only upon request because of their very large volume. To be able to understand the results as best as possible, I estimate all the specifications in Tables 3, 4, D1, and D2 (i.e., specifications estimated by OLS and by 2SLS implementing the IV strategy for all key regressors, for the offshoring intensity variable(s) only while controlling or not controlling for robot adoption, and for the robot adoption variable only while controlling or not controlling for offshoring).

From the removal of either industry, the estimates of the offshoring intensity and robot adoption variables are, by and large, similar to the main ones, but there is also lower or loss

^{E6}To calculate Rotemberg weights, I implement the method proposed by the related literature (e.g., [Goldsmith-Pinkham et al., 2020](#)). In particular, I first residualise the endogenous key regressors and respective instruments by partialling out the controls (log of value added, aggregate capital intensity, country fixed effects) and then produce the first-stage estimates by regressing the residualised endogenous variables on their residualised instruments. As the residualised endogenous regressors and instruments vary by country and industry, in the next step, I calculate the unweighted means of these variables across countries by industry before I calculate the product of the two and the first-stage estimate to obtain the numerator of the Rotemberg weight for each industry. Subsequently, I sum the Rotemberg weight numerators over industries to obtain the Rotemberg weight denominator. Calculating the ratio of the two variables yields a Rotemberg weight for each industry examined. Note that I implement this method manually, rather than using the relevant Stata code (*bartik.weight*) developed by [Goldsmith-Pinkham et al. \(2020\)](#), as there is more than one endogenous regressors that I instrument for, of which those for offshoring intensities are not of shift-share form and that for robot adoption, while resembling those of the shift-share literature, it is not identical to them.

of significance for some estimates. In the absence of the transport equipment industry, issues of significance occur when I instrument for the key regressors, but only when I distinguish between high- and lower-income offshoring destination countries (see Panels (c)–(d), (e)–(f), (g)–(h), and (i)–(j) of Figure E5). Instead, the estimates of the aggregate offshoring intensity remain statistically significant. As the Rotemberg weight of this industry for the latter key regressor is the second largest, similarly to the weights for the intensities of offshoring to high- and lower-income countries, Rotemberg weights may not fully account for the difference in the results. Although I observe the same pattern from both 2SLS and OLS estimations when the sample does not include the electrical and optical equipment industry, the reverse pattern is also present in some 2SLS results. In particular, the estimates of the intensity of offshoring to lower-income countries are statistically significant, while those of the aggregate offshoring intensity and the intensity of offshoring to high-income countries are not (see Panels (a)–(b), (c)–(d), (e)–(f), (g)–(h), and (i)–(j) of Figure E6). Again, through the lens of the Rotemberg weights, these differences in the results could be viewed as puzzling, given that the weight of the electrical and optical equipment industry for the estimate of the intensity of offshoring to lower-income countries is the largest, while the respective weights for the intensity of offshoring to high-income countries and aggregate offshoring intensity rank fourth and fifth and, especially in the second case, with a large gap relative to those of the industries that are ranked first and second.

Overall, although the main results may be sensitive to some extent to the well-documented relatively high intensity of offshoring activities undertaken by the transport equipment and electrical and optical equipment industries, it is also likely that the differences detected reflect how offshoring, robots, and other types of capital interact with each other and to different degrees across industries (recall the relevant discussion that I have made in Section 4.1 to rationalise some changes in the significance of the estimates of key regressors across specifications).

Industry-level share of routine tasks in 1980 For the construction of the benchmark robot adoption variable and its instrument, I have used the industry-level share of routine tasks in 1990, which is the most recent year prior to the start year of the sample for which this measure is available. Using, instead, the values of this measure for 1980—the earliest year for which this measure is available—does not alter the main OLS and 2SLS results (Panels A and B of Table E2). This suggests that results are insensitive to the construction of this regressor based on historical and persistent differences in industries’ potential for automation (Acemoglu & Restrepo, 2020; Blanas, 2024). Although using lagged values of the shares component may weaken the selected instruments (Borusyak et al., 2025), I confirm that this is not the case. The instruments are relevant, as suggested by the first-stage estimates (available upon request), and the conclusions about instrument strength and weak-IV robustness of the estimates are the same as those in the main analysis.

Alternative construction of instrumental variables The IV strategy that I have imple-

mented throughout the econometric analysis relies on the construction of offshoring intensity and robot adoption measures for countries similar to those in the benchmark sample. In a variant of this strategy, I use as instruments the offshoring intensity and robot adoption measures for the US (IV–OFF–USA, IV–AUT–USA).^{E7} As the US pertains to the main sample, using US-specific information for the construction of the instruments could violate the exclusion restriction. Thus, I make the leave-one-out approach while implementing this IV by excluding the US from the sample (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2025). The rationale behind this strategy is that the average industry in the remaining high-income countries of the sample have been emulating global trends of offshoring expansion and technological innovations that are best represented by the US (e.g., Michaels et al., 2014; Blanas, 2024). The estimates of all key regressors maintain their signs, but except for those of robot adoption that also largely maintain their significance levels, the estimates of offshoring intensities have lower significance or turn insignificant. Also, the first-stage estimates, which are available upon request, point to the relevance of the instruments, but there are serious concerns over their strength. In fact, the Lewis-Mertens tests point to weak instruments in all specifications and, unlike the main results, the Stock-Yogo tests fail whenever applicable. Yet, similarly to the main results, the estimates are robust to weak instruments in most specifications (Table E3).

The conclusions about instrument relevance and strength and weak-IV robustness also hold when I implement the same variant of the IV strategy in estimations of specifications in stacked differences to allow for the US-specific shifter component of the instrument for robot adoption to play an identifying role (Borusyak et al., 2025). However, in contrast to the estimations of the specifications in long differences where some significance is maintained, none of the estimates obtained from stacked differences is significant and, on top of that, some of these switch signs. The second-stage results and relevant tests are shown in Panel A of Table E4, while the first-stage results are available upon request. Implementing the variant of the IV strategy on annual data yields estimates that largely maintain their significance, but the estimates of robot adoption have opposite signs (Panel B of the same table). The first-stages (available upon request) point to the relevance of the instruments, but concerns over instrument strength remain, albeit these are less severe compared to the estimations of the specifications in long or stacked differences. Also, the estimates are robust to weak instruments in all specifications but one. Judging by the results obtained from the leave-one-out version of the IV strategy, I view the original version as more reliable.

In a similar exercise, I test further the robustness of the main results to the use of a US-specific shifter component in the instrument for robot adoption. In particular, I estimate the

^{E7}For robot adoption, this implies that the shifter component of the instrument is the variable for US robot imports, while the shares component continues to be the industry-level share of routine tasks in 1990. However, recall from the discussion in Section 3.2 that the use of a different shifter component in the instrument for robot adoption is just a re-scaling of the variable and has no identifying role in estimations of long-differenced specifications, but does have an identifying role in estimations of specifications in stacked differences or on annual data. I do all three exercises using the US-specific shifter component. In long-differenced specifications, this is only for consistency with the instruments for the offshoring intensities.

specifications in stacked differences and on annual data while using as a shifter component the US-wide robot adoption measure of [Acemoglu & Restrepo \(2020\)](#), which has been constructed based on data from the International Federation of Robotics. The measure is available for 1993–2014 and thus covers the period of my analysis. This check is also useful in case the IFR data are less subject to measurement error compared to the UN Comtrade data. Again, I retain the original shares component and adopt the leave-one-out approach by excluding the US from the sample (IV–AUT–AR–USA). In these 2SLS estimations, I instrument offshoring intensities according to the original version of the IV strategy (IV–OFF–OC). I also make reduced-form estimations by regressing the outcome variables directly on the instruments for offshoring intensities and robot adoption.

The reduced-form estimates bear a close resemblance to those in Figures D3 and 4 and some of the estimates of robot adoption have higher statistical significance (Panel A of Tables E5 and E6). Similarly, the 2SLS estimations yield estimates that are consistent with those in Tables D7–D8 and 3, and the significance of several of these—especially of robot adoption—is higher (Panel B of Tables E5 and E6). The first-stage results of the 2SLS estimations, which are available upon request, point to the relevance of the instruments and, similarly to the main results, although there may be some concerns over instrument strength, the estimates of most specifications are weak-IV robust.^{E8}

Additional automation technologies Throughout the econometric analysis, I have focused on one of the most important industrial automation technologies, robots. Following [Acemoglu & Restrepo \(2021\)](#), I consider other nine industrial automation technologies and create similar adoption measures to that of robot adoption. The nine additional technologies are: dedicated machinery, including industrial robots (DEDIC. MACH.), 3-D printing machines (3-D PRINT), automatic data processing machines (DATA PROC.), automatic conveyors (CONVEYORS), automatic regulating instruments (REGUL. INSTR.), electronic calculating machines (CALC. MACH.), automatic machine tools (MACH. TOOLS), automatic welding machines (WELD. MACH.), and automatic textile, knitting and weaving machines (TEXT. MACH.). I identify these technologies by their HS 1996 codes, as explained in Appendix A.2. Apart from imports of automatic textile machines, which exhibited a downward trend, and imports of calculating machines, which exhibited an erratic trend and increased only slightly between 1996 and 2005, the average country’s imports of the rest of the automation technologies exhibited similar trends to those of industrial robots (Panels (a)–(i) of Figure C6).^{E9} These trends are also observed by country, although heterogeneity in the magnitude of the growth rates is salient (Panels (b)–(j) of Figure C1). Also, the trends of imports of the additional automation technologies by the five high-income countries that are used for the

^{E8}Results and conclusions from these exercises hold when I use as a shifter in the instrument for robot adoption the relevant measure of [Acemoglu & Restrepo \(2020\)](#) for Germany, which is also available for 1993–2014, and after excluding this country from the main sample (results available upon request).

^{E9}The average growth rates of imports of the nine additional automation technologies are: 71% (DEDIC. MACH.), 32% (3-D PRINT), 67% (DATA PROC.), 13% (CONVEYORS), 117% (REGUL. INSTR.), 91% (CALC. MACH.), 18% (MACH. TOOLS), 59% (WELD. MACH.), and -32% (TEXT. MACH.).

construction of the instruments are very similar to those of the countries of the main sample (Panels (b)–(j) of Figures C9 and C10).

With these trends in mind, I replace the robot adoption measure with one of the additional measures at a time and estimate the main specifications in stacked differences and on annual data by 2SLS and in long differences, stacked differences, and on annual data by OLS. Because of the large volume of results, I show the 2SLS estimates obtained based on specifications in stacked differences (Panels (a), (c), (e), (g), (i), (k), (m), (o), and (q) of Figure E7) and on annual data (Panels (b), (d), (f), (h), (j), (l), (n), (p), and (r) of the same figure) with the two offshoring components and robot adoption as the key regressors and make all the rest available upon request. According to Figure E7, sign switches of the coefficient estimates of the offshoring intensity and control variables are uncommon, and despite some loss of significance in a few panels, these estimates are largely consistent with the main ones. These observations largely hold in all other estimations that I make in this robustness check. The 2SLS estimates of the measures of adoption of calculating machines, machine tools, and textile machines have almost always opposite signs to those of robot adoption and are mostly statistically insignificant. By contrast, the 2SLS estimates of the measures of adoption of dedicated, 3-D printing, data processing and welding machines, and of automatic conveyors and regulating instruments have mostly similar signs and significance levels to those of the estimates of robot adoption. I observe a very similar pattern relative to the estimates of robot adoption when I estimate the specifications with aggregate offshoring intensity as a key regressor by 2SLS or OLS.

The pattern of the OLS estimates obtained from estimations of specifications in long or stacked differences or on annual data with the two offshoring components as key regressors is more nuanced. In particular, there are positive and significant associations of the adoption of automatic conveyors and welding machines with the wage bill share of the oldest workers, which are in line with that of robot adoption, but the associations of the adoption of the other automation technologies with the same outcome variable are statistically insignificant. In addition, unlike robot adoption, there are no significant associations of the measures of adoption of the additional automation technologies with the wage bill shares of young workers. Unique exception is an association of the adoption of textile machines with this outcome variable, which is significant at 5% and positive, rather than negative. This positive and significant association, which is consistent with the 2SLS estimates, is likely explained by the documented decline, rather than rise, in the adoption of this type of technology (recall the trends in Panel (j) of Figure C1 and Panel (i) of Figure C6). Also in contrast to robot adoption, the measures of adoption of 3-D printing machines, machine tools, and welding machines are negatively associated with the wage bill share of the middle-aged and their coefficient estimates in the wage bill share equations for the young are positive, rather than negative, albeit insignificant.^{E10}

^{E10}It is noteworthy that the aforementioned similarities and differences relative to the main results are also identified when I instrument the additional automation technology adoption measures but not the offshoring

Elimination of industry-level control variables from the specifications As discussed in the main part of the analysis, some of the evidence that I have derived may point to interactions of the offshoring activities and utilisation of robots with the utilisation of other types of capital. Also, econometrically, the fact that the aggregate capital intensity is measured for years after the year in which the shares component of the instrument for robot adoption is measured may imply that the former variable is affected by the latter, which may yield biased estimates (DiNardo & Lee, 2011; Goldsmith-Pinkham et al., 2020). Motivated by these conceptual and econometric issues, I re-estimate the main specifications by OLS and 2SLS without controlling for aggregate capital intensity. The 2SLS estimates are displayed in Panels (a) and (b) of Figure E8 and the OLS estimates are available upon request. In the absence of this control, statistical significance of the coefficient estimates of the key regressors is largely unchanged. However, the coefficient estimates of the aggregate offshoring intensity, the intensity of offshoring to high-income countries, and robot adoption are smaller than the main ones, while those of the intensity of offshoring to lower-income countries are larger.^{E11} As the issues raised above may also apply to the log of value added, I perform an additional check by re-estimating the main specifications after excluding both the aggregate capital intensity and the log of value added. The estimates obtained are very similar in qualitative terms, but quantitative changes of most estimates are non-negligible (Panels (c) and (d) of the same figure).

Use of fixed and pre-determined values of industry-level control variables An alternative way to address the issues raised in the previous exercise is to use fixed and pre-determined values of the two industry-level controls (e.g., Autor et al., 2013). Estimating the main specifications by OLS and 2SLS with the log of value added and aggregate capital intensity measured in 1990 produces very similar results to the main ones. The 2SLS estimates are shown in Panels (a) and (b) of Figure E9 and the OLS estimates are available upon request.^{E12} This check is akin to estimations on annual data of specifications with interactions of start-of-sample values of the industry-level controls with year dummies (DiNardo & Lee, 2011; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2025). I do this additional exercise by replacing the time-varying log of value added and aggregate capital intensity with their values in 1990 interacted with year dummies and obtain results that are very similar to the main ones. The 2SLS estimates are displayed in Panels (a) and (b) of Figure E10 and the

intensity measures and when I estimate the specifications with each of the nine automation technology measures by OLS and 2SLS after eliminating the offshoring intensity measures. These additional results are available upon request. In all 2SLS estimations of this robustness exercise, the first-stage results point to the relevance of the selected instruments, although there may be some concerns over their strength. The first-stage results are also available upon request.

^{E11} Considering the other automation technologies yields coefficient estimates of the key regressors that are very similar in terms of sign and significance to those obtained from estimations in which aggregate capital intensity is controlled for. Again, I view the changes in magnitudes of the coefficient estimates of the key regressors, especially of the intensity of offshoring to lower-income countries, as evidence of how they interact with other forms of capital. Results from these additional estimations are available upon request.

^{E12} Using the values of the two industry-level controls in 1980, 1982, or 1996 also produces very similar results to the main ones (available upon request). Using the 1996 values is a less preferred choice, as the shares component of the robot adoption variable corresponds to 1990.

OLS estimates are available upon request. Interacting the values of the log of value added and aggregate capital intensity in 1980, 1982, or 1996 with year dummies also yields results that are very similar to the main ones (available upon request).

Use of alternative specification weights or no use of weights For the construction of the main specification weights, I have relied on the total number of hours worked by persons engaged. To check the sensitivity of the main results to the use of alternative variables, I re-estimate the main specifications by OLS and 2SLS with weights constructed based on the total number of hours worked by salaried employees, the total number of persons engaged, or the total number of salaried employees.

In addition, regardless of the variable used for their construction, the main specification weights are measured at the initial sample year (1996) and thus do not account for possible changes in the industrial structures of countries over the ten-year period examined. To control for this possibility, I estimate the specifications while implementing an alternative weighting scheme. In particular, I use as weights the simple average of each industry’s share of the number of hours worked by persons engaged in the total number of hours worked by persons engaged of the manufacturing and market service industries examined across years in 1996–2005 (Graetz & Michaels, 2017; Blanas, 2024). Following the recommendation of Borusyak et al. (2025), I also estimate the main specifications without using weights. In all cases, I obtain results that are very similar to the main ones. Results obtained from 2SLS estimations are shown in Panels (a)–(b), (c)–(d), and (e)–(f) of Figure E11 and Panels (a)–(b) and (c)–(d) of Figure E12, while results from OLS estimations are available upon request.^{E13}

Pre-trends To check whether the main 2SLS results are driven by pre-trends, I do placebo tests by taking advantage of relevant data availability in the March 2008 release of the EU KLEMS database and replacing the contemporaneous changes in wage bill shares with changes between 1982 and 1989, 1989 and 1995, or 1982 and 1995. Considering the first period is more appropriate than the other two, as it precedes not only the start year of the sample but also the year to which the share of routine tasks corresponds (Borusyak et al., 2025). Yet, considering the other two sub-periods has the advantage of covering years until before the start year of the sample. In addition to estimating specifications with placebo outcomes by 2SLS, I estimate reduced-form versions of these by OLS (i.e., placebo outcomes regressed directly on the instruments for offshoring intensities and robot adoption).

The 2SLS estimates of offshoring intensities are statistically insignificant and almost all of these have opposite signs to those of the main estimates. On top of that, there is not a single specification in which the estimates of offshoring to high- and lower-income countries are statistically different from each other, which is also in sharp contrast to the main results. I view these estimates and statistics as clear evidence of no violation of the parallel trends assumption for the identification of the offshoring effects. Apart from a couple of insignificant

^{E13}In additional results that are available upon request, I show that implementing the alternative weighting scheme using the total number of hours worked by salaried employees, the total number of persons engaged, or the total number of salaried employees also yields very similar results to the main ones.

estimates of robot adoption with opposite signs, the rest have the same signs to the main ones and three of these, corresponding to the specifications for the young, are significant at 10% or 5% (Panels A–C of Table E7). I make the same observations based on the reduced-form estimates (Panels (a)–(b), (c)–(d), and (e)–(f) of Figure E13). In the specification for the young with the two offshoring components where the placebo estimate of robot adoption is significant at 5%, the fraction of the main estimate accounted for by the adjusted placebo estimate far exceeds 100% and thus not reported. Shares higher than 100% appear in most specifications with the two offshoring components.^{E14}

The other two negative and significant placebo estimates of robot adoption correspond to the specifications for the young with aggregate offshoring intensity as the other key regressor and the wage bill share change between 1982 and 1989 or 1982 and 1995 as the dependent variable. By contrast, the corresponding placebo estimate in the specification with the wage bill share change between the most recent years, 1989 and 1995, as the dependent variable is statistically insignificant. In addition to being insignificant in the most proximate years to the start year of the sample, the magnitude of the adjusted placebo estimate of robot adoption is much smaller than those in the earlier and overall pre-sample periods. This is also evident from the shares of the main estimates that are accounted for by the adjusted placebo estimates. While the shares of the adjusted placebo estimates in 1982–1989 and 1982–1995 are 51% and 38%, respectively, the share in 1989–1995 is only 24.6%. In the specifications for the middle-aged and older workers, the fractions of the main estimates of robot adoption that are accounted for by the respective adjusted placebo estimates vary widely across pre-sample periods and the patterns of their magnitudes differ between the two age groups. In particular, the adjusted placebo estimate in the specification for the middle-aged accounts for 11% (1982–1989), 49% (1982–1995), or 97.3% (1989–1995) of the main estimate, and the adjusted placebo estimate in the specification for older workers accounts for 16.4% (1982–1995) or 96.6% (1982–1989) of the main estimate. The adjusted placebo estimate in the specification for older workers when the outcome variable corresponds to 1989–1995 has opposite sign to the main one and thus its share is not disclosed.

Industry fixed effects controlled for The incorporation of industry fixed effects in the main specifications does not allow for their estimation by 2SLS, given that the instruments vary only by industry. Yet, this set of fixed effects controls for cross-industry differences in factors that are closely related to the key regressors and can impact wage bill shares—most notably, import competition and technological sophistication. Equally importantly, the same

^{E14}Note that, as the specifications in each column of the three panels differ only in the pre-sample period coverage, the coefficient estimates of each regressor in the specifications with outcome variables for 1982–1989 and 1989–1995 add up to the respective estimates in the specifications with outcome variables for 1982–1995. Any small discrepancies are attributed to rounding errors. However, precisely because of the different pre-sample coverage, the placebo estimates are not comparable across panels. To make them comparable, I adjust them ($\hat{\beta}_{AUT,adj}^{placebo}$) by multiplying their values by the ratio of the number of year-to-year wage bill share changes in 1996–2005 (9) to the number of year-to-year changes in 1982–1989 (7), 1989–1995 (6), and 1982–1995 (13). I adjust their standard errors in the same manner. $\hat{\beta}_{AUT,adj}^{placebo}/\hat{\beta}_{AUT}^{main}$ (%) is the percentage share of an adjusted placebo estimate in the main estimate reported in Table 3.

