Industrial automation as a driver of job creation through greater integration into GVCs[*]

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Abstract

The evidence on the final effect of industrial automation on employment is still inconclusive. We argue that automation leads to employment creation when there are greater trade opportunities because productivity growth lead to scale effects that outweigh displacement effects, in line with the traditional argument of trade gains based on *comparative advantages* but *augmented by automation*. On the import side, industrial automation increases the demand for raw materials and standardized intermediate inputs. On the export side, an increased production at lower cost benefits from greater access to the world market. Exploiting cross-country variation in population aging combined with global industry trends in robot adoption, we find that industries experiencing greater automation exhibit higher increments in their (backward and forward) participation in GVCs, output and employment, than less exposed industries; and no differential effects on the average wage or labor's share of value added. Interestingly, our estimates suggest that greater integration into GVCs is associated with both increased robot adoption and employment gains from automation. Finally, we find that growing robot adoption in industry's export destinations is related to increased robot adoption in the domestic market, which supports a demand-driven explanation for automation.

Keywords: Robot Adoption, Industrial Automation, Global Value Chains, Employment, Wages, Labor Share.

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I Introduction

Motivation 1: highly heterogeneous effects on the impact of robot adoption on employment and wages. Summarize key stylized facts from extensive literature revision (hundreds of papers?). Perhaps we could plot the harmonized point estimates as you already did.

Why? put simply: automation causes both displacement effects and employment gains. Displacement effects reduce labor demand for specific tasks and jobs. Employment creation comes from (i) new tasks/jobs, and (ii) previous tasks/jobs from increasing demand for goods and services spurred by productivity growth. Presumably, these effects should be larger if productivity gains materialize in higher wages.

Motivation 2: evidence shows that automation concentrates on the largest and most productive firms (many of them are MNCs), highly engaged in international trade and integrated into GVCs. Also, there is recent evidence on positive spillovers for firms that trade with superstars and MNCs; which reinforce the importance of measuring the impact of automation technologies taking into account cross–country and cross–industry linkages.

This paper: argues that automation leads to employment creation when there are greater trade opportunities because productivity growth lead to scale effects that outweigh displacement effects, in line with the traditional argument of trade gains based on *comparative advantages* but *augmented* by the adoption of automation technologies.

Data: Stock of robots by industry-year sourced from the IFR (1993–2022). Industry employment, output, VA, average wage, imports, exports, and measures of integration into GVCs (1995–2020) obtained from the OECD's Trade in Employment and Trade in VA datasets (2023 edition). Cross-country population aging (between 1990 and 2020) sourced from the UN World population prospects. **Cross-country-industry panel dataset:** comprising the period 1995–2020; including 56 countries and 22 industries. The sample covers 73.9 percent of world's population in 1995 and 68.9 in 2020; robot adopters have lower population growth (and are aging faster) that non-adopters; and represents 82.8 (84.6) percent of global GDP in 1995 (2020); i.e. GDP per capita grew relatively more in countries adopting robots.

Methodology: Acemoglu and Restrepo (2022) document that countries experiencing faster aging adopted more industrial robots because they faced with a lower relative supply of middle-age workers specializing in manual production tasks. Exploiting this finding, we use demographic change as a source of exogenous cross-country variation in the incentives to automate; that we combine with global industry trends in robot adoption that capture advances in technology, availability and prices, acting as exogenous supply shifters for robot adoption in each industry-country pair.

Main findings:

1. Industries experiencing greater automation exhibit higher relative increases in their participation in GVCs, output and employment, than less exposed industries; and no differential effects on the average wage or labor's share of value added.

2. Employment gains from automation are related to greater integration (backward and forward) into GVCs.

3. Greater integration into GVCs is related to increasing adoption of robots.

4. Growing robot adoption in industry's export destinations is related to increased robot adoption in the domestic market, which supports a demand-driven explanation for automation.

Simple reasoning: On the import side, industrial automation increases the demand for raw materials and standardized intermediate inputs; some of these inputs are produced using industrial robots and traded through GVCs. On the export side, an increased production at lower cost benefits from a greater access to the world market, which is facilitated by greater integration into GVCs.

II Data and trends

II.1 Industrial automation and employment

The measure of automation is based on the stock of industrial robots (sourced from the International Federation of Robotics, IFR). It varies at the country-industry-year level. The industry disaggregation used by the IFR follows the 2-digits ISIC Rev. 4. Fig. 1 depicts the industry composition of the global stock of robots in 1995, 2007 and 2020. The global stock of robots increased by 64 percent between 1995 and 2007 (from 0.6 million to 0.99 million) and much more markedly (by 193 percent) between 2007 and 2020 (reaching 2.9 million of operational units). Three industries account for more than two thirds of the global stock of robots in 2020: automotive (38.7 percent), computers and electronics (20.3) and electrical equipment (10); followed by rubber and plastics (6.5), metal products (5.4), industrial machinery (4.9), toys and miscellaneous manufacturing (4.4 percent), food and beverages (3.5). The industries that exhibit the greater relative increase in the stock of robots between 1995 and 2020 are rubber and plastics, computers and electronics and pharmaceuticals and cosmetics.

Fig. 2 shows a positive and significant correlation between the change in global industry employment and robot adoption between 1995 and 2020 (the sample is restricted to manufacturing industries, which concentrate the bulk of robot adoption). The three industries with the highest robot adoption (automotive, computers and electronics, and electrical equipment) exhibit a global increase in employment of 4.71, 9.23 and 5.97 million workers, respectively; while the four industries with falling employment (mineral products, wood and furniture, basic metals and paper and printing) present a very low adoption of robotics (which is close to zero en three of these four industries).

We calculate the stock of robots per thousand workers in the baseline year (1995), so the variation in robot adoption by country-industry comes only from the temporal variation in the stock of robots:

$$Robot\ Adoption_{cjt} = \frac{Stock\ of\ Robots_{cjt}}{L_{cj,1995}/1000}$$

where c, j and t index countries, industries and time, respectively. Employment by country-industry in 1995 comes from the OECD Industry Employment dataset (2023 edition).

II.2 Integration into GVCs

Integration into GVCs is a relevant determinant of country's integration into the global economy. There are at least two measures of participation into GVCs.

Backward participation in GVCs refers to the extent to which a country's exports incorporate value added from imported inputs. In other words, it measures how much a country relies on foreign inputs to produce goods and services that are then exported. The typical measure is given by re-exported intermediate imports as a share of total intermediate