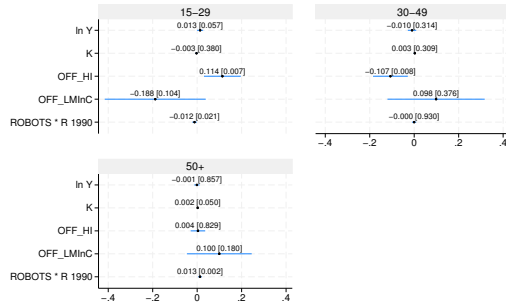
set of fixed effects controls for cross-industry labour mobility, which is a mechanism through which workers might have adjusted to the expansion of offshoring and automation.

Relative to the main results, most of the OLS estimates obtained when industry fixed effects are controlled for maintain their signs but only a few of these also maintain their significance, while there are other coefficient estimates that switch signs and lose significance (Panels (a) and (b) of Figure E14). In particular, aggregate offshoring intensity continues to be positively associated with the wage bill share of young workers and negatively associated with the wage bill share of the middle-aged. Similarly, the association of the intensity of offshoring to high-income countries with the wage bill share of the middle-aged remains negative and significant and the association of robot adoption with the wage bill share of the oldest workers remains positive and significant. By contrast, there are no statistically significant associations of these two key regressors with the wage bill share of the young. In addition, the coefficient estimates of the intensity of offshoring to lower-income countries and of the log of output have mostly opposite signs and are all statistically insignificant.

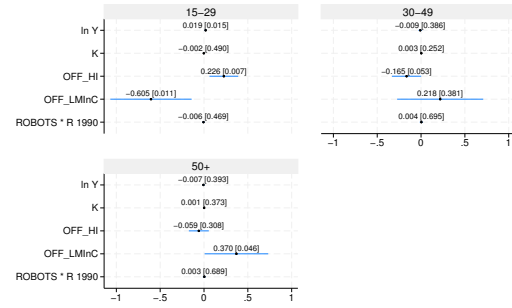
These changes likely point to collinearities between industry fixed effects and these variables, especially the intensity of offshoring to lower-income countries. This may not be surprising, given the similar development levels and attitudes towards offshoring and automation of the countries examined. In other words, the average industry in the high-income countries of my sample is likely to have emulated general trends of offshoring and automation adoption. Note that reductions or losses of significance and sign switches have also been observed by previous studies incorporating industry fixed effects in specifications estimated on long-differenced data (Michaels et al., 2014) or industry-year fixed effects in specifications estimated on annual data (Blanas, 2024). Shifts of the three age groups of workers across industries may constitute an additional explanation for the absence of significant effects of some key regressors on wage bill shares.

Mean reversion According to descriptive statistics produced in Section 2.2, the outcome variables of the main specifications might have exhibited mean-reverting dynamics. For instance, some industries of the sample have both relatively high initial wage bill shares of the oldest workers and relatively high growth rates of these variables. To control for mean-reverting dynamics, I re-estimate the main specifications after augmenting these with the wage bill shares of the middle-aged and older workers in 1996 (Michaels et al., 2014; Acemoglu & Restrepo, 2020; Blanas, 2024). The 2SLS results obtained are very similar to the main ones (Panels (a) and (b) of Figure E15), and this also holds true for the OLS results (available upon request).

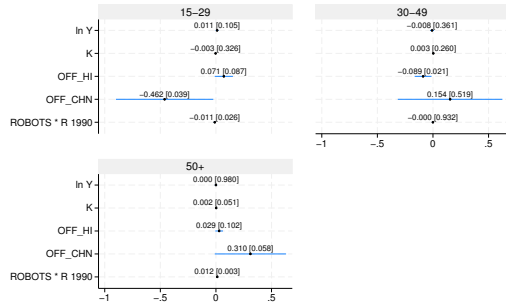
Figure E1: Offshoring to high-income countries and to lower-income countries other than China or to China, industrial robots, and wage bill shares by age



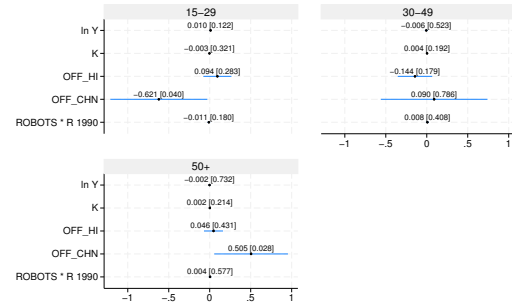
(a) OLS, offshoring to LMI save for China



(b) IV-OFF-OC & IV-AUT-OC, offshoring to LMI save for China



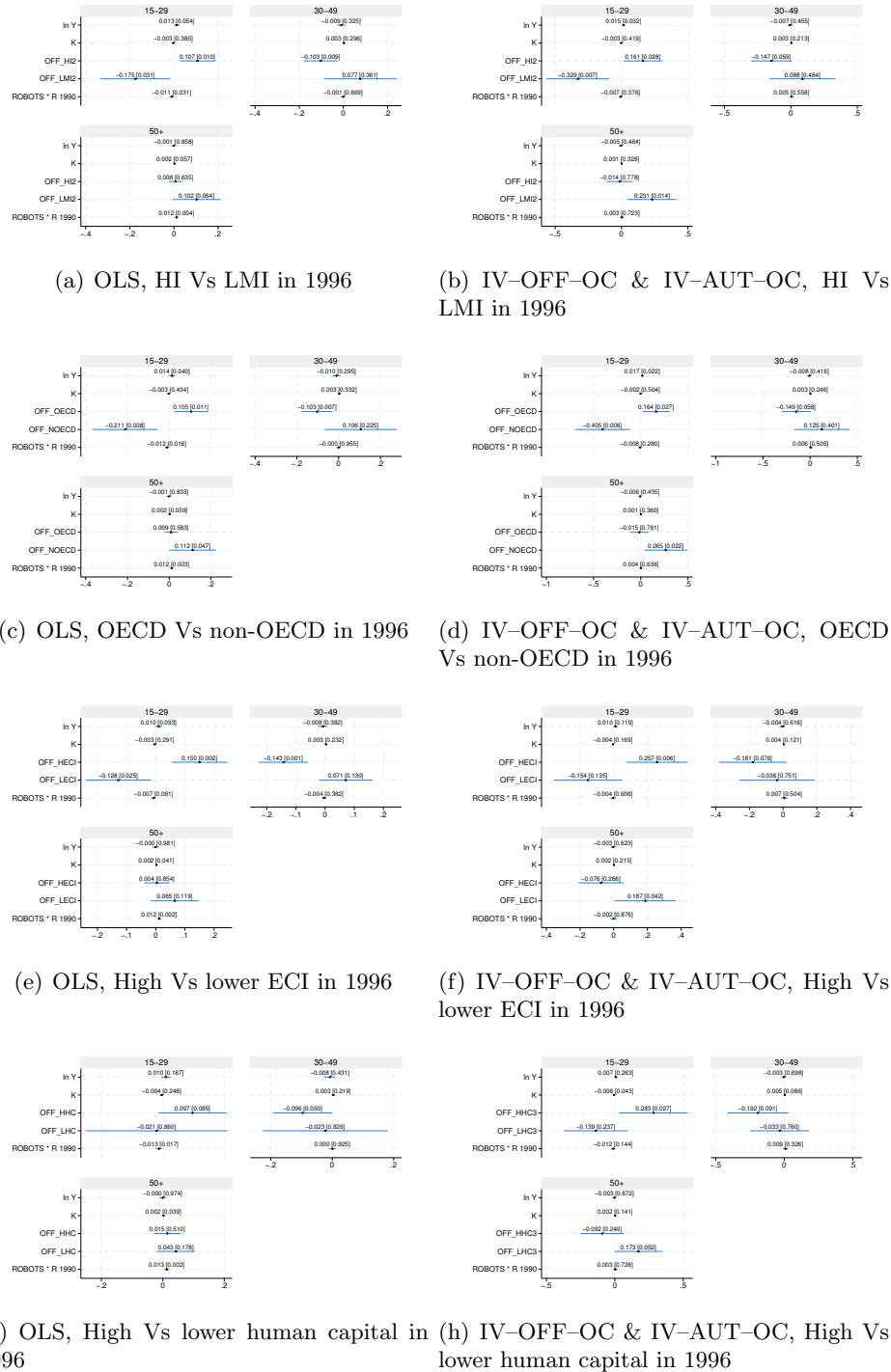
(c) OLS, offshoring to China



(d) IV-OFF-OC & IV-AUT-OC, offshoring to China

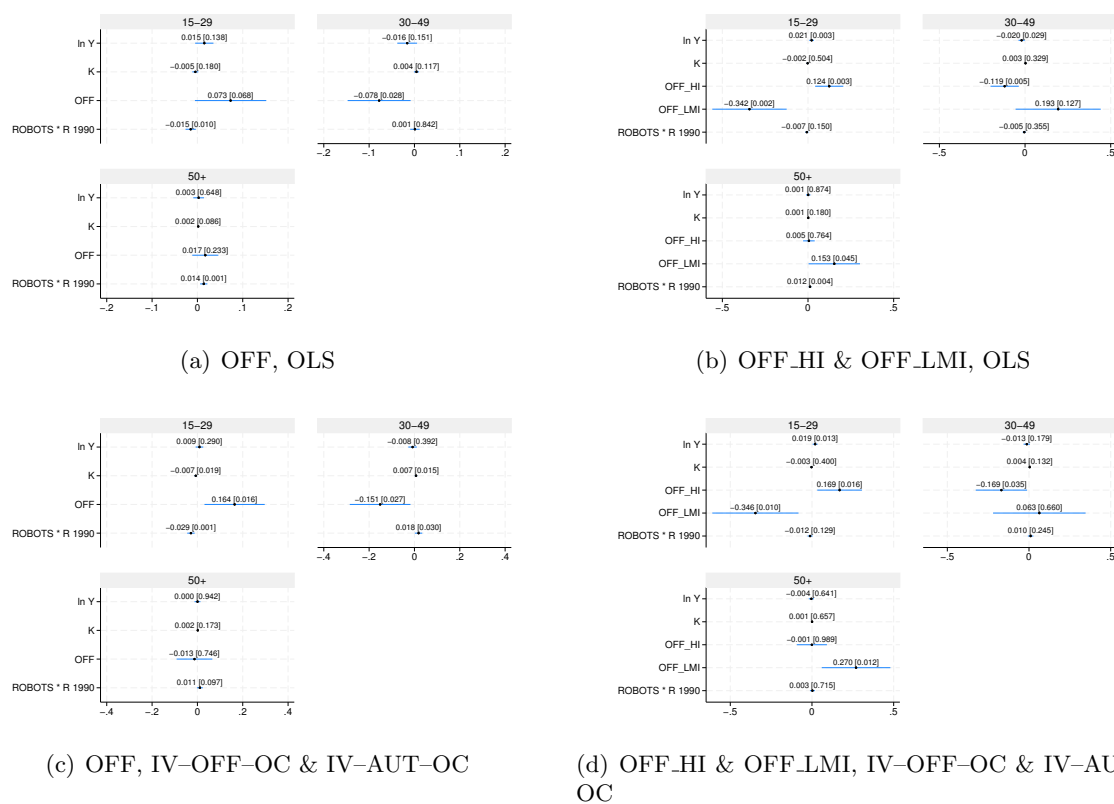
Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors in Panels (a) and (c) and Panels (b) and (d), respectively. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Figure E2: Offshoring, industrial robots, and wage bill shares by age, alternative classifications of offshoring destination countries



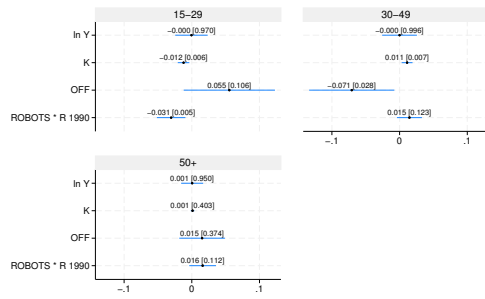
Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors in Panels (a), (c), (e), (g) and Panels (b), (d), (f), (h), respectively. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. For the description of the classification of offshoring destination countries by income, OECD membership status, export complexity, and human capital abundance, see Section 4.1.1 and Appendix A.1.

Figure E3: Offshoring, industrial robots, and wage bill shares by age, Japan and Germany excluded

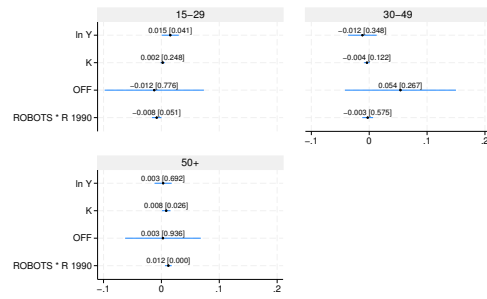


Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors in Panels (a)–(b) and Panels (c)–(d), respectively. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

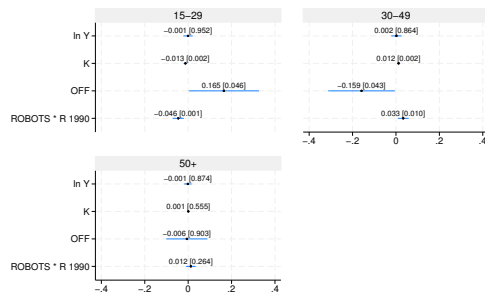
Figure E4: Offshoring, industrial robots, and wage bill shares by age, countries with relatively high Vs low EPL



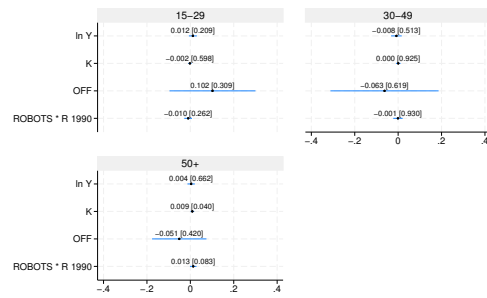
(a) OFF, High EPL, OLS



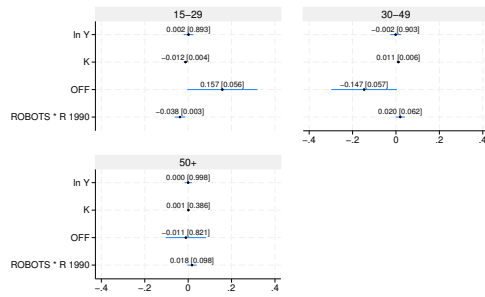
(b) OFF, Low EPL, OLS



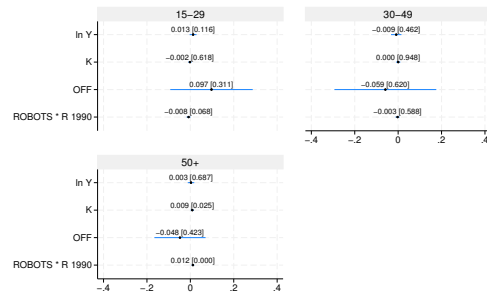
(c) OFF, High EPL, IV-OFF-OC & IV-AUT-OC



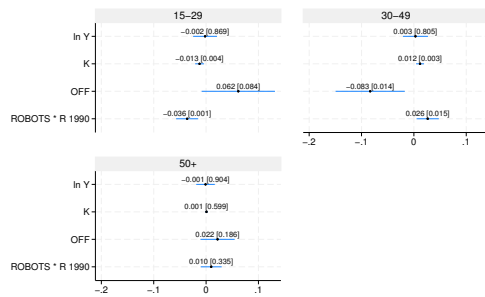
(d) OFF, Low EPL, IV-OFF-OC & IV-AUT-OC



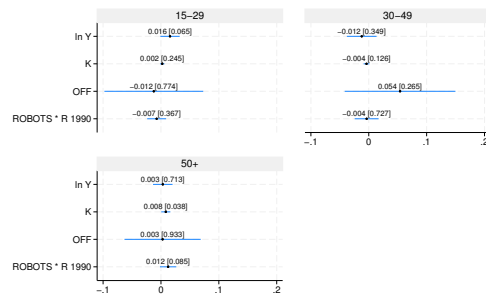
(e) OFF, High EPL, IV-OFF-OC



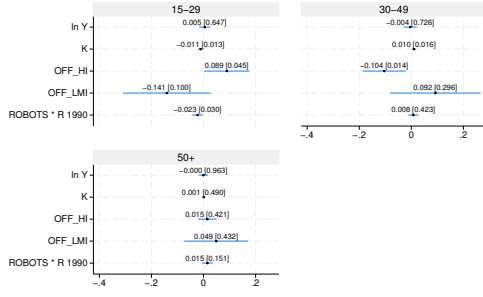
(f) OFF, Low EPL, IV-OFF-OC



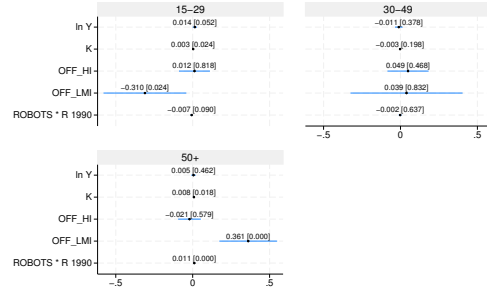
(g) OFF, High EPL, IV-AUT-OC



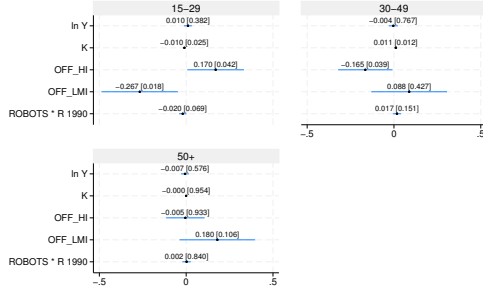
(h) OFF, Low EPL, IV-AUT-OC



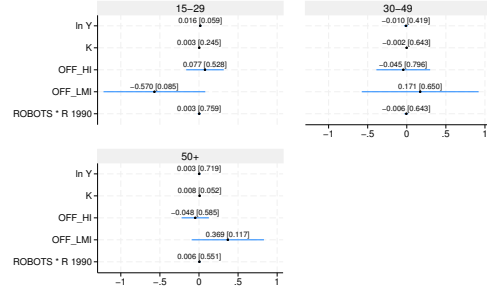
(i) OFF_HI & OFF_LMI, High EPL, OLS



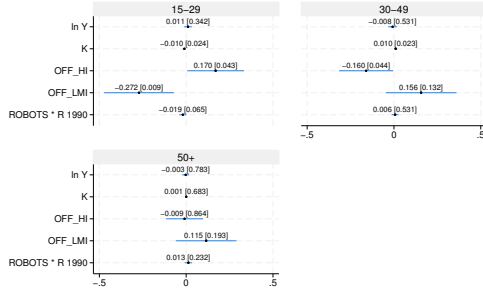
(j) OFF_HI & OFF_LMI, Low EPL, OLS



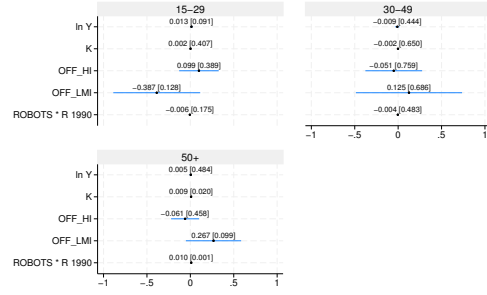
(k) OFF_HI & OFF_LMI, High EPL, IV-OFF-OC & IV-AUT-OC



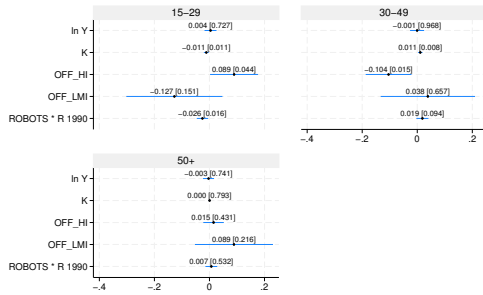
(l) OFF_HI & OFF_LMI, Low EPL, IV-OFF-OC & IV-AUT-OC



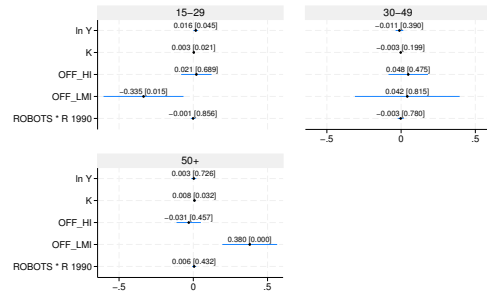
(m) OFF_HI & OFF_LMI, High EPL, IV-OFF-OC



(n) OFF_HI & OFF_LMI, Low EPL, IV-OFF-OC



(o) OFF_HI & OFF_LMI, High EPL, IV-AUT-OC



(p) OFF_HI & OFF_LMI, Low EPL, IV-AUT-OC

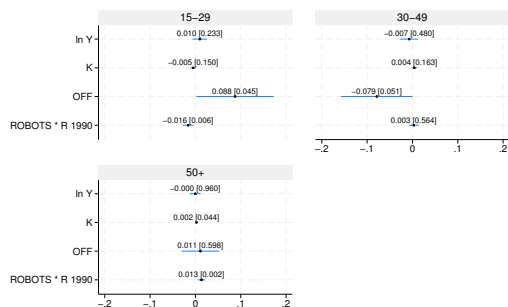
Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors on the sample of countries with relatively high EPL strictness in Panels (a), (c), (e), (g), (i), (k), (m), and (o) and on the sample of countries with relatively low EPL strictness in Panels (b), (d), (f), (h), (j), (l), (n), and (p). The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. For the classification of countries by EPL strictness, see Appendix A.3.

Table E1: Rotemberg weights based on the estimates in Table 3

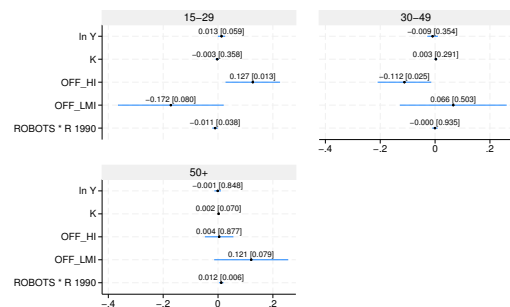
Panel A: Endogenous key regressor: OFF		
NACE Rev. 1.1	Industry name	Rotemberg weight
23	Coke, Refined Petroleum Products and Nuclear Fuel	0.429
34T35	Transport Equipment	0.368
27T28	Basic Metals and Fabricated Metal Products	0.073
17T19	Textiles, Textile Products, Leather and Footwear	0.049
30T33	Electrical and Optical Equipment	0.037
Panel B: Endogenous key regressor: OFF_HI		
NACE Rev. 1.1	Industry name	Rotemberg weight
34T35	Transport Equipment	0.315
23	Coke, Refined Petroleum Products and Nuclear Fuel	0.28
17T19	Textiles, Textile Products, Leather and Footwear	0.187
30T33	Electrical and Optical Equipment	0.163
27T28	Basic Metals and Fabricated Metal Products	0.023
Panel C: Endogenous key regressor: OFF_LMI		
NACE Rev. 1.1	Industry name	Rotemberg weight
30T33	Electrical and Optical Equipment	0.412
34T35	Transport Equipment	0.245
17T19	Textiles, Textile Products, Leather and Footwear	0.188
27T28	Basic Metals and Fabricated Metal Products	0.039
20	Wood and Products of Wood and Cork	0.030
Panel C: Endogenous key regressor: ROBOTS * R		
NACE Rev. 1.1	Industry name	Rotemberg weight
29	Machinery and Equipment, n.e.c.	0.177
27T28	Basic Metals and Fabricated Metal Products	0.114
17T19	Textiles, Textile Products, Leather and Footwear	0.106
34T35	Transport Equipment	0.086
25	Rubber and Plastics Products	0.083

Notes: Top 5 industries in descending order in terms of Rotemberg weights for each key regressor in the specifications of Table 3.

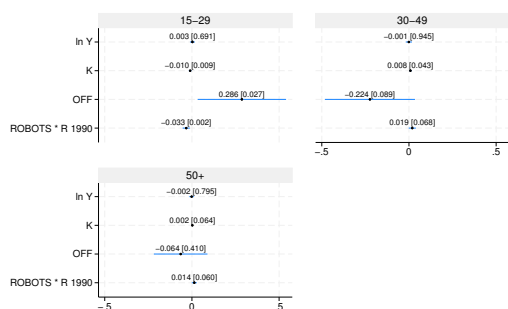
Figure E5: Offshoring, industrial robots, and wage bill shares by age, Transport equipment industry excluded



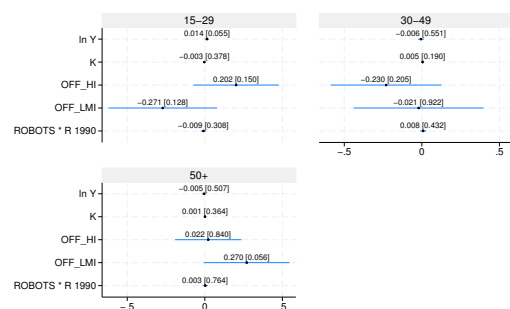
(a) OFF, OLS



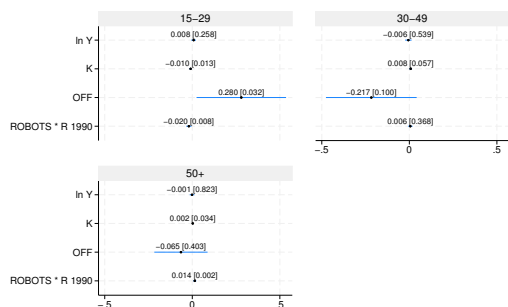
(b) OFF_HI & OFF_LMI, OLS



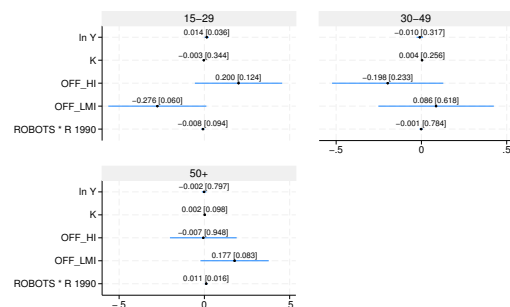
(c) OFF, IV-OFF-OC & IV-AUT-OC



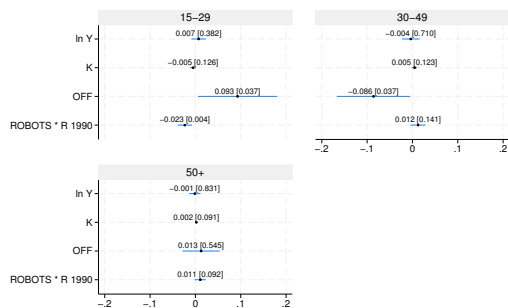
(d) OFF_HI & OFF_LMI, IV-OFF-OC & IV-AUT-OC



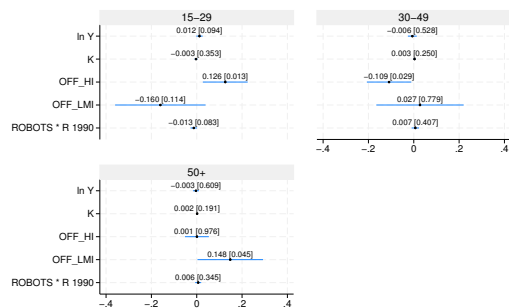
(e) OFF, IV-OFF-OC



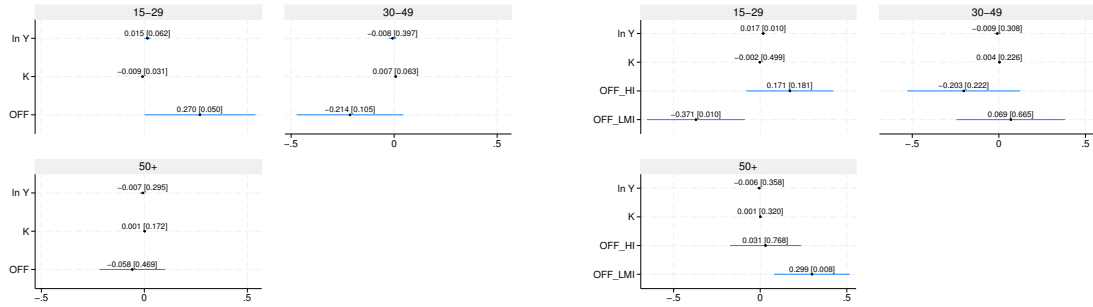
(f) OFF_HI & OFF_LMI, IV-OFF-OC



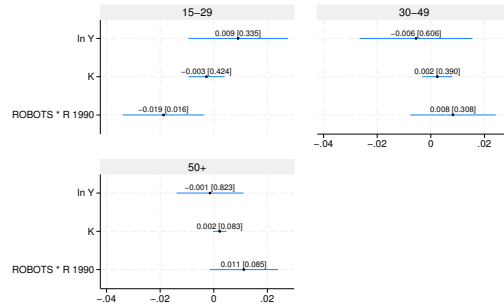
(g) OFF, IV-AUT-OC



(h) OFF_HI & OFF_LMI, IV-AUT-OC



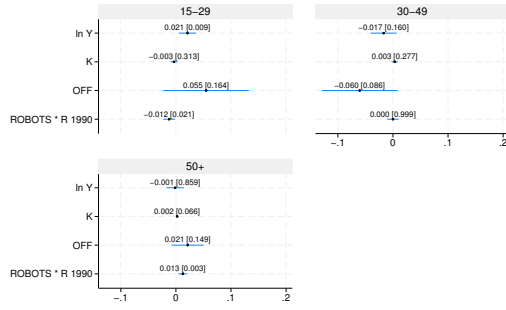
(i) OFF, IV-OFF-OC, robot adoption not controlled for (j) OFF_HI & OFF_LMI, IV-OFF-OC, robot adoption not controlled for



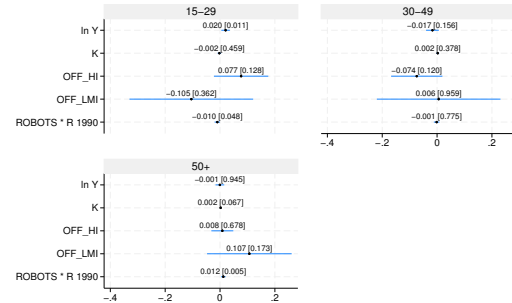
(k) IV-AUT-OC, offshoring intensities not controlled for

Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors in Panels (a)–(b) and Panels (c)–(k), respectively. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

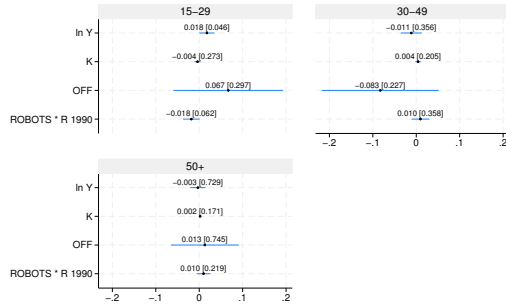
Figure E6: Offshoring, industrial robots, and wage bill shares by age, Electrical and optical equipment industry excluded



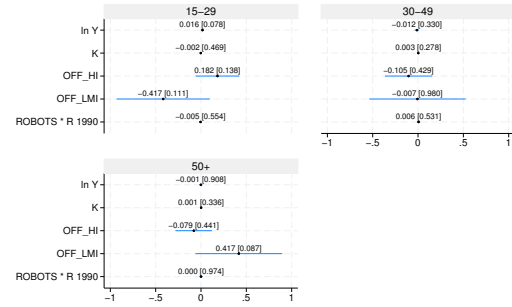
(a) OFF, OLS



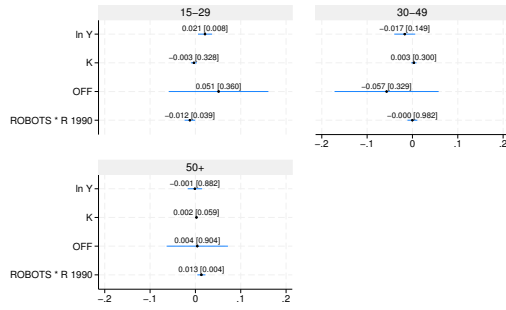
(b) OFF_HI & OFF_LMI, OLS



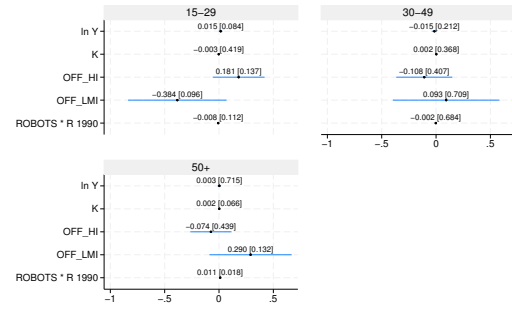
(c) OFF, IV-OFF-OC & IV-AUT-OC



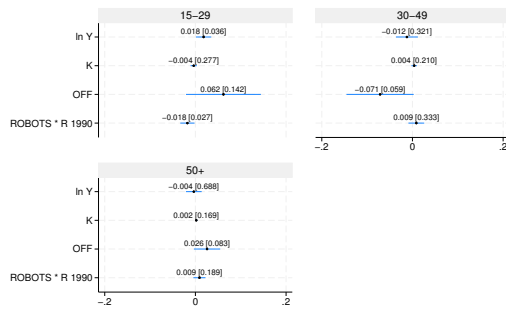
(d) OFF_HI & OFF_LMI, IV-OFF-OC & IV-AUT-OC



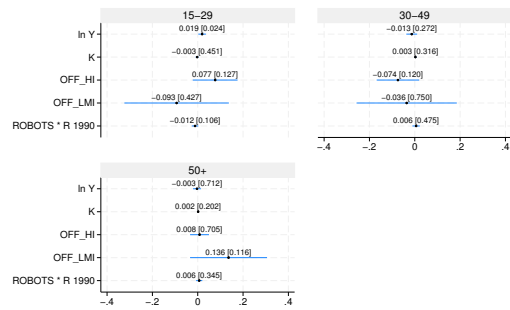
(e) OFF, IV-OFF-OC



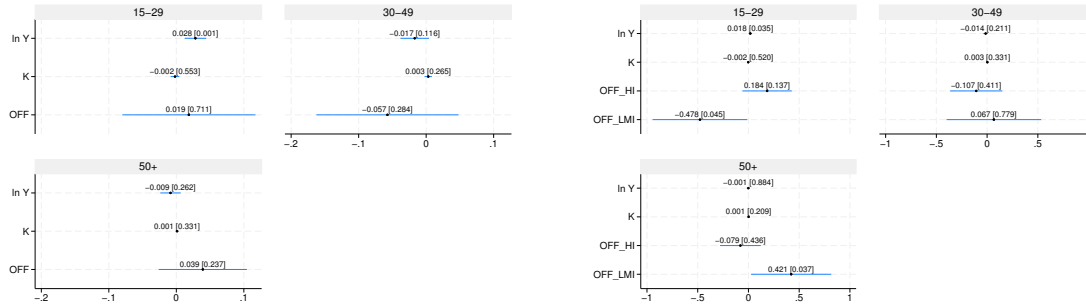
(f) OFF_HI & OFF_LMI, IV-OFF-OC



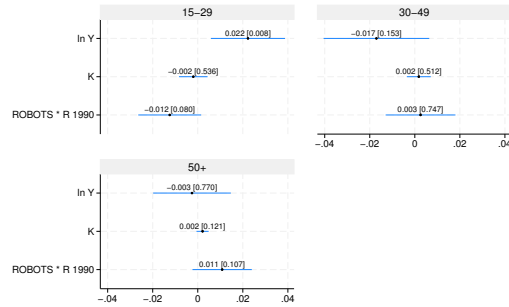
(g) OFF, IV-AUT-OC



(h) OFF_HI & OFF_LMI, IV-AUT-OC



(i) OFF, IV-OFF-OC, robot adoption not controlled for (j) OFF_HI & OFF_LMI, IV-OFF-OC, robot adoption not controlled for



(k) IV-AUT-OC, offshoring intensities not controlled for

Notes: OLS and 2SLS estimations of specifications in long differences with robust standard errors in Panels (a)–(b) and Panels (c)–(k), respectively. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Table E2: Offshoring, industrial robots, and wage bill shares by age, industry-level share of routine tasks in 1980

Panel A: OLS						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.011 [0.008]	-0.0076 [0.010]	-0.0012 [0.006]	0.014** [0.007]	-0.0094 [0.009]	-0.0021 [0.006]
K	-0.0040 [0.003]	0.0039 [0.003]	0.0022* [0.001]	-0.0027 [0.003]	0.0027 [0.003]	0.0020* [0.001]
OFF	0.062* [0.03]	-0.069** [0.03]	0.020 [0.01]			
OFF_HI				0.10** [0.04]	-0.10*** [0.04]	0.0096 [0.02]
OFF_LMI				-0.18** [0.08]	0.077 [0.09]	0.10* [0.06]
ROBOTS * R 1980	-0.014*** [0.005]	0.0021 [0.005]	0.012*** [0.004]	-0.0094** [0.005]	-0.0010 [0.005]	0.011*** [0.004]
Observations	231	231	229	231	231	229
R ²	0.467	0.660	0.711	0.481	0.662	0.713
H ₀ : $\beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00333	0.0804	0.133
Panel B: 2SLS, IV-OFF-OC and IV-AUT-OC						
Dep var: Wsh	(1) 15-29	(2) 30-49	(3) 50+	(4) 15-29	(5) 30-49	(6) 50+
ln Y	0.0074 [0.007]	-0.0032 [0.009]	-0.0024 [0.006]	0.016** [0.007]	-0.0075 [0.010]	-0.0058 [0.007]
K	-0.0062** [0.003]	0.0057** [0.003]	0.0021* [0.001]	-0.0024 [0.003]	0.0033 [0.003]	0.0012 [0.001]
OFF	0.14** [0.06]	-0.13** [0.06]	-0.010 [0.04]			
OFF_HI				0.15** [0.07]	-0.14* [0.08]	-0.0095 [0.05]
OFF_LMI				-0.34*** [0.1]	0.086 [0.1]	0.24** [0.1]
ROBOTS * R 1980	-0.025*** [0.008]	0.015* [0.008]	0.011* [0.006]	-0.0059 [0.007]	0.0054 [0.009]	0.0016 [0.008]
Observations	231	231	229	231	231	229
R ²	0.0537	0.00547	0.0521	0.108	0.0369	0.0380
H ₀ : $\beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00107	0.165	0.0488
Kleibergen-Paap rk LM	14.19	14.19	14.59	14.99	14.99	15.37
Kleibergen-Paap rk LM (p-value)	0.000165	0.000165	0.000133	0.000108	0.000108	0.0000885
Kleibergen-Paap Wald rk F	8.468	8.468	8.526	7.977	7.977	8.171
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	6.910	6.910	7.451	5.687	5.687	6.178
Lewis-Mertens critical value	35.91	35.86	39.22	50.79	50.76	50.41
Wald χ^2	10.66	5.290	2.796	16.59	5.087	13.04
Wald χ^2 (p-value)	0.00485	0.0710	0.247	0.000859	0.166	0.00454
AR χ^2	7.622	4.428	2.673	8.871	3.808	12.42
AR χ^2 (p-value)	0.0221	0.109	0.263	0.0311	0.283	0.00608
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-OC ROBOTS: IV-AUT-OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-OC ROBOTS: IV-AUT-OC		

Notes: OLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6) of Panel B. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table E3: Offshoring, industrial robots, and wage bill shares by age, IV-OFF-USA and IV-AUT-USA

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	-0.0022 [0.01]	0.0016 [0.01]	0.00058 [0.007]	0.015** [0.007]	-0.0090 [0.01]	-0.0035 [0.007]
K	-0.012** [0.005]	0.0090* [0.005]	0.0030** [0.001]	-0.0028 [0.004]	0.0033 [0.003]	0.0018 [0.001]
OFF	0.33* [0.2]	-0.24 [0.2]	-0.10 [0.1]			
OFF_HI				0.15 [0.10]	-0.15 [0.1]	-0.00024 [0.07]
OFF_LMI				-0.32** [0.1]	0.14 [0.1]	0.17* [0.09]
ROBOTS * R 1990	-0.043*** [0.02]	0.023* [0.01]	0.020** [0.009]	-0.0092 [0.008]	0.0027 [0.010]	0.0077 [0.008]
Observations	210	210	208	210	210	208
R^2	0.177	0.609	0.671	0.476	0.665	0.707
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.00338	0.0866	0.0855
Kleibergen-Paap rk LM	2.828	2.828	2.576	9.911	9.911	10.34
Kleibergen-Paap rk LM (p-value)	0.0927	0.0927	0.108	0.00164	0.00164	0.00130
Kleibergen-Paap Wald rk F	1.270	1.270	1.154	3.042	3.042	3.146
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	0.920	0.920	0.893	1.986	1.986	2.181
Lewis-Mertens critical value	37.29	37.27	39.12	51.05	51.04	50.73
Wald χ^2	7.747	2.923	5.567	15.85	3.939	12.19
Wald χ^2 (p-value)	0.0208	0.232	0.0618	0.00122	0.268	0.00675
AR χ^2	7.983	3.063	5.924	7.961	2.697	9.590
AR χ^2 (p-value)	0.0185	0.216	0.0517	0.0468	0.441	0.0224
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
	ln Y, K: no IV			ln Y, K: no IV		
IV strategy	OFF: IV-OFF-USA			OFF_HI, OFF_LMI: IV-OFF-USA		
	ROBOTS: IV-AUT-USA			ROBOTS: IV-AUT-USA		

Notes: 2SLS estimations of specifications in long differences in columns (1)–(3) and (4)–(6). The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table E4: Offshoring, industrial robots, and wage bill shares by age, stacked differences or annual data, IV-OFF-USA and IV-AUT-USA

Panel A: Stacked differences						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.020*	-0.010	-0.0083	0.027*	-0.012	-0.015
	[0.01]	[0.01]	[0.007]	[0.02]	[0.01]	[0.01]
K	-0.0036	0.0051	0.00041	-0.00088	0.0022	-0.0017
	[0.003]	[0.004]	[0.001]	[0.004]	[0.004]	[0.003]
OFF	0.17	-0.18	0.022			
	[0.2]	[0.1]	[0.08]			
OFF_HI				-0.068	-0.23	0.30
				[0.4]	[0.3]	[0.4]
OFF_LMI				-0.75	0.12	0.63
				[0.6]	[0.4]	[0.6]
ROBOTS * R 1990	0.017	-0.012	-0.0065	0.035	-0.0095	-0.025
	[0.01]	[0.01]	[0.009]	[0.03]	[0.02]	[0.03]
Observations	418	420	416	418	420	416
R ²	0.364	0.566	0.594	0.248	0.573	0.280
H ₀ : β _{OFF_HI} = β _{OFF_LMI} (p-value)				0.00162	0.0669	0.157
Kleibergen-Paap rk LM	3.181	3.925	3.250	0.619	0.865	0.653
Kleibergen-Paap rk LM (p-value)	0.0745	0.0476	0.0714	0.432	0.352	0.419
Kleibergen-Paap Wald rk F	1.565	1.943	1.598	0.195	0.272	0.205
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	1.960	2.137	1.991	0.450	0.518	0.470
Lewis-Mertens critical value	28.64	27.11	28.70	31.34	31.13	31.47
Wald χ ²	9.042	7.588	0.544	12.65	8.891	2.152
Wald χ ² (p-value)	0.0109	0.0225	0.762	0.00545	0.0308	0.541
AR χ ²	10.82	8.131	0.554	17.79	9.231	8.342
AR χ ² (p-value)	0.00448	0.0172	0.758	0.000486	0.0264	0.0394
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-USA ROBOTS: IV-AUT-USA			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-USA ROBOTS: IV-AUT-USA		

Panel B: Annual data						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.026***	-0.020***	-0.0055	0.024***	-0.019***	-0.0047
	[0.006]	[0.007]	[0.005]	[0.005]	[0.007]	[0.005]
K	-0.0042**	0.0045**	0.00020	-0.00018	0.00080	-0.000058
	[0.002]	[0.002]	[0.0008]	[0.001]	[0.001]	[0.0008]
OFF	0.19**	-0.20***	0.0063			
	[0.08]	[0.07]	[0.04]			
OFF_HI				0.080	-0.094	0.017
				[0.06]	[0.06]	[0.04]
OFF_LMI				-0.54***	0.37***	0.18**
				[0.1]	[0.1]	[0.09]
ROBOTS * R 1990	0.034**	-0.027*	-0.0073	0.021*	-0.017	-0.0041
	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.010]
Observations	2077	2079	2070	2077	2079	2070
R ²	0.973	0.961	0.986	0.979	0.966	0.986
H ₀ : β _{OFF_HI} = β _{OFF_LMI} (p-value)				6.48e-11	0.00000804	0.0395
Kleibergen-Paap rk LM	18.90	18.89	19.23	20.47	20.56	20.41
Kleibergen-Paap rk LM (p-value)	0.0000138	0.0000139	0.0000116	0.00000605	0.00000577	0.00000624
Kleibergen-Paap Wald rk F	8.473	8.470	8.609	6.039	6.068	6.014
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	12.90	12.90	12.56	8.056	8.081	7.989
Lewis-Mertens critical value	30.67	30.47	30.70	40.55	40.56	40.85
Wald χ ²	15.07	13.12	0.433	48.85	21.91	9.137
Wald χ ² (p-value)	0.000533	0.00141	0.805	1.40e-10	0.0000682	0.0275
AR χ ²	23.22	16.82	0.458	43.58	19.70	9.274
AR χ ² (p-value)	0.00000908	0.000223	0.795	1.85e-09	0.000196	0.0259
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
IV strategy	ln Y, K: no IV OFF: IV-OFF-USA ROBOTS: IV-AUT-USA			ln Y, K: no IV OFF_HI, OFF_LMI: IV-OFF-USA ROBOTS: IV-AUT-USA		

Notes: 2SLS estimations of specifications in stacked differences in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of specifications on annual data in columns (1)–(3) and (4)–(6) of Panel B. The equations in Panel A include country-year fixed effects and those in Panel B include country-industry and country-year fixed effects. The equations in all panels are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table E5: Offshoring, industrial robots, and wage bill shares by age, stacked differences, reduced-form and 2SLS, IV-OFF-OC and IV-AUT-AR-USA

Panel A: OLS						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.0065 [0.009]	-0.0069 [0.01]	-0.0022 [0.006]	0.0082 [0.009]	-0.0073 [0.01]	-0.0034 [0.006]
K	-0.0043 [0.003]	0.0011 [0.002]	0.0013 [0.001]	-0.0039 [0.003]	0.00099 [0.002]	0.0011 [0.001]
OFF OC	0.032** [0.02]	-0.038** [0.02]	0.0057 [0.010]			
OFF_HI OC				0.043** [0.02]	-0.048** [0.02]	0.0048 [0.01]
OFF_LMI OC				-0.23** [0.1]	0.075 [0.1]	0.16** [0.08]
ROBOTS USA * R 1990	-0.069*** [0.02]	0.026 [0.02]	0.040** [0.02]	-0.047** [0.02]	0.016 [0.02]	0.028 [0.02]
Observations	418	420	416	418	420	416
R^2	0.463	0.605	0.608	0.469	0.606	0.610
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.0136	0.327	0.0497
Panel B: 2SLS, IV-OFF-OC and IV-AUT-AR-USA						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.0029 [0.010]	-0.00076 [0.01]	-0.00057 [0.006]	0.0081 [0.010]	-0.0069 [0.01]	-0.0027 [0.006]
K	-0.0052** [0.003]	0.0052** [0.002]	0.0014 [0.001]	-0.0039 [0.003]	0.0021 [0.002]	0.00086 [0.001]
OFF	0.19*** [0.07]	-0.17** [0.08]	-0.024 [0.04]			
OFF_HI				0.16** [0.06]	-0.15** [0.07]	-0.0043 [0.05]
OFF_LMI				-0.16 [0.2]	0.035 [0.2]	0.13 [0.1]
ROBOTS * R 1990	-0.043*** [0.01]	0.024* [0.01]	0.019** [0.010]	-0.024* [0.01]	0.011 [0.01]	0.012 [0.01]
Observations	418	420	416	418	420	416
R^2	-0.383	-0.132	-0.0785	-0.0791	-0.0201	-0.0212
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				0.0281	0.248	0.161
Kleibergen-Paap rk LM	18.74	15.86	18.73	17.85	16.51	17.89
Kleibergen-Paap rk LM (p-value)	0.0000150	0.0000683	0.0000151	0.0000239	0.0000483	0.0000234
Kleibergen-Paap Wald rk F	11.90	10.36	11.89	6.198	5.772	6.204
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	16.77	14.00	16.68	9.327	8.486	9.297
Lewis-Mertens critical value	30.56	28.84	30.57	37.93	37.77	38.09
Wald χ^2	10.16	5.080	5.735	18.18	6.254	16.01
Wald χ^2 (p-value)	0.00621	0.0788	0.0569	0.000404	0.0999	0.00113
AR χ^2	13.49	5.551	6.839	16.06	6.161	14.12
AR χ^2 (p-value)	0.00118	0.0623	0.0327	0.00110	0.104	0.00274
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
ln Y, K: no IV						
IV strategy	OFF: IV-OFF-OC			OFF_HI, OFF_LMI: IV-OFF-OC		
	ROBOTS: IV-AUT-AR-USA			ROBOTS: IV-AUT-AR-USA		

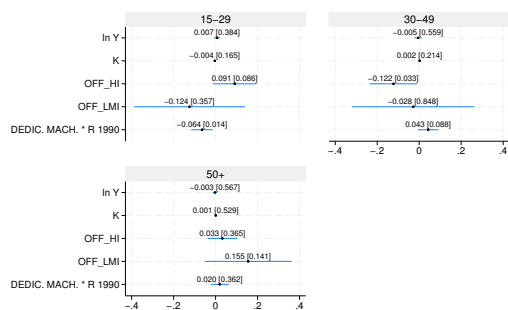
Notes: OLS estimations of reduced-form specifications in stacked differences in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of specifications in stacked differences in columns (1)–(3) and (4)–(6) of Panel B. The equations in both panels include country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table E6: Offshoring, industrial robots, and wage bill shares by age, annual data, reduced-form and 2SLS, IV-OFF-OC and IV-AUT-AR-USA

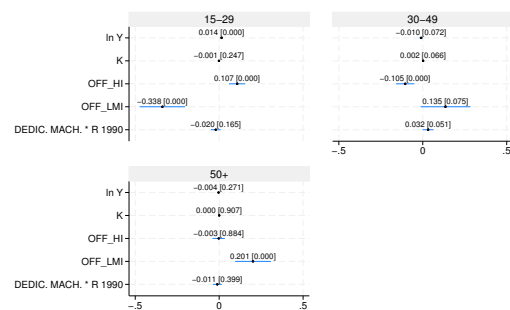
Panel A: OLS						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.010** [0.005]	-0.0096 [0.006]	0.000059 [0.004]	0.013*** [0.004]	-0.011* [0.006]	-0.00068 [0.004]
K	-0.0018 [0.001]	0.0015 [0.001]	0.00092* [0.0005]	-0.0016 [0.001]	0.0014 [0.001]	0.00083 [0.0005]
OFF OC	0.049*** [0.01]	-0.051*** [0.01]	0.0025 [0.007]			
OFF_HI OC				0.051*** [0.01]	-0.052*** [0.01]	0.00066 [0.008]
OFF_LMI OC				-0.26*** [0.06]	0.16** [0.07]	0.096** [0.05]
ROBOTS USA * R 1990	-0.066*** [0.01]	0.026** [0.01]	0.041*** [0.009]	-0.040*** [0.01]	0.0080 [0.01]	0.034*** [0.01]
Observations	2098	2100	2089	2098	2100	2089
R^2	0.981	0.967	0.987	0.981	0.967	0.987
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				7.56e-08	0.00244	0.0471
Panel B: 2SLS, IV-OFF-OC and IV-AUT-AR-USA						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	0.0059 [0.005]	-0.0071 [0.006]	0.0020 [0.004]	0.014*** [0.004]	-0.014** [0.007]	0.00056 [0.004]
K	-0.0048*** [0.001]	0.0043*** [0.001]	0.0012** [0.0006]	-0.0018 [0.001]	0.0016 [0.001]	0.00086 [0.0006]
OFF	0.15*** [0.03]	-0.13*** [0.03]	-0.012 [0.02]			
OFF_HI				0.12*** [0.02]	-0.11*** [0.03]	-0.013 [0.02]
OFF_LMI				-0.31*** [0.07]	0.22*** [0.08]	0.085 [0.06]
ROBOTS * R 1990	-0.040*** [0.006]	0.021*** [0.006]	0.020*** [0.005]	-0.015*** [0.006]	0.00037 [0.007]	0.015*** [0.006]
Observations	2077	2079	2070	2077	2079	2070
R^2	-0.243	-0.0610	-0.0390	0.0335	0.0242	-0.0131
$H_0: \beta_{OFF_HI} = \beta_{OFF_LMI}$ (p-value)				1.26e-09	0.000168	0.0991
Kleibergen-Paap rk LM	85.59	85.43	86.92	111.7	111.6	112.4
Kleibergen-Paap rk LM (p-value)	2.21e-20	2.40e-20	1.13e-20	4.20e-26	4.39e-26	2.88e-26
Kleibergen-Paap Wald rk F	46.67	46.58	47.32	41.65	41.61	41.90
Stock-Yogo critical value	7.03	7.03	7.03	N/A	N/A	N/A
Lewis-Mertens test statistic	12.94	12.94	12.39	10.06	10.06	9.608
Lewis-Mertens critical value	30.28	29.95	30.75	36.50	36.50	36.61
Wald χ^2	10.22	3.812	5.038	16.30	3.692	15.47
Wald χ^2 (p-value)	0.00602	0.149	0.0805	0.000984	0.297	0.00145
AR χ^2	6.910	3.144	4.629	8.063	2.696	13.87
AR χ^2 (p-value)	0.0316	0.208	0.0988	0.0447	0.441	0.00309
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
ln Y, K: no IV						
IV strategy						
	OFF: IV-OFF-OC			OFF_HI, OFF_LMI: IV-OFF-OC		
	ROBOTS: IV-AUT-AR-USA			ROBOTS: IV-AUT-AR-USA		

Notes: OLS estimations of reduced-form specifications on annual data in columns (1)–(3) and (4)–(6) of Panel A and 2SLS estimations of specifications on annual data in columns (1)–(3) and (4)–(6) of Panel B. The equations in both panels include country-industry and country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

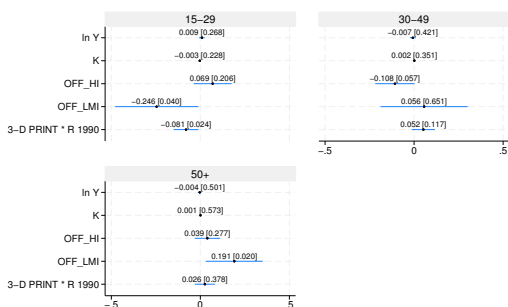
Figure E7: Offshoring, additional automation technologies, and wage bill shares by age, stacked differences and annual data, IV-OFF-OC and IV-AUT-OC



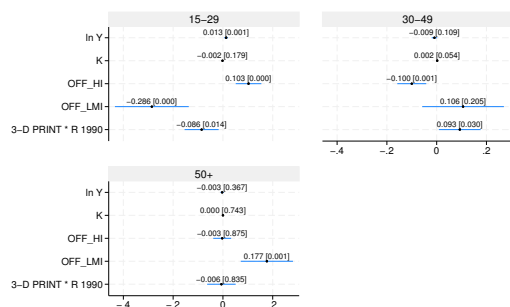
(a) Stacked diff., dedicated machinery



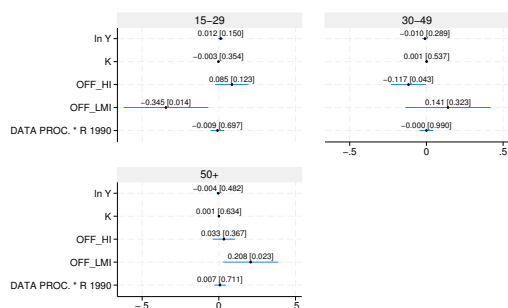
(b) Annual data, dedicated machinery



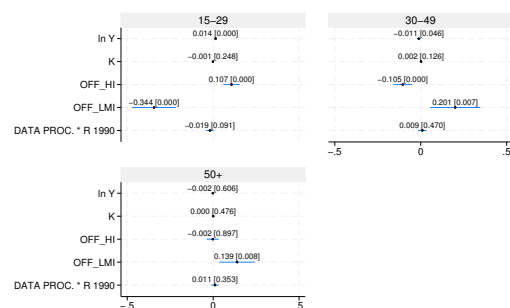
(c) Stacked diff., 3-D printing machines



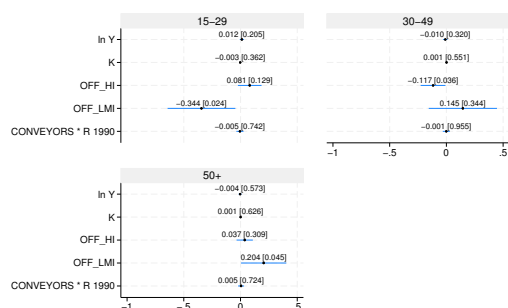
(d) Annual data, 3-D printing machines



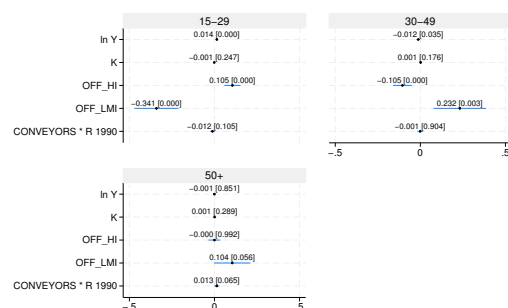
(e) Stacked diff., data processing machines



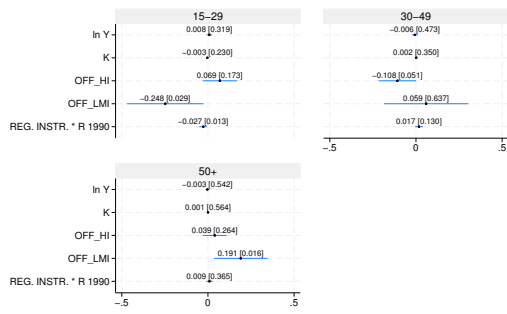
(f) Annual data, data processing machines



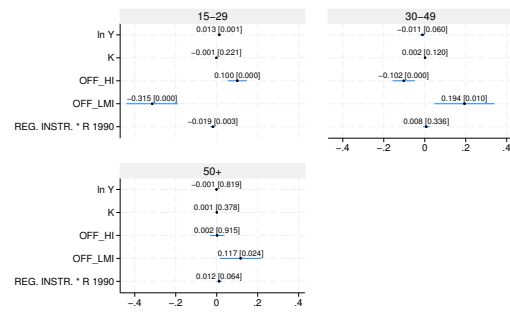
(g) Stacked diff., automatic conveyors



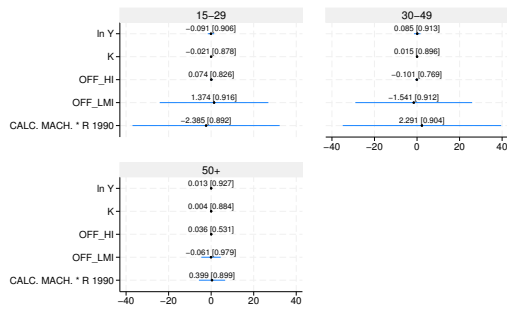
(h) Annual data, automatic conveyors



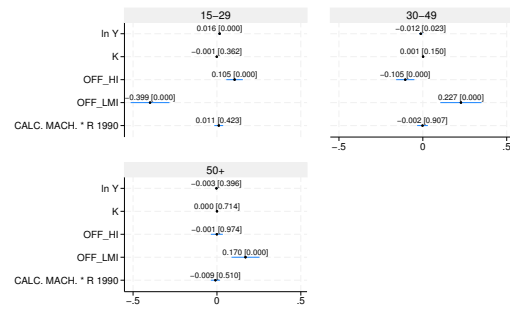
(i) Stacked diff., regulating instruments



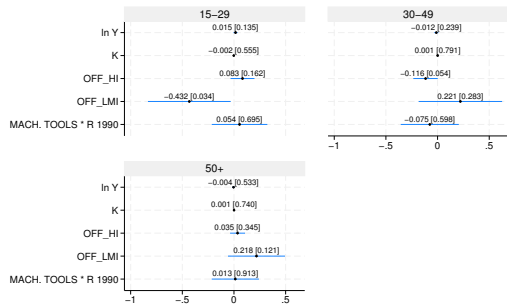
(j) Annual data, regulating instruments



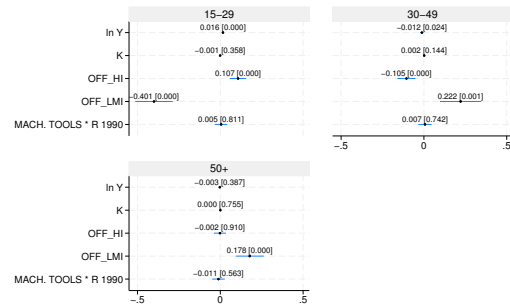
(k) Stacked diff., calculating machines



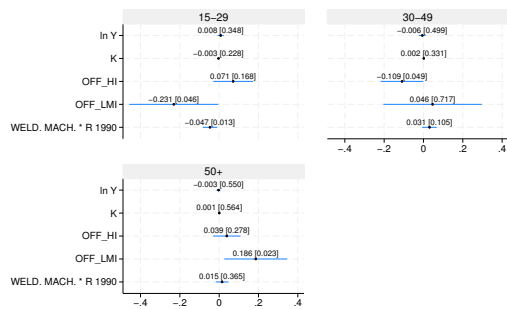
(l) Annual data, calculating machines



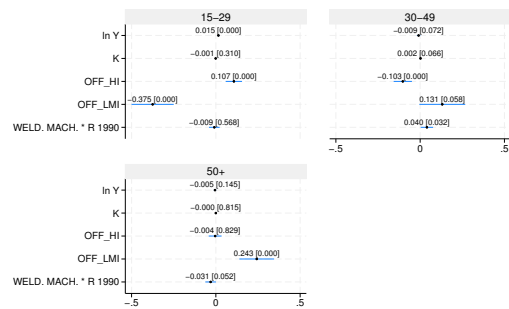
(m) Stacked diff., machine tools



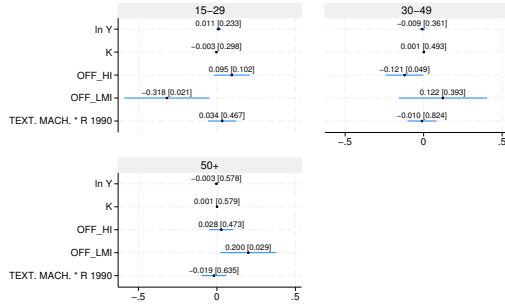
(n) Annual data, machine tools



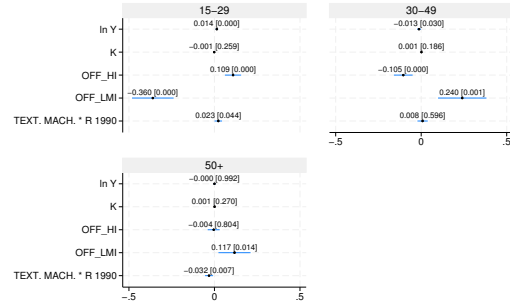
(o) Stacked diff., welding machines



(p) Annual data, welding machines



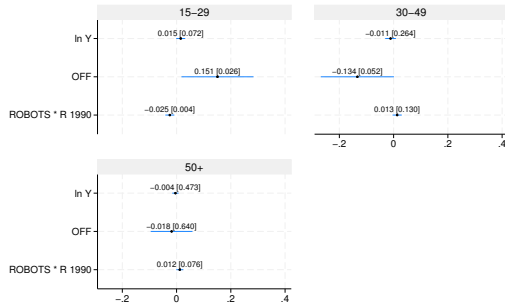
(q) Stacked diff., textile machines



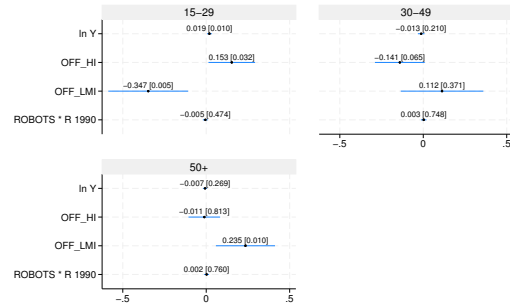
(r) Annual data, textile machines

Notes: 2SLS estimations of specifications in stacked differences and on annual data with robust standard errors in Panels (a), (c), (e), (g), (i), (k), (m), (o), (q) and Panels (b), (d), (f), (h), (j), (l), (n), (p), (r), respectively. The equations in Panels (a), (c), (e), (g), (i), (k), (m), (o), (q) include country-year fixed effects and those in Panels (b), (d), (f), (h), (j), (l), (n), (p), (r) include country-industry and country-year fixed effects. The equations in all panels are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

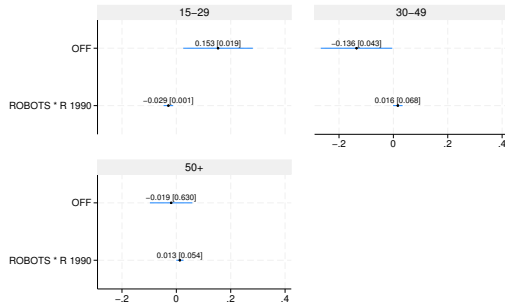
Figure E8: Offshoring, industrial robots, and wage bill shares by age, no industry-level controls, IV-OFF-OC and IV-AUT-OC



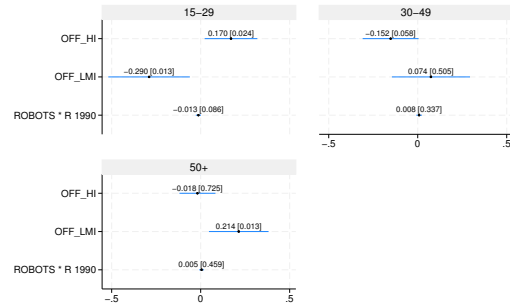
(a) OFF, aggregate capital intensity not controlled for



(b) OFF_HI & OFF_LMI, aggregate capital intensity not controlled for



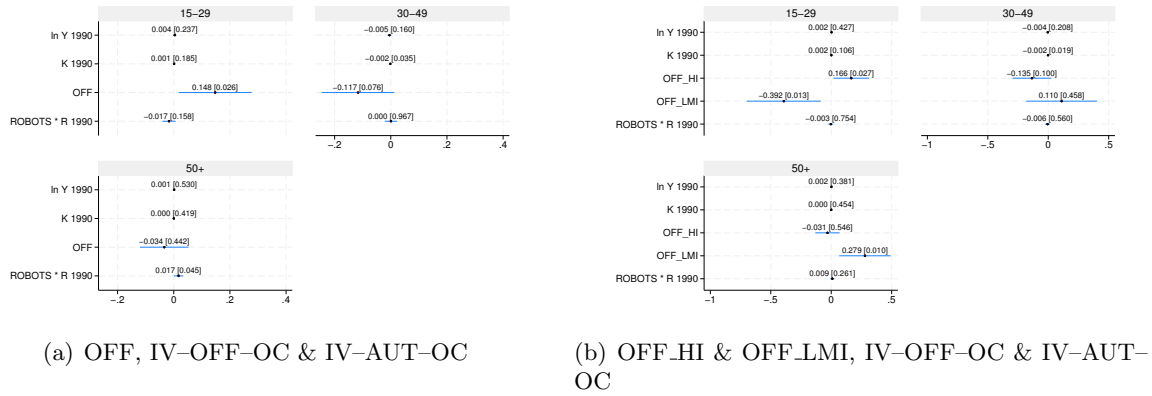
(c) OFF, no industry-level controls



(d) OFF_HI & OFF_LMI, no industry-level controls

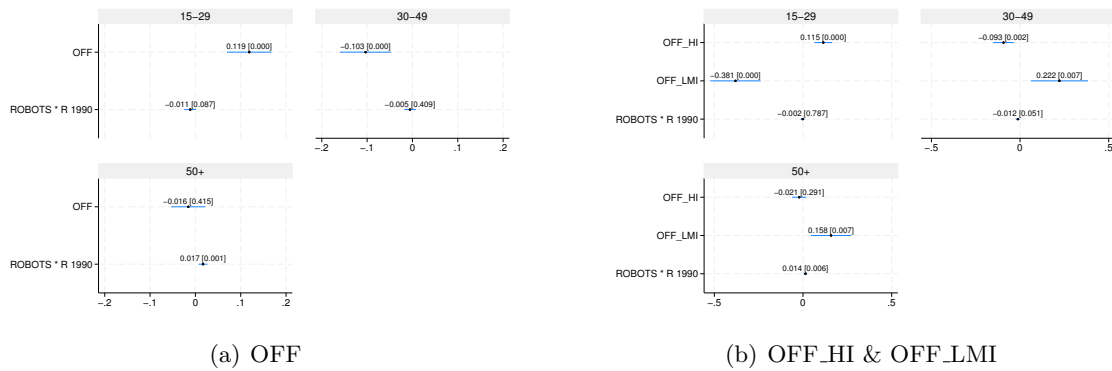
Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Figure E9: Offshoring, industrial robots, and wage bill shares by age, industry-level controls measured in 1990, IV-OFF-OC and IV-AUT-OC



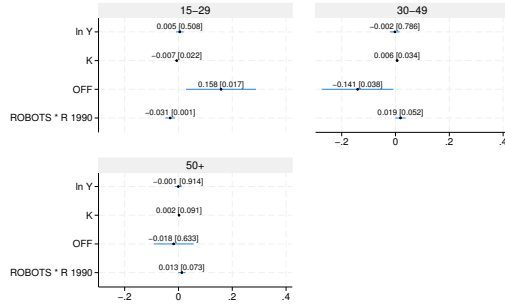
Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Figure E10: Offshoring, industrial robots, and wage bill shares by age, annual data, industry-level controls in 1990 interacted with year dummies, IV-OFF-OC & IV-AUT-OC

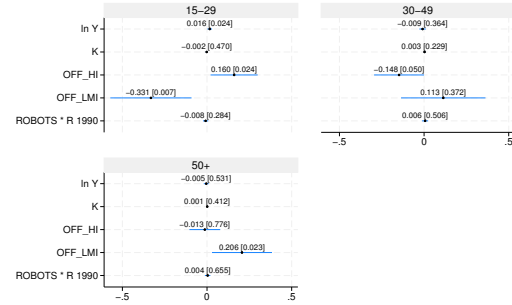


Notes: 2SLS estimations of specifications on annual data with robust standard errors. The equations include country-industry and country-year fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

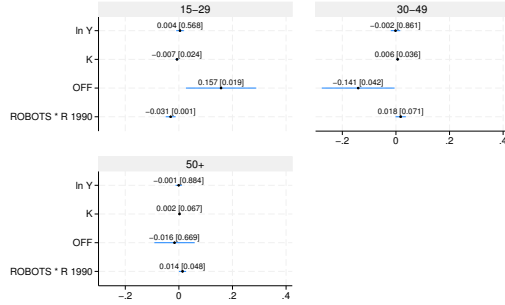
Figure E11: Offshoring, industrial robots, and wage bill shares by age, variants of main specification weights, IV-OFF-OC and IV-AUT-OC



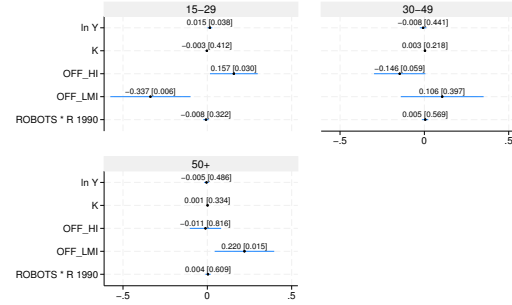
(a) OFF, first variant of the main weights



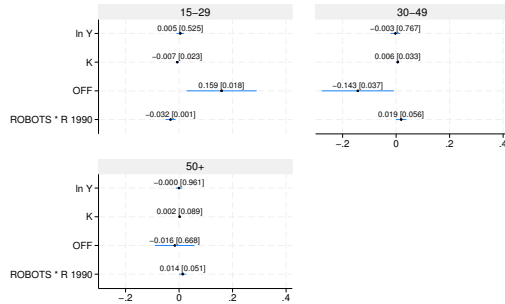
(b) OFF_HI & OFF_LMI, first variant of the main weights



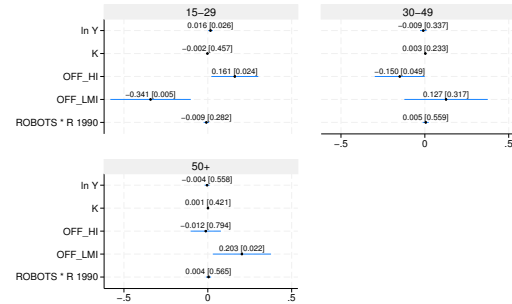
(c) OFF, second variant of the main weights



(d) OFF_HI & OFF_LMI, second variant of the main weights



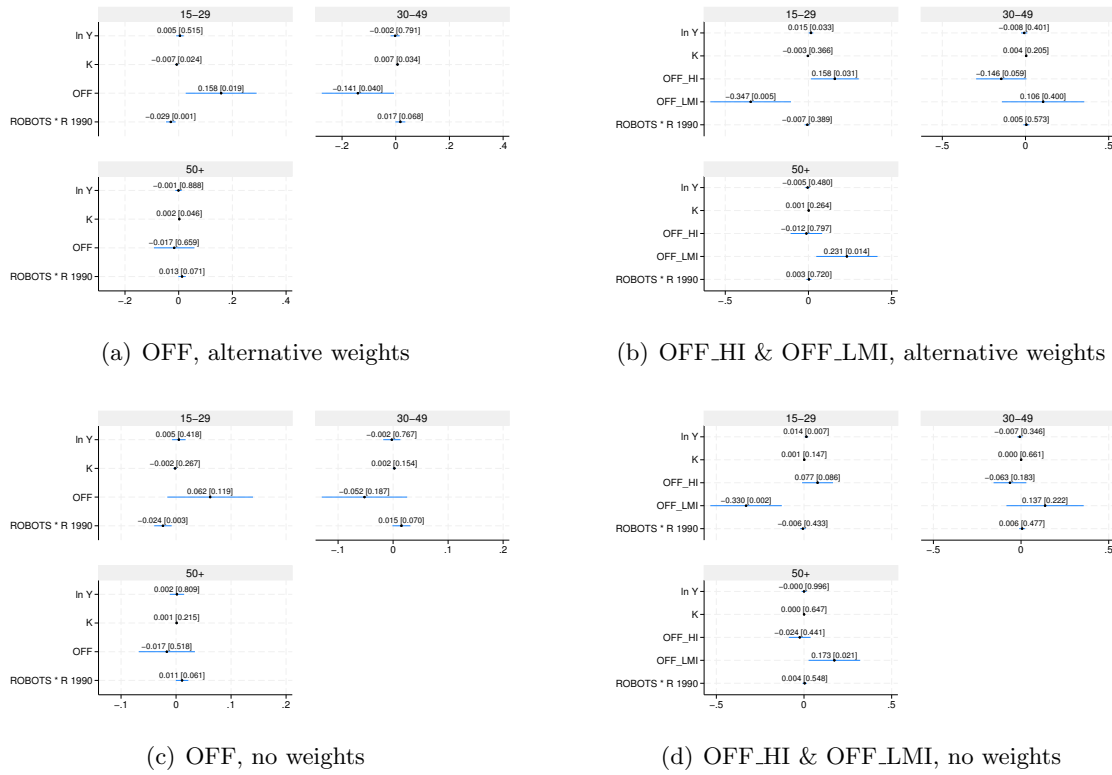
(e) OFF, third variant of the main weights



(f) OFF_HI & OFF_LMI, third variant of the main weights

Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by salaried employees of the manufacturing and market service industries examined in 1996 (Panels (a) and (b)), each industry's share in the total number of persons engaged of the manufacturing and market service industries examined in 1996 (Panels (c) and (d)), or each industry's share in the total number of salaried employees of the manufacturing and market service industries examined in 1996 (Panels (e) and (f)).

Figure E12: Offshoring, industrial robots, and wage bill shares by age, alternative or no specification weights, IV-OFF-OC and IV-AUT-OC



Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by the simple average of each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined across the years examined (Panels (a) and (b)) or are not weighted (Panels (c) and (d)).

Table E7: Offshoring, industrial robots, and wage bill shares by age, pre-trends

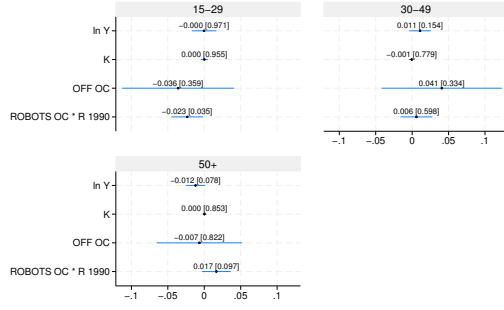
Panel A: Long-differenced wage bill shares, 1982–1989						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	-0.0014 [0.009]	0.011 [0.008]	-0.011 [0.007]	-0.0039 [0.01]	0.014 [0.009]	-0.011 [0.008]
K	0.00014 [0.002]	-0.00076 [0.002]	0.00047 [0.001]	-0.00074 [0.002]	0.00010 [0.002]	0.00048 [0.002]
OFF	-0.050 [0.06]	0.060 [0.07]	-0.013 [0.05]			
OFF_HI				-0.050 [0.07]	0.054 [0.08]	-0.0055 [0.05]
OFF_LMI				0.16 [0.1]	-0.14 [0.2]	-0.019 [0.1]
ROBOTS * R 1990	-0.012* [0.007]	0.0014 [0.007]	0.0097 [0.006]	-0.018** [0.008]	0.0080 [0.008]	0.0097 [0.007]
Observations	205	208	203	205	208	203
R ²	-0.0306	-0.0284	0.0119	-0.0252	-0.00350	0.0113
H ₀ : β _{OFF_HI} = β _{OFF_LMI} (p-value)				0.222	0.258	0.923
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$	-0.0148	0.00185	0.0124	-0.0234	0.0103	0.0124
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$ (s.e.)	[0.00868]	[0.00888]	[0.00781]	[0.00987]	[0.0100]	[0.00919]
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}/\hat{\beta}_{\text{main}}^{\text{AUT}}$ (%)	50.98	11.02	96.6	>> 100	>> 100	>> 100
IV strategy	ln Y, K: no IV OFF: IV–OFF–OC ROBOTS: IV–AUT–OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV–OFF–OC ROBOTS: IV–AUT–OC		

Panel B: Long-differenced wage bill shares, 1989–1995						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	-0.0048 [0.01]	0.00042 [0.01]	0.0047 [0.008]	-0.0041 [0.01]	-0.00023 [0.01]	0.0043 [0.009]
K	-0.0022 [0.002]	-0.00090 [0.002]	0.0036* [0.002]	-0.0021 [0.002]	-0.0012 [0.002]	0.0037* [0.002]
OFF	-0.068 [0.06]	0.0077 [0.08]	0.067 [0.04]			
OFF_HI				-0.091 [0.08]	0.021 [0.10]	0.080 [0.06]
OFF_LMI				-0.14 [0.2]	0.060 [0.2]	0.094 [0.1]
ROBOTS * R 1990	-0.0048 [0.008]	0.011 [0.008]	-0.0062 [0.005]	-0.0034 [0.009]	0.0094 [0.009]	-0.0062 [0.007]
Observations	209	210	206	209	210	206
R ²	-0.00728	0.0230	0.0392	-0.0266	0.0128	0.0422
H ₀ : β _{OFF_HI} = β _{OFF_LMI} (p-value)				0.812	0.859	0.891
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$	-0.00716	0.0164	-0.00923	-0.00517	0.0141	-0.00926
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$ (s.e.)	[0.0120]	[0.0120]	[0.00770]	[0.0136]	[0.0141]	[0.0106]
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}/\hat{\beta}_{\text{main}}^{\text{AUT}}$ (%)	24.61	97.32	–	71.06	>> 100	–
IV strategy	ln Y, K: no IV OFF: IV–OFF–OC ROBOTS: IV–AUT–OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV–OFF–OC ROBOTS: IV–AUT–OC		

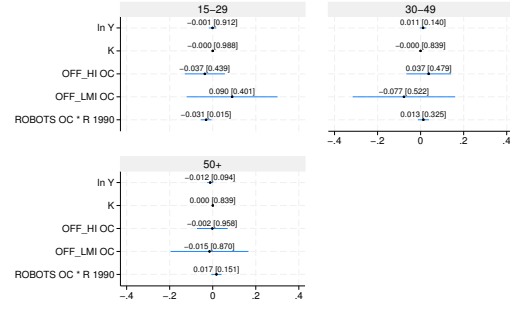
Panel C: Long-differenced wage bill shares, 1982–1995						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Wsh	15-29	30-49	50+	15-29	30-49	50+
ln Y	-0.0055 [0.01]	0.010 [0.01]	-0.0064 [0.01]	-0.0071 [0.01]	0.012 [0.02]	-0.0066 [0.02]
K	-0.0021 [0.003]	-0.0022 [0.004]	0.0041 [0.003]	-0.0028 [0.003]	-0.0015 [0.004]	0.0042 [0.003]
OFF	-0.12 [0.10]	0.067 [0.1]	0.056 [0.08]			
OFF_HI				-0.14 [0.1]	0.075 [0.1]	0.077 [0.09]
OFF_LMI				0.0021 [0.2]	-0.069 [0.3]	0.073 [0.2]
ROBOTS * R 1990	-0.016 [0.01]	0.012 [0.01]	0.0030 [0.009]	-0.021* [0.01]	0.017 [0.01]	0.0032 [0.01]
Observations	205	208	203	205	208	203
R ²	-0.0344	-0.000706	0.0183	-0.0217	0.0109	0.0207
H ₀ : β _{OFF_HI} = β _{OFF_LMI} (p-value)				0.559	0.571	0.986
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$	-0.0111	0.00824	0.00211	-0.0145	0.0115	0.00220
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}$ (s.e.)	[0.00749]	[0.00735]	[0.00613]	[0.00836]	[0.00891]	[0.00805]
$\hat{\beta}_{\text{placebo}}^{\text{AUT,adj}}/\hat{\beta}_{\text{main}}^{\text{AUT}}$ (%)	38.05	49.02	16.38	>> 100	>> 100	68.4
IV strategy	ln Y, K: no IV OFF: IV–OFF–OC ROBOTS: IV–AUT–OC			ln Y, K: no IV OFF_HI, OFF_LMI: IV–OFF–OC ROBOTS: IV–AUT–OC		

Notes: 2SLS estimations of specifications in long differences in all three panels. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. The dependent variable is the wage bill share change between 1982 and 1989 (Panel A), 1989 and 1995 (Panel B), or 1982 and 1995 (Panel C). Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The adjusted placebo estimate ($\hat{\beta}_{AUT,adj}^{placebo}$) in each panel is calculated as the product between the corresponding placebo estimate of $ROBOTS * R1990$ and the ratio of the number of year-to-year wage bill share changes in 1996–2005 (9) to the number of year-to-year changes in 1982–1989 (7), 1989–1995 (6), and 1982–1995 (13). The standard error of each adjusted placebo estimate is adjusted in the same manner. $\hat{\beta}_{AUT,adj}^{placebo} / \hat{\beta}_{AUT}^{main}$ (%) is the percentage share of the adjusted placebo estimate in the main estimate reported in Table 3. The symbol ">> 100" indicates that the calculated share is much greater than 100% and thus not disclosed. The symbol "–" indicates that share is negative due to opposite signs of the adjusted placebo and main estimates.

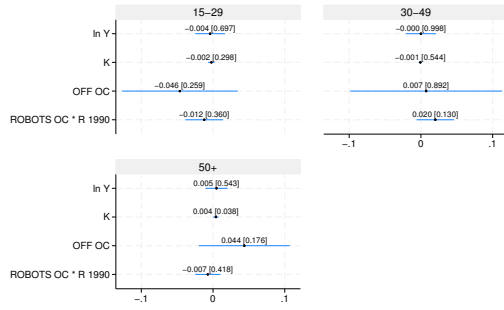
Figure E13: Offshoring, industrial robots, and wage bill shares by age, pre-trends, reduced-form, IV-OFF-OC and IV-AUT-OC



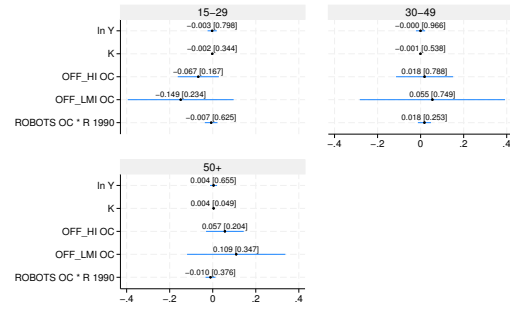
(a) OFF, 1982-1989



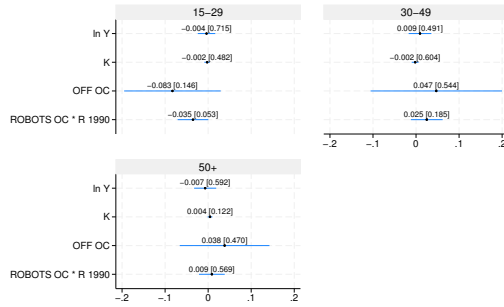
(b) OFF_HI & OFF_LMI, 1982-1989



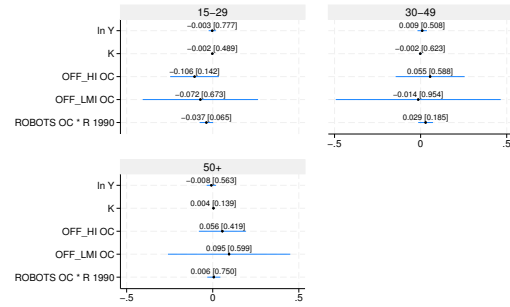
(c) OFF, 1989-1995



(d) OFF_HI & OFF_LMI, 1989-1995



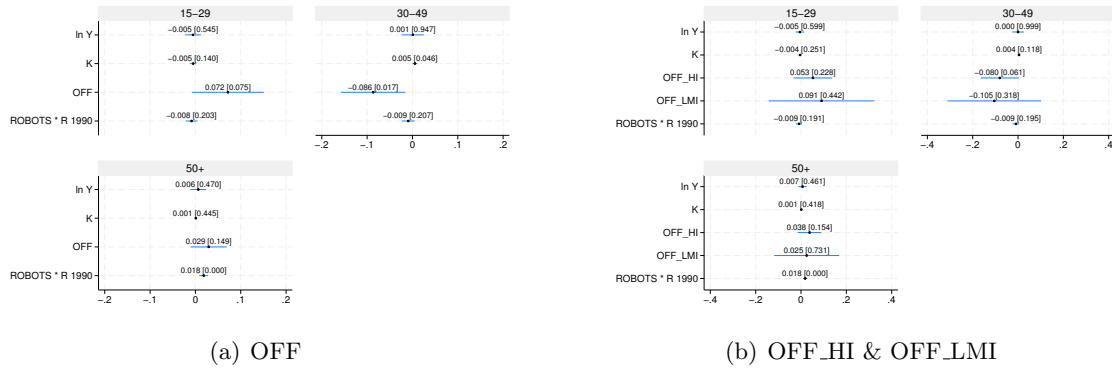
(e) OFF, 1982-1995



(f) OFF_HI & OFF_LMI, 1982-1995

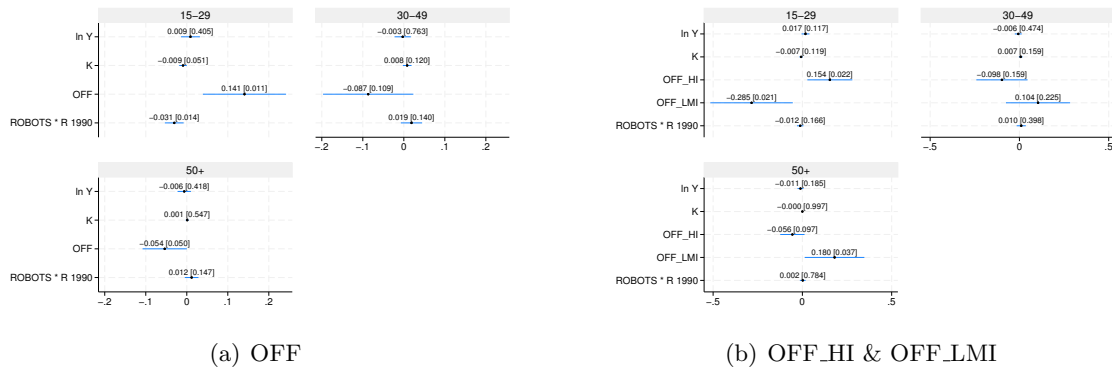
Notes: OLS estimations of reduced-form specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. The dependent variable is the wage bill share change between 1982 and 1989 (Panels (a) and (b)), 1989 and 1995 (Panels (c) and (d)), or 1982 and 1995 (Panels (e) and (f)).

Figure E14: Offshoring, industrial robots, and wage bill shares by age, industry fixed effects controlled for



Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and industry fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996.

Figure E15: Offshoring, industrial robots, and wage bill shares by age, IV-OFF-OC and IV-AUT-OC, mean reversion



Notes: 2SLS estimations of specifications in long differences with robust standard errors. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 1996. The coefficient estimates of the wage bill shares of the middle-aged and older workers in the initial sample year (1996) are not disclosed for the sake of exposition.

F Quantification of the effects of offshoring and robot adoption

To quantify the effects of the offshoring intensity and robot adoption variables, as these are shown in columns (4)–(6) of Panel B of Table 3 and columns (4)–(6) of Panels A and B of Table 4, I take the following steps. First, I calculate the sample mean percentage point changes of the three key regressors and the wage bill shares of the three age groups of workers between 1996 and 2005 according to the methodology described in Appendix B.1. Then, I multiply the percentage point changes of the sample means by the corresponding coefficient estimates to obtain the magnitudes of the individuals effects of the three key regressors on the wage bill shares of the three age groups of workers. Subsequently, I sum over the individual effects of the two offshoring intensity variables and the individual effects of all three key regressors to obtain the magnitudes of the joint effects of offshoring to high- and lower-income countries and the magnitudes of the joint effects of offshoring and robot adoption, respectively. For each individual and joint effect, I do the relevant F-test to obtain its statistical significance. Finally, I calculate the ratios of the magnitudes of the individual and joint effects to the sample mean percentage point changes of the wage bill shares of the three age groups and multiply them by 100 to obtain the percentage contributions of the individual and joint effects to wage bill share changes.

Results of the quantification exercises are shown in Tables F1, F2, and F3. Offshoring to high-income countries caused a statistically significant increase in the wage bill share of young workers, that is, it shifted their wage bill share in the opposite direction to that of the actual change. The magnitude of this increase is 2% (significant at 5%) or 1.3% (significant at 5%) of the percentage point decline in the wage bill share of this age group over the period examined. By contrast, offshoring to lower-income countries and robot adoption induced shifts in the wage bill share of young workers in the same direction as the actual one. The former key regressor accounts for 6.8% (significant 1%), 6.6% (significant 1%), or 3.3% (significant 10%) of the percentage point decline in the wage bill share of this age group and robot adoption for 32.6% (significant at 10%), 19.8% (significant at 10%), or 17.8% (insignificant). The joint effect of the two offshoring intensity measures accounts for 4.8% (significant at 10%), 4.6% (significant at 5%), or 2% (statistically insignificant) of the percentage point decline in the wage bill share of the young, while the joint effect of all three key regressors accounts for

34.5% (significant at 5%), 24.5% (significant at 5%), or 22.7% (statistically insignificant).

Except for a statistically significant decline in the wage bill share of middle-aged workers induced by offshoring to high-income countries that runs counter to the direction of the actual change of this outcome variable, the individual contributions of the other two key regressors and all joint contributions induced shifts in the same direction as the actual one but are statistically insignificant. It is also worth noting that the individual and joint contributions of the three key regressors almost always induce wage bill share shifts that are much larger than the actual ones, implying that there were other factors, such as demographic ageing, that exerted effects in the opposite direction.

As for the individual and joint contributions to the observed wage bill share change of older workers, once again, offshoring to high-income countries induced a shift in the opposite direction (decline) to the actual one (increase) or in the same direction, but the effect is statistically insignificant. Instead, offshoring to lower-income countries caused a statistically significant increase in the wage bill share of older workers, accounting for 4.7% (significant at 5%), 3.3% (significant at 5%), or 2.7% (significant at 5%) of the percentage point change of this outcome variable. The individual contribution of robot adoption to the percentage point increase of the same outcome variable is 27% (significant at 5%), 16.8% (insignificant), or 7.9% (insignificant). Jointly, offshoring to high- and lower-income countries account for 4.6% (significant at 5%), 3% (significant at 5%), or 2.8% (significant at 5%) of the decline in the wage bill share of older workers, while all three key regressors account for 30% (significant at 1%), 19.6% (statistically insignificant), or 12.5% (statistically insignificant).

Although I have argued and provided much evidence in favour of the split into offshoring to high- and lower-income countries, for the scope of the quantification exercise, it is also useful to quantify the individual and joint contributions of aggregate offshoring intensity and robot adoption using the estimates in columns (1)–(3) of Panel B of Table 3. Besides, these estimates have been produced while the Stock-Yogo test, unlike the Lewis-Mertens test, points to strong instruments, and are less sensitive, if at all, to some critical robustness checks, such as the elimination of industries with relatively high Rotemberg weights (e.g., electronics, transport equipment). Also, similarly to the estimates produced when offshoring is split into its two components, the estimates are exposure-robust. Implementing the methodology described above, I obtain the results shown in Table F4.

Aggregate offshoring intensity caused an increase in the wage bill share of young workers

(significant at 5%), a decline in the wage bill share of the middle-aged (significant at 5%), while the decline in the wage bill share of older workers is insignificant. These contributions account for 6.5%, more than 100%, and 0.74% of the respective actual changes, but are in opposite directions to the actual ones. The pattern of the quantified effects of aggregate offshoring intensity resembles closely the pattern of the quantified effects of the intensity of offshoring to high-income countries detected in Table F1. Robot adoption caused a decline in the wage bill share of the young and increases in the wage bill shares of the middle-aged and older workers, accounting for 71.5% (significant at 1%), more than 100% (significant at 10%), and 32% (significant at 10%) of the respective actual changes. Similarly, the joint effect of aggregate offshoring intensity and robot adoption caused a decline in the wage bill share of the young and increases in the wage bill shares of the middle-aged and older workers, accounting for 65% (significant at 1%), more than 100% (significant at 10%), and 31% (significant at 10%) of the respective actual changes. The individual contributions of robot adoption and its joint contributions with aggregate offshoring intensity accord with the directions of the actual changes of the three outcome variables. However, relative to the respective quantified effects in Table F1, the effects are not only larger, but also statistically significant.

In sum, the quantification analysis reveals that offshoring to high-income countries and aggregate offshoring exerted sizeable effects, but in opposite directions to those of the actual changes of the wage bill shares of the three age groups. Instead, the effects of offshoring to lower-income countries and robot adoption were sizeable and in the same directions as those of the actual changes. Jointly, offshoring to high- and lower-income countries exerted mostly significant and sizeable effects on the wage bill share of the young and older workers. Albeit sizeable, the significance of the joint effects of offshoring and robot adoption depends on which key regressors are treated as endogenous or which offshoring variable(s) are used as key regressors. In particular, although the joint effects are statistically insignificant when all three key regressors are instrumented (Table F1), the joint effects on the wage bill shares of the young and older workers are statistically and economically significant when I instrument only the offshoring intensities (Table F2) or when I use the aggregate offshoring intensity, rather than its two components, as a key regressor (Table F4).

Finally, it is important to note that the quantified effects of offshoring intensities should be viewed as lower bounds, while the quantified effects of robot adoption as upper bounds. This is because, as revealed in the robustness exercise on pre-trends, the majority of the placebo

estimates of the offshoring intensities are insignificant and have opposite signs to the main ones, while the majority of the placebo estimates of robot adoption, albeit insignificant, have the same signs. In this light, I abstract from making comparisons between the quantitative importance of the offshoring effects and the quantitative importance of the robot adoption effects.

To be able to understand the extent to which the effects on wage bill shares operated through hours worked adjustments, I also implement the methodology described above to quantify the effects on the shares of hours worked by the three age groups of workers, as these have been identified in columns (4)–(6) of Panel B of Table 5. Results of this quantification exercise are shown in Table F5 and discussed in Section 4.3.

Table F1: Quantification of the individual and joint effects of offshoring and industrial robots on wage bill shares by age, based on the estimates in columns (4)–(6) of Panel B of Table 3

	(1) Wsh ^{15–29}	(2) Wsh ^{30–49}	(3) Wsh ⁵⁰⁺
Coefficient estimate of OFF_HI	0.16**	-0.14*	-0.012
Coefficient estimate of OFF_LMI	-0.33***	0.091	0.23**
Coefficient estimate of ROBOTS * R 1990	-0.007	0.005	0.003
Sample mean percentage point change of the OFF_HI (1996–2005)	0.005	0.005	0.005
Sample mean percentage point change of the OFF_LMI (1996–2005)	0.008	0.008	0.008
Sample mean percentage point change of the ROBOTS (1996–2005)	1.709	1.709	1.709
Sample mean of R 1990	0.560	0.560	0.560
Sample mean percentage point change of the Wsh ^{15–29} (1996–2005)	-0.039	–	–
Sample mean percentage point change of the Wsh ^{30–49} (1996–2005)	–	0.0001	–
Sample mean percentage point change of the Wsh ⁵⁰⁺ (1996–2005)	–	–	0.039
Magnitude of OFF_HI effect (row (1) * row (4))	0.0008	-0.0007	-0.0001
F-test H_0 : row (1) * row (4) = 0 (p-value)	[0.031]	[0.061]	[0.808]
Contribution of OFF_HI effect (%)	-2	>> 100	-0.15
Magnitude of OFF_LMI effect (row (2) * row (5))	-0.0026	0.0007	0.0018
F-test H_0 : row (2) * row (5) = 0 (p-value)	[0.007]	[0.468]	[0.014]
Contribution of OFF_LMI effect (%)	6.8	>> 100	4.7
Magnitude of ROBOTS * R 1990 effect (row (3) * row (6) * row (7))	-0.0070	0.0051	0.0031
F-test H_0 : row (3) * row (6) * row (7) = 0 (p-value)	[0.352]	[0.552]	[0.690]
Contribution of ROBOTS * R 1990 effect (%)	17.89	>> 100	7.93
Magnitude of joint OFF_HI and OFF_LMI effect	-0.0019	0.0000	0.0018
F-test H_0 : joint OFF_HI and OFF_LMI effect = 0 (p-value)	[0.075]	[0.994]	[0.017]
Joint contribution of OFF_HI and OFF_LMI effects (%)	4.79	7.42	4.55
Magnitude of joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect	-0.0088	0.0051	0.0048
F-test H_0 : joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect = 0 (p-value)	[0.207]	[0.524]	[0.504]
Joint contribution of OFF_HI, OFF_LMI and ROBOTS * R 1990 effect (%)	22.68	>> 100	12.48

Notes: For the description of the methodology for the quantification of the individual and joint effects of offshoring intensities and robot adoption, see Appendix F. The symbol ">> 100" indicates that the (absolute) percentage contribution is much greater than 100% and thus not disclosed.

Table F2: Quantification of the individual and joint effects of offshoring and industrial robots on wage bill shares by age, based on the estimates in columns (4)–(6) of Panel A of Table 4

	(1) Wsh ^{15–29}	(2) Wsh ^{30–49}	(3) Wsh ⁵⁰⁺
Coefficient estimate of OFF_HI	0.157**	-0.137*	-0.020
Coefficient estimate of OFF_LMI	-0.324***	0.157	0.160**
Coefficient estimate of ROBOTS * R 1990	-0.008*	-0.002	0.011**
Sample mean percentage point change of the OFF_HI (1996–2005)	0.005	0.005	0.005
Sample mean percentage point change of the OFF_LMI (1996–2005)	0.008	0.008	0.008
Sample mean percentage point change of the ROBOTS (1996–2005)	1.709	1.709	1.709
Sample mean of R 1990	0.560	0.560	0.560
Sample mean percentage point change of the Wsh ^{15–29} (1996–2005)	-0.039	–	–
Sample mean percentage point change of the Wsh ^{30–49} (1996–2005)	–	0.0001	–
Sample mean percentage point change of the Wsh ⁵⁰⁺ (1996–2005)	–	–	0.039
Magnitude of OFF_HI effect (row (1) * row (4))	0.0008	-0.0007	-0.0001
F-test H_0 : row (1) * row (4) = 0 (p-value)	[0.027]	[0.071]	[0.663]
Contribution of OFF_HI effect (%)	-2.02	>> 100	-0.26
Magnitude of OFF_LMI effect (row (2) * row (5))	-0.0026	0.0013	0.0013
F-test H_0 : row (2) * row (5) = 0 (p-value)	[0.003]	[0.182]	[0.025]
Contribution of OFF_LMI effect (%)	6.66	>> 100	3.3
Magnitude of ROBOTS * R 1990 effect (row (3) * row (6) * row (7))	-0.0077	-0.0020	0.0105
F-test H_0 : row (3) * row (6) * row (7) = 0 (p-value)	[0.090]	[0.670]	[0.011]
Contribution of ROBOTS * R 1990 effect (%)	19.81	>> 100	27.07
Magnitude of joint OFF_HI and OFF_LMI effect	-0.0018	0.0006	0.0012
F-test H_0 : joint OFF_HI and OFF_LMI effect = 0 (p-value)	[0.047]	[0.542]	[0.029]
Joint contribution of OFF_HI and OFF_LMI effects (%)	4.64	>> 100	3.04
Magnitude of joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect	-0.0095	-0.0015	0.0117
F-test H_0 : joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect = 0 (p-value)	[0.031]	[0.744]	[0.003]
Joint contribution of OFF_HI, OFF_LMI and ROBOTS * R 1990 effect (%)	24.45	>> 100	30.11

Notes: For the description of the methodology for the quantification of the individual and joint effects of offshoring intensities and robot adoption, see Appendix F. The symbol ">> 100" indicates that the (absolute) percentage contribution is much greater than 100% and thus not disclosed.

Table F3: Quantification of the individual and joint effects of offshoring and industrial robots on wage bill shares by age, based on the estimates in columns (4)–(6) of Panel B of Table 4

	(1) Wsh ^{15–29}	(2) Wsh ^{30–49}	(3) Wsh ⁵⁰⁺
Coefficient estimate of OFF_HI	0.103**	-0.099**	0.007
Coefficient estimate of OFF_LMI	-0.161**	0.035	0.130**
Coefficient estimate of ROBOTS * R 1990	-0.013**	0.007	0.007
Sample mean percentage point change of the OFF_HI (1996–2005)	0.005	0.005	0.005
Sample mean percentage point change of the OFF_LMI (1996–2005)	0.008	0.008	0.008
Sample mean percentage point change of the ROBOTS (1996–2005)	1.709	1.709	1.709
Sample mean of R 1990	0.560	0.560	0.560
Sample mean percentage point change of the Wsh ^{15–29} (1996–2005)	-0.039	–	–
Sample mean percentage point change of the Wsh ^{30–49} (1996–2005)	–	0.0001	–
Sample mean percentage point change of the Wsh ⁵⁰⁺ (1996–2005)	–	–	0.039
Magnitude of OFF_HI effect (row (1) * row (4))	0.0005	-0.0005	0.0000
F-test H_0 : row (1) * row (4) = 0 (p-value)	[0.011]	[0.010]	[0.682]
Contribution of OFF_HI effect (%)	-1.32	>> 100	0.09
Magnitude of OFF_LMI effect (row (2) * row (5))	-0.0013	0.0003	0.0010
F-test H_0 : row (2) * row (5) = 0 (p-value)	[0.057]	[0.675]	[0.032]
Contribution of OFF_LMI effect (%)	3.3	>> 100	2.69
Magnitude of ROBOTS * R 1990 effect (row (3) * row (6) * row (7))	-0.0127	0.0067	0.0065
F-test H_0 : row (3) * row (6) * row (7) = 0 (p-value)	[0.066]	[0.385]	[0.304]
Contribution of ROBOTS * R 1990 effect (%)	32.55	>> 100	16.78
Magnitude of joint OFF_HI and OFF_LMI effect	-0.0008	-0.0002	0.0011
F-test H_0 : joint OFF_HI and OFF_LMI effect = 0 (p-value)	[0.279]	[0.751]	[0.025]
Joint contribution of OFF_HI and OFF_LMI effects (%)	1.98	>> 100	2.77
Magnitude of joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect	-0.0135	0.0065	0.0076
F-test H_0 : joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect = 0 (p-value)	[0.044]	[0.385]	[0.222]
Joint contribution of OFF_HI, OFF_LMI and ROBOTS * R 1990 effect (%)	34.54	>> 100	19.55

Notes: For the description of the methodology for the quantification of the individual and joint effects of offshoring intensities and robot adoption, see Appendix F. The symbol ">> 100" indicates that the (absolute) percentage contribution is much greater than 100% and thus not disclosed.

Table F4: Quantification of the individual and joint effects of offshoring and industrial robots on wage bill shares by age, based on the estimates in columns (1)–(3) of Panel B of Table 3

	(1) Wsh ^{15–29}	(2) Wsh ^{30–49}	(3) Wsh ⁵⁰⁺
Coefficient estimate of OFF	0.16**	-0.14**	-0.018
Coefficient estimate of ROBOTS * R 1990	-0.029***	0.017*	0.013*
Sample mean percentage point change of the OFF (1996–2005)	0.016	0.016	0.016
Sample mean percentage point change of the ROBOTS (1996–2005)	1.709	1.709	1.709
Sample mean R 1990	0.560	0.560	0.560
Sample mean percentage point change of the Wsh ^{15–29} (1996–2005)	-0.039	–	–
Sample mean percentage point change of the Wsh ^{30–49} (1996–2005)	–	0.0001	–
Sample mean percentage point change of the Wsh ⁵⁰⁺ (1996–2005)	–	–	0.039
Magnitude of OFF effect (row (1) * row (3))	0.0025	-0.0022	-0.0003
F-test H_0 : row (1) * row (3) = 0 (p-value)	[0.019]	[0.043]	[0.643]
Contribution of OFF effect (%)	-6.46	>> 100	-0.74
Magnitude of ROBOTS * R 1990 effect (row (2) * row (4) * row (5))	-0.0279	0.0161	0.0123
F-test H_0 : row (2) * row (4) * row (5) = 0 (p-value)	[0.001]	[0.073]	[0.065]
Contribution of ROBOTS * R 1990 effect (%)	71.52	>> 100	31.73
Magnitude of joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect	-0.0253	0.0139	0.0120
F-test H_0 : joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect = 0 (p-value)	[0.002]	[0.099]	[0.060]
Joint contribution of OFF_HI, OFF_LMI and ROBOTS * R 1990 effect (%)	65.06	>> 100	30.99

Notes: For the description of the methodology for the quantification of the individual and joint effects of offshoring intensities and robot adoption, see Appendix F. The symbol “>> 100” indicates that the (absolute) percentage contribution is much greater than 100% and thus not disclosed.

Table F5: Quantification of the individual and joint effects of offshoring and industrial robots on hours worked shares by age, based on the estimates in columns (4)–(6) of Panel B of Table 5

	(1) Hsh ^{15–29}	(2) Hsh ^{30–49}	(3) Hsh ⁵⁰⁺
Coefficient estimate of OFF_HI	0.157	-0.148*	-0.010
Coefficient estimate of OFF_LMI	-0.457***	0.208	0.236**
Coefficient estimate of ROBOTS * R 1990	-0.014	0.011	0.005
Sample mean percentage point change of the OFF_HI (1996–2005)	0.005	0.005	0.005
Sample mean percentage point change of the OFF_LMI (1996–2005)	0.008	0.008	0.008
Sample mean percentage point change of the ROBOTS (1996–2005)	1.709	1.709	1.709
Sample mean of R 1990	0.560	0.560	0.560
Sample mean percentage point change of the Hsh ^{15–29} (1996–2005)	-0.039	–	–
Sample mean percentage point change of the Hsh ^{30–49} (1996–2005)	–	0.0004	–
Sample mean percentage point change of the Hsh ⁵⁰⁺ (1996–2005)	–	–	0.039
Magnitude of OFF_HI effect (row (1) * row (4))	0.0008	-0.0007	-0.0000
F-test H_0 : row (1) * row (4) = 0 (p-value)	[0.105]	[0.090]	[0.861]
Contribution of OFF_HI effect (%)	-2.01	>> 100	-0.13
Magnitude of OFF_LMI effect (row (2) * row (5))	-0.0037	0.0017	0.0019
F-test H_0 : row (2) * row (5) = 0 (p-value)	[0.006]	[0.147]	[0.026]
Contribution of OFF_LMI effect (%)	9.35	>> 100	4.89
Magnitude of ROBOTS * R 1990 effect (row (3) * row (6) * row (7))	-0.0136	0.0104	0.0045
F-test H_0 : row (3) * row (6) * row (7) = 0 (p-value)	[0.175]	[0.280]	[0.559]
Contribution of ROBOTS * R 1990 effect (%)	34.65	>> 100	11.74
Magnitude of joint OFF_HI and OFF_LMI effect	-0.0029	0.0009	0.0018
F-test H_0 : joint OFF_HI and OFF_LMI effect = 0 (p-value)	[0.056]	[0.452]	[0.031]
Joint contribution of OFF_HI and OFF_LMI effects (%)	7.34	>> 100	4.76
Magnitude of joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect	-0.0164	0.0113	0.0064
F-test H_0 : joint OFF_HI, OFF_LMI and ROBOTS * R 1990 effect = 0 (p-value)	[0.076]	[0.205]	[0.381]
Joint contribution of OFF_HI, OFF_LMI and ROBOTS * R 1990 effect (%)	41.99	>> 100	16.5

Notes: For the description of the methodology for the quantification of the individual and joint effects of offshoring intensities and robot adoption, see Appendix F. The symbol ">> 100" indicates that the (absolute) percentage contribution is much greater than 100% and thus not disclosed.

G Supplementary analysis for the 2000s and 2010s

As stressed in Section 2.1, later releases of the EU KLEMS database than the one used in the main analysis provide no labour information for most of the industries of the benchmark sample. On top of that, labour information is unavailable in all years for two of the eleven countries of the benchmark sample (Australia and USA) and available only as of 2008 for other two countries (Denmark and Japan). These limitations notwithstanding, conducting an analysis similar to the main one for more recent years could be particularly useful in its own right and in relation to the main analysis.

To this end, I optimally combine information from the 2025 release of the EU KLEMS with the 2016 release of the WIOD and the UN Comtrade database to create a sample comprising the total manufacturing sector and five market service industries in seven of the eleven advanced countries of the main sample for 2000–2014 or 2000–2019. The seven countries, listed in Panel A of Table G1, are Austria, Finland, Germany, Italy, the Netherlands, Spain, and the United Kingdom (i.e., all those of the main sample except for Australia, Denmark, Japan, and the USA). The sectors and industries, listed in Panel B of the same table, are classified according to NACE Rev. 2.^{G1} The analysis on the effects of offshoring is conducted in 2000–2014 because this is the period for which information on imports of intermediates is available in the WIOD. The analysis on the effects of robot adoption is conducted in both 2000–2014 and 2000–2019, as information on imports of robots is available for all these years.^{G2}

To get an idea of how the outcome and key explanatory variables evolved over the more recent periods, I conduct a similar descriptive statistics analysis to that in Section 2.2. The aggregate offshoring intensity and the intensity of offshoring to high-income countries increased further over 2000–2014, although the largest increases occurred in the five years before the global financial crisis of 2008–2009 and two years after it (Panels (a) and (b) of Figure G1). The average growth rates of the two variables were lower than those observed in 1996–2005

^{G1}Unlike the previous releases of the EU KLEMS and WIOD that I use in the main analysis, the releases used in the supplementary analysis rely on the NACE Rev. 2 classification of industries. In relation to the main sample, all market service industries are available in the supplementary sample except for “Other business activities”, but the wholesale and retail industries are aggregated (NACE Rev. 2: G). Also, as stressed earlier, the supplementary sample comprises aggregate manufacturing (NACE Rev. 2: C), but none of the individual industries of that sector.

^{G2}The latter analysis could be conducted until 2021 thanks to available information for the years 2020 and 2021 in the UN Comtrade and 2025 release of the EU KLEMS databases, but I exclude the two additional years to avoid introducing a bias in the estimates due to the COVID-19 pandemic outbreak. Still, in results that are available upon request, I show that the effects of robot adoption identified for the longest sample period are similar to those identified for the two shorter periods.

Table G1: Countries and industries, 2000–2019

Panel A: Countries		
Country	ISO code	Country Name
	AUT	Austria
	DEU	Germany
	ESP	Spain
	FIN	Finland
	GBR	United Kingdom
	ITA	Italy
	NLD	Netherlands
Panel B: Industries		
NACE Rev. 2		Industry Name
	C	Total manufacturing
	G	Wholesale and retail trade
	H	Transport and storage
	J	Information and communication
	K	Financial intermediation
	L	Real estate

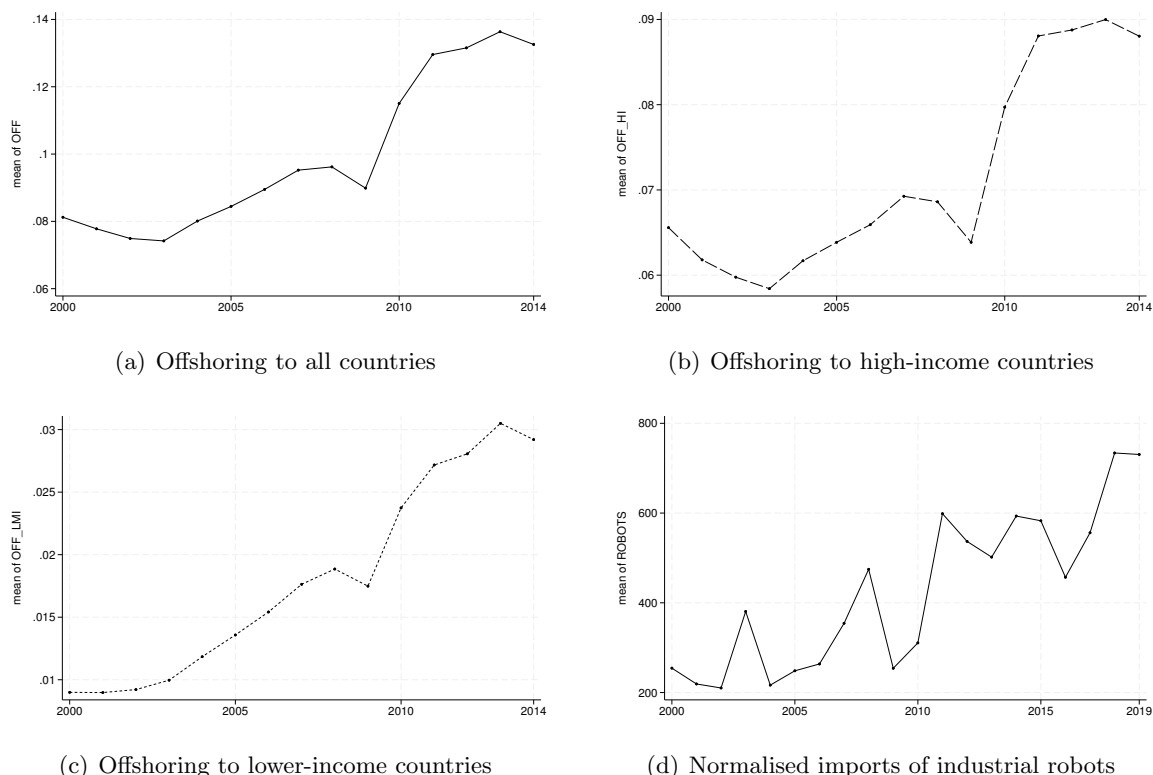
Source: Release 2025 of the EU KLEMS, release 2016 of the WIOD, and UN Comtrade.

(42.5% and 24%, respectively, according to the bottom of Panel B of Table G4). The intensity of offshoring to lower-income countries grew more rapidly and thus continued to catch-up in terms of levels relative to offshoring to high-income countries (Panel (c) of Figure G1), although its average growth rate was also lower than that observed in the main analysis (207.2% according to the bottom of Panel B of Table G4). Similar patterns and trends largely hold by country (Panels A and B of Table G4) and by industry (Panels A and B of of Table G5). Imports of robots by the countries examined also rose over the period examined (Panel (d) of Figure G1), but in contrast to the offshoring intensities, they did so at an even faster rate than the period 1996–2005 (191.2%).^{G3}

As for the wage bill shares of the three age groups, that of the young continued to decline, that of the older workers continued to increase, and in contrast to the 1996–2005 period, that of the middle-aged trended downwards overall (Figure G2). The average decline of the wage bill share of the middle-aged was 9.6%, while the average decline of the wage bill share of

^{G3}The Netherlands experienced the fastest average growth rate in this regard (778%), followed by Germany (247%) and Italy (140%), which also happen to be among the top global producers of robots, as mentioned earlier (Panel (a) of Figure G4). Also, similarly to the main analysis, I provide suggestive evidence on the relevance of the selected instruments for the offshoring and robot adoption measures by showing that the patterns and trends of the offshoring intensity and robot adoption measures for the group of the other five high-income countries (Belgium, France, Ireland, Luxembourg, Sweden) bear a close resemblance to those of the main variables (Panels (a)–(d) of Figure G5, Panel (b) of Figure G4, and Tables G6 and G7).

Figure G1: Offshoring intensities and imports of industrial robots, 2000–2014 or 2000–2019

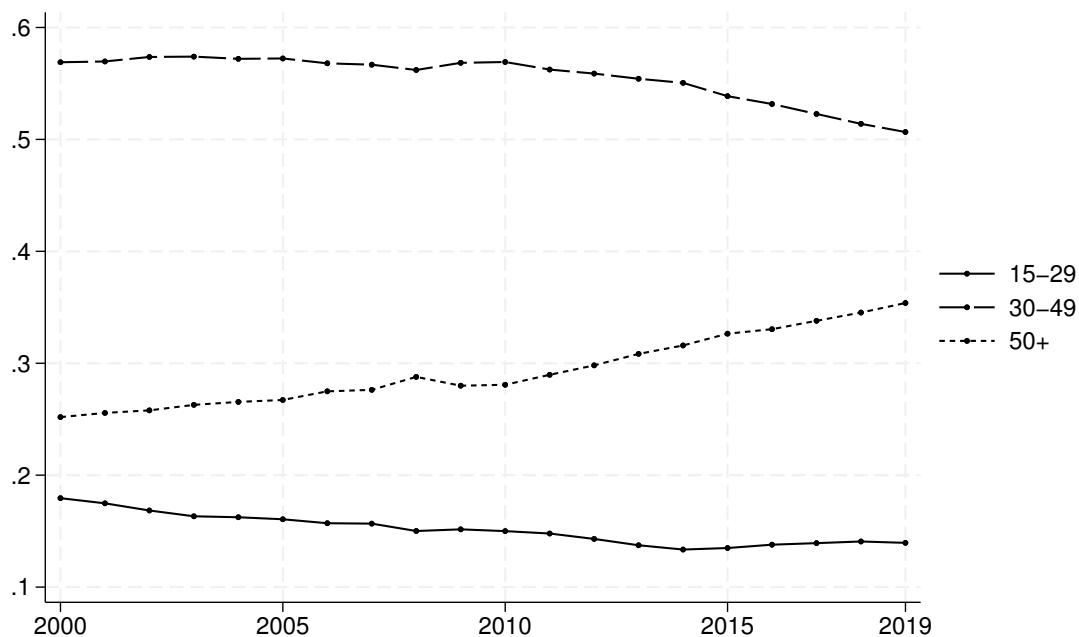


Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added (Panel (a)); *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added (Panel (b)); *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added (Panel (c)); *ROBOTS*: Imports of industrial robots from the world normalised by the corresponding values in 1996 (Panel (d)). Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. Robots are identified by their HS 1996 code (847950). For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on release 2016 of the WIOD, the World Bank's Historical Country Classification By Income, and release 2025 of the EU KLEMS (Panels (a)–(c)) and on UN Comtrade (Panel (d)).

the young and average increase of the wage bill share of older workers were larger than those in the 1996–2005 period (19.9% and 38.7%, respectively, according to the bottom of Panel B of Table G8). Despite some mixed patterns and trends for the service industries, the shift of economic activity away from manufacturing and towards services continued in 2000–2019 (Table G9), and, in line with the 1996–2005 period, the actual changes in wage bill shares of the three age groups occurred predominantly within, rather than between, industries (Table G10).

Figure G2: Wage bill shares by age group, 2000–2019



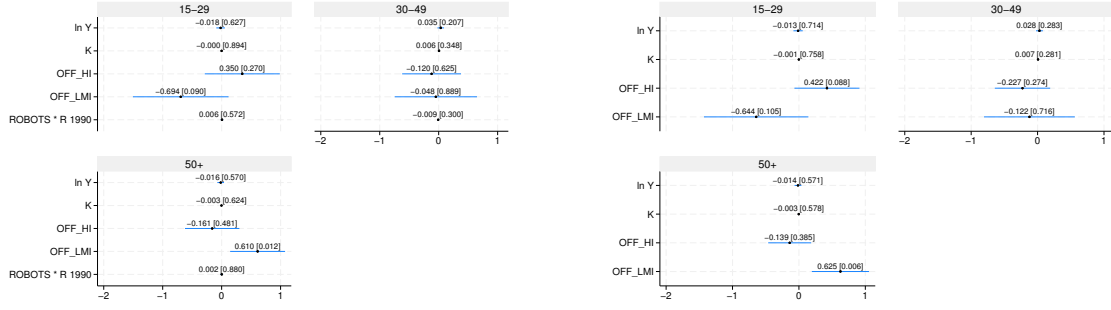
Notes: *Wsh*: Wage bill shares of young workers (aged 15–29), middle-aged workers (aged 30–49) and older workers (aged 50+). For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author’s calculations based on the 2025 release of the EU KLEMS.

Despite the relatively limited cross-country and especially cross-industry variation in the supplementary sample, the econometric analysis yields results that are largely consistent with those of the main analysis. Panel (a) of Figure G3 displays the results obtained from OLS estimations of the main specifications in Eq. (2) on the supplementary sample.^{G4} A higher intensity of offshoring to lower-income countries is associated with a lower wage bill share of the young and a higher wage bill share of the older workers, with the two associations being significant at 10% and 5%, respectively. The associations of the intensity of offshoring to high-income countries and robot adoption with the wage bill shares of all three age groups are statistically insignificant. However, the association of the intensity of offshoring to high-income countries with the wage bill share of the young is positive and significant at 10% when I re-estimate the specifications after removing the robot adoption variable (Panel (b)

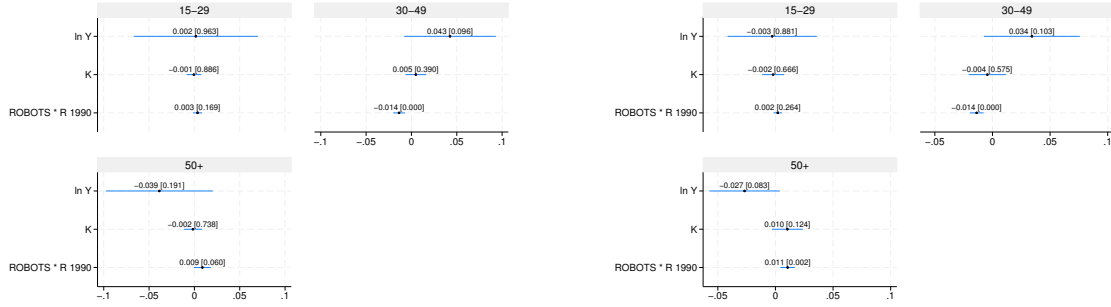
^{G4}As the supplementary sample starts in the year 2000, I use as specification weights each industry’s share of hours worked by persons engaged in the total hours worked by persons engaged of the manufacturing and service industries examined in 2000. Also, I calculate the shares of routine tasks of aggregate manufacturing and the wholesale and retail trade sector in 1990 as unweighted averages of the shares of routine tasks of their constituent industries, as these have been calculated in the main analysis.

Figure G3: Offshoring, industrial robots, and wage bill shares by age, OLS, 2000–2014 or 2000–2019



(a) Offshoring intensities and robot adoption as the key regressors, 2000–2014

(b) Offshoring intensities as the only key regressors, 2000–2014



(c) Robot adoption as the only key regressor, 2000–2014

(d) Robot adoption as the only key regressor, 2000–2019

Notes: OLS estimations of specifications in long differences with robust standard errors in all panels. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 2000.

of the same figure). The rest of the results remain largely unchanged except for the positive association of the intensity of offshoring to lower-income countries with the wage bill share of the older workers becoming significant at 1% and its negative association with the wage bill share of the young turning marginally insignificant. Also, the association of robot adoption with the wage bill share of the middle-aged is negative and significant at 1% and its association with the wage bill share of older workers is positive and significant at 10%, when I re-estimate the specifications after removing the offshoring intensity variables (Panel (c) of the same figure). The former association of robot adoption maintains its level of significance and the latter association becomes significant at 1% when I estimate the specifications of Panel (c) on the sample covering the 2000–2019 period (Panel (d) of the same figure).

Estimating the main specifications by 2SLS based on the IV strategies for offshoring intensity and robot adoption variables (IV–OFF–OC, IV–AUT–OC) produces insignificant

second-stage estimates of all key regressors and problematic first-stage statistics. In particular, the p-values of the under-identification tests exceed 10%, the F values of Kleibergen-Paap Wald and Lewis-Mertens test statistics raise significant concerns over the strength of the instruments, and the AR test passes in one column only. These issues also arise when I estimate the main specifications by 2SLS after excluding the robot adoption variable (Panels A and B of Table G2). Given that the instruments vary only by industry, these issues are likely attributed to the relatively limited industry variation in the supplementary sample. For this reason, I rely on the results shown in Table G3, which are obtained from 2SLS estimations of the specifications with the robot adoption variable as the single key regressor on the sample covering the 2000–2019 period. According to column (3) of the table, robot adoption exerted a positive effect on the wage bill share of older workers, albeit the relevant estimate is significant only at 10%. The estimates of robot adoption in the other two columns are negative but statistically insignificant. As for the first-stage results, the under-identification test passes successfully and the first-stage estimates (available upon request) point to the relevance of the instruments. Yet, the Stock-Yogo and Lewis-Mertens tests raise concerns over instrument strength, while the Wald and AR tests suggest that only the estimates in the third column are robust under weak instruments.^{G5}

^{G5}Results are very similar when I estimate the specifications of Table G3 by 2SLS for the 2000–2014 period and when I estimate the reduced-form versions of the specifications for the 2000–2019 period. These additional results are available upon request.

Table G2: Offshoring, industrial robots, and wage bill shares by age, 2SLS, 2000–2014

Panel A: IV–OFF–OC and IV–AUT–OC			
	(1)	(2)	(3)
Dep var: Wsh	15-29	30-49	50+
ln Y	-0.083 [2.1]	0.45 [8.6]	-0.30 [5.5]
K	-0.016 [0.2]	0.046 [0.6]	-0.023 [0.4]
OFF_HI	6.74 [116.4]	-25.4 [467.9]	15.2 [297.1]
OFF_LMI	-7.58 [148.8]	31.0 [599.2]	-19.0 [380.9]
ROBOTS * R 1990	-0.051 [0.3]	-0.0045 [1.4]	0.044 [0.9]
Observations	39	39	39
R ²	-16.47	-299.1	-147.8
Kleibergen-Paap rk LM	0.00386	0.00386	0.00386
Kleibergen-Paap rk LM (p-value)	0.950	0.950	0.950
Kleibergen-Paap Wald rk F	0.000892	0.000892	0.000892
Stock-Yogo critical value	N/A	N/A	N/A
Lewis-Mertens test statistic	0.000437	0.000437	0.000437
Lewis-Mertens critical value	36.15	36.84	37.12
Wald χ^2	0.345	0.0221	0.0157
Wald χ^2 (p-value)	0.951	0.999	0.999
AR χ^2	6.376	4.416	4.504
AR χ^2 (p-value)	0.0947	0.220	0.212
Hansen J	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A
	ln Y, K: no IV		
IV strategy	OFF_HI, OFF_LMI: IV–OFF–OC ROBOTS: IV–AUT–OC		

Panel B: IV–OFF–OC, robot adoption not controlled for			
	(1)	(2)	(3)
Dep var: Wsh	15-29	30-49	50+
ln Y	-0.20 [2.5]	0.44 [5.4]	-0.19 [2.4]
K	-0.020 [0.2]	0.046 [0.5]	-0.020 [0.2]
OFF_HI	11.9 [156.1]	-24.9 [328.9]	10.6 [143.2]
OFF_LMI	-14.8 [192.8]	30.4 [406.5]	-12.7 [177.1]
Observations	39	39	39
R ²	-28.84	-63.89	-25.85
Kleibergen-Paap rk LM	0.00803	0.00803	0.00803
Kleibergen-Paap rk LM (p-value)	0.929	0.929	0.929
Kleibergen-Paap Wald rk F	0.00288	0.00288	0.00288
Stock-Yogo critical value	7.03	7.03	7.03
Lewis-Mertens test statistic	0.000992	0.000992	0.000992
Lewis-Mertens critical value	32.45	33.11	33.30
Wald χ^2	0.00668	0.0101	0.0317
Wald χ^2 (p-value)	0.997	0.995	0.984
AR χ^2	0.276	2.941	4.667
AR χ^2 (p-value)	0.871	0.230	0.0969
Hansen J	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A
	ln Y, K: no IV		
IV strategy	OFF_HI, OFF_LMI: IV–OFF–OC		

Notes: 2SLS estimations of specifications in long differences in all columns of the two panels. The equations in both panels include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 2000. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

Table G3: Industrial robots and wage bill shares by age, IV–AUT–OC, 2000–2019

	(1)	(2)	(3)
Dep var: Wsh	15-29	30-49	50+
ln Y	-0.0057 [0.02]	0.035* [0.02]	-0.025 [0.02]
K	-0.0044 [0.007]	-0.0036 [0.007]	0.012 [0.008]
ROBOTS * R 1990	-0.0094 [0.01]	-0.0096 [0.008]	0.017* [0.009]
Observations	39	39	39
R^2	-0.241	0.272	0.237
Kleibergen-Paap rk LM	5.681	5.681	5.681
Kleibergen-Paap rk LM (p-value)	0.0171	0.0171	0.0171
Kleibergen-Paap Wald rk F	5.551	5.551	5.551
Stock-Yogo critical value	16.38	16.38	16.38
Lewis-Mertens test statistic	4.567	4.567	4.567
Lewis-Mertens critical value	14.20	14.23	14.23
Wald χ^2	0.804	1.434	3.984
Wald χ^2 (p-value)	0.370	0.231	0.0459
AR χ^2	1.202	0.819	3.154
AR χ^2 (p-value)	0.273	0.366	0.0757
Hansen J	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A
IV strategy	ln Y, K: no IV ROBOTS: IV–AUT–OC		

Notes: 2SLS estimations of specifications in long differences in all columns. The equations include country fixed effects and are weighted by each industry's share in the total hours worked by persons engaged of the manufacturing and market service industries examined in 2000. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors. The Stock-Yogo critical values are produced based on 10% maximal IV size and the Lewis-Mertens critical values are produced based on 5% significance and 10% tolerance.

G.1 Additional descriptive statistics in the supplementary analysis

Table G4: Offshoring intensities by country, 2000–2014

Panel A: Mean levels in 2000			
Country	OFF	OFF_HI	OFF_LMI
Austria	0.097	0.084	0.011
Finland	0.072	0.057	0.010
Germany	0.084	0.064	0.013
Italy	0.067	0.051	0.008
Netherlands	0.104	0.084	0.010
Spain	0.089	0.078	0.005
United Kingdom	0.055	0.042	0.005
Unweighted mean	0.081	0.066	0.009
Panel B: Mean percentage changes in 2000–2014			
Country	OFF	OFF_HI	OFF_LMI
Austria	48.65	27.72	114.45
Finland	66.71	45.87	206.43
Germany	32.35	11.88	158.09
Italy	35.72	16.81	259.85
Netherlands	69.09	46.10	325.76
Spain	4.42	-13.70	185.09
United Kingdom	40.35	32.03	200.52
Unweighted mean	42.47	23.82	207.17

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on the 2016 release of the WIOD, the World Bank's Historical Country Classification By Income, and the 2025 release of the EU KLEMS.

Table G5: Offshoring intensities by industry, 2000–2014

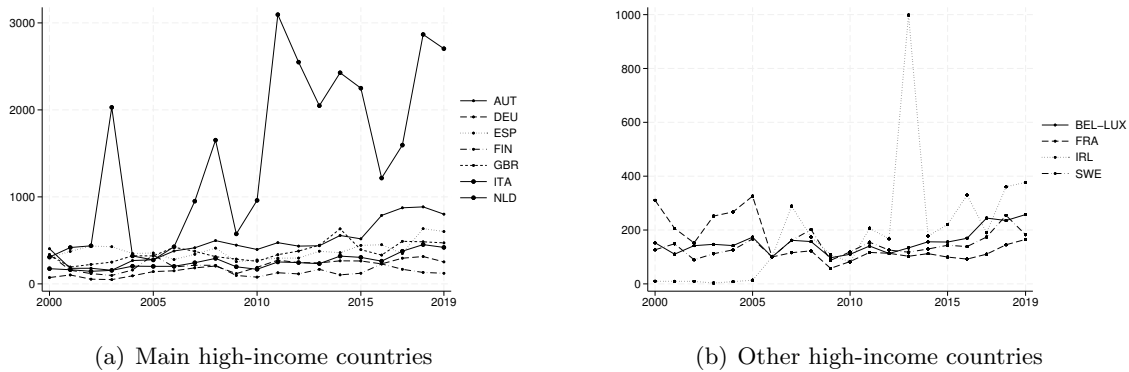
Panel A: Mean levels in 2000			
Industry	OFF	OFF_HI	OFF_LMI
C	0.2060	0.1662	0.0229
G	0.0023	0.0017	0.0002
H	0.0222	0.0169	0.0024
J	0.0118	0.0106	0.0008
K	0.0170	0.0156	0.0003
L	0.0008	0.0006	0.0001

Panel B: Mean percentage changes in 2000–2014			
Industry	OFF	OFF_HI	OFF_LMI
C	62.62	35.32	235.00
G	34.15	28.52	208.33
H	64.12	25.61	264.36
J	7.95	3.00	153.31
K	-5.70	-16.27	-7.31
L	19.98	-20.14	298.72

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on the 2016 release of the WIOD, the World Bank's Historical Country Classification By Income, and the 2025 release of the EU KLEMS.

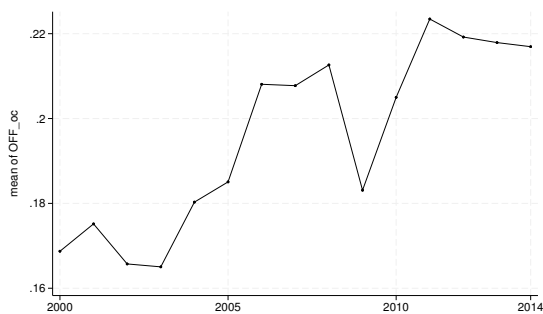
Figure G4: Imports of industrial robots by country, 2000–2019



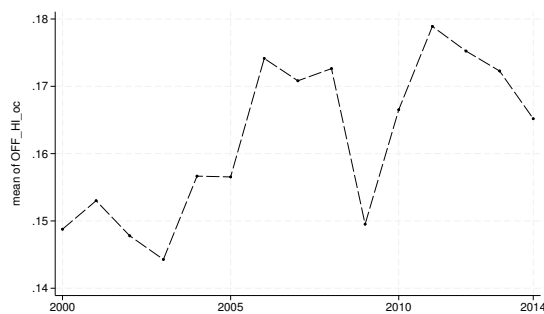
Notes: Imports of industrial robots from the world by the countries of the supplementary sample (Panel (a)) and by other five high-income countries (Panel (b)) normalised by the corresponding values in 1996. Robots are identified by their HS 1996 code (847950).

Source: Author's calculations based on UN Comtrade.

Figure G5: Offshoring intensities and imports of industrial robots, 2000–2014 or 2000–2019, group of other high-income countries



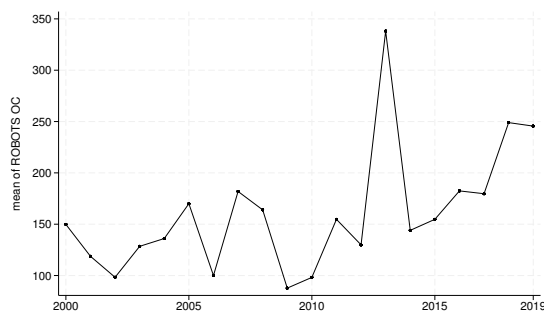
(a) Offshoring to all countries



(b) Offshoring to high-income countries



(c) Offshoring to lower-income countries



(d) Normalised imports of industrial robots

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added (Panel (a)); *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added (Panel (b)); *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added (Panel (c)); *ROBOTS*: Imports of industrial robots from the world normalised by the corresponding values in 1996 (Panel (d)). Offshoring destination countries are classified by their income level according to the World Bank's Historical Country Classification By Income. High-income (Lower-income): offshoring destination countries are labeled as high-income (upper-middle-income, lower-middle-income or low-income) for at least half of the years of the period examined. Robots are identified by their HS 1996 code (847950). For the calculation of the sample means of the variables, see Appendix B.1.

Source: Author's calculations based on release 2016 of the WIOD, the World Bank's Historical Country Classification By Income, and release 2025 of the EU KLEMS (Panels (a)–(c)) and on UN Comtrade (Panel (d)).

Table G6: Offshoring intensities by country, 2000–2014, group of other high-income countries

Panel A: Mean levels in 2000			
Country	OFF	OFF_HI	OFF_LMI
Belgium	0.195	0.166	0.016
France	0.074	0.064	0.004
Ireland	0.142	0.111	0.007
Luxembourg	0.341	0.321	0.004
Sweden	0.092	0.081	0.005
Unweighted mean	0.169	0.149	0.007
Panel B: Mean percentage changes in 2000–2014			
Country	OFF	OFF_HI	OFF_LMI
Belgium	70.59	46.63	272.70
France	75.05	65.96	349.19
Ireland	178.01	194.39	687.08
Luxembourg	506.09	602.60	5562.89
Sweden	45.89	24.98	536.09
Unweighted mean	175.13	186.91	1481.59

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on the 2016 release of the WIOD, the World Bank's Historical Country Classification By Income, and the 2025 release of the EU KLEMS.

Table G7: Offshoring intensities by industry, 2000–2014, group of other high-income countries

Panel A: Mean levels in 2000			
Industry	OFF	OFF_HI	OFF_LMI
C	0.3244	0.2865	0.0181
G	0.0047	0.0038	0.0001
H	0.0569	0.0434	0.0016
J	0.0120	0.0107	0.0006
K	0.2234	0.2000	0.0010
L	0.0000	0.0000	0.0000
Panel B: Mean percentage changes in 2000–2014			
Industry	OFF	OFF_HI	OFF_LMI
C	10.28	-4.96	304.37
G	181.51	203.12	702.79
H	321.52	359.88	1600.38
J	1090.46	1238.82	13929.75
K	34.22	-1.54	7.59
L	178.59	285.99	1605.04

Notes: *OFF*: Ratio of real imports of a country-industry pair from the same industry of all available countries to real gross value added; *OFF_HI*: Ratio of real imports of a country-industry pair from the same industry of high-income countries to real gross value added; *OFF_LMI*: Ratio of real imports of a country-industry pair from the same industry of lower-income countries to real gross value added. For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on the 2016 release of the WIOD, the World Bank's Historical Country Classification By Income, and the 2025 release of the EU KLEMS.

Table G8: Wage bill shares of age groups by country and by industry, 2000–2019

Panel A: By country						
Country	Mean level			Mean % ch.		
	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺
Austria	0.211	0.607	0.183	-16.61	-1.93	25.11
Finland	0.180	0.528	0.293	-2.01	-8.68	19.08
Germany	0.147	0.610	0.242	-11.09	-23.79	67.90
Italy	0.136	0.576	0.294	-26.24	-11.47	35.53
Netherlands	0.215	0.523	0.257	-18.33	-15.10	50.94
Spain	0.206	0.535	0.259	-49.00	6.37	28.30
United Kingdom	0.162	0.603	0.235	-15.81	-12.77	44.25
Unweighted mean	0.179	0.569	0.252	-19.87	-9.62	38.73

Panel B: By industry						
Industry	Mean level			Mean % ch.		
	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺	Wsh ^{15–29}	Wsh ^{30–49}	Wsh ⁵⁰⁺
C	0.168	0.586	0.249	-21.66	-12.00	42.79
G	0.210	0.543	0.246	-16.86	-8.22	34.61
H	0.138	0.561	0.300	-11.59	-12.13	32.98
J	0.180	0.630	0.189	-28.29	-4.88	52.27
K	0.130	0.602	0.269	-21.56	-10.14	42.37
L	0.117	0.553	0.341	-2.04	-11.55	22.30

Notes: Wsh: Wage bill shares of young workers (aged 15–29), middle-aged workers (aged 30–49) and older workers (aged 50+). For the calculation of initial sample means of the variables and sample means of their percentage changes, see Appendix B.1.

Source: Author's calculations based on the 2025 release of the EU KLEMS.

Table G9: Employment and value added shares of industries, 2000–2019

Industry	Mean level 2000					
	EMPsh	EMPEsh	HEMPsh	HEMPEsh	VAsh	GOsh
C	0.168	0.186	0.175	0.200	0.161	0.273
G	0.158	0.151	0.159	0.148	0.111	0.101
H	0.053	0.055	0.058	0.061	0.056	0.061
J	0.029	0.030	0.030	0.032	0.027	0.033
K	0.029	0.032	0.029	0.033	0.051	0.041
L	0.010	0.010	0.010	0.009	0.102	0.072
Industry	Mean % ch. 2000–2005					
	EMPsh	EMPEsh	HEMPsh	HEMPEsh	VAsh	GOsh
C	-27.545	-28.372	-26.103	-27.397	-1.174	-5.267
G	-6.182	-1.699	-7.710	-3.287	8.188	3.047
H	-5.248	-5.726	-4.376	-5.120	-8.003	3.107
J	13.189	10.211	17.155	13.098	88.287	49.187
K	-17.487	-20.109	-13.696	-17.115	-2.246	3.408
L	25.756	26.230	29.935	28.562	9.541	-0.198

Notes: EMPsh, EMPEsh, HEMPsh, HEMPEsh, VAsh, GOsh denote, respectively, shares of an industry in economy-wide total number of persons engaged, total number of salaried employees, total hours worked by persons engaged, total hours worked by salaried employees, value added, and gross output.

Source: Authors' calculations based on the 2025 release of the EU KLEMS.

Table G10: Between- and within-industry percentage point changes of wage bill shares of age groups by country, 2000–2019

	ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}		ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}		ΔWsh^{15-29}		ΔWsh^{30-49}		ΔWsh^{50+}	
	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries	Between Industries	Within Industries
Austria	-0.004	-0.029	0.000	-0.010	0.001	0.038	-0.005	0.038	-0.001	0.038	-0.001	0.038	1	1	1	1	1	1
Germany	-0.009	-0.014	0.001	-0.121	0.009	0.136	-0.014	0.136	-0.011	0.136	-0.011	0.136	1	1	1	1	1	1
Denmark	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1	1	1	1	1	1
Spain	-0.024	-0.083	0.013	0.028	-0.005	0.055	-0.029	0.055	-0.008	0.055	-0.008	0.055	1	1	1	1	1	1
Finland	0.020	-0.009	-0.003	-0.040	0.002	0.047	0.031	0.047	0.007	0.047	0.007	0.047	0	0	0	0	0	0
United Kingdom	-0.005	-0.020	0.001	-0.059	0.002	0.080	-0.009	0.080	-0.003	0.080	-0.003	0.080	1	1	1	1	1	1
Italy	0.005	-0.031	-0.002	-0.057	-0.004	0.083	0.010	0.083	0.005	0.083	0.005	0.083	1	1	1	1	1	1
Japan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1	1	1	1	1	1
Netherlands	0.002	-0.025	-0.000	-0.054	-0.003	0.081	0.004	0.081	0.003	0.081	0.003	0.081	1	1	1	1	1	1
Unweighted mean	-0.002	-0.023	0.001	-0.035	-0.000	0.058	-0.001	0.058	-0.001	0.058	-0.001	0.058	—	—	—	—	—	—
Unweighted median	0.000	-0.020	0.000	-0.040	0.000	0.055	0.000	0.055	0.000	0.055	0.000	0.055	—	—	—	—	—	—

Notes: Wsh^{15-29} , Wsh^{30-49} and Wsh^{50+} denote shares of self-employed individuals, informal workers, and informal-sector workers, respectively. I first calculate the between-industry, within-industry, and interaction components by country-industry pair, and then, sum each component over industries by country: $\sum_i \Delta Wsh_{i,c}^{15-29}$, $\sum_i Wsh_{i,c}^{15-29,2000} \Delta Wsh_{i,c}^{15-29}$, where $Wsh_{i,c}$ is the share of industry i 's total employment in country c 's aggregate employment, Δ signifies the percentage point change of a variable between 2000 and 2019, and $g \in \{15-29, 30-49, 50+\}$. The interaction component is calculated as $\sum_i \Delta Wsh_{i,c}^{15-29} Wsh_{i,c}^{15-29,2000}$. The within-industry component is calculated as $\sum_i Wsh_{i,c}^{15-29} \Delta Wsh_{i,c}^{15-29}$. The interaction component is calculated as $\sum_i \Delta Wsh_{i,c}^{15-29} Wsh_{i,c}^{15-29,2000}$. Value one (zero) in the last three columns indicates that the within-industry component is larger (smaller) than the between-industry component for the three labour variables.

Source: Authors' calculations based on the 2025 release of the EU KLEMS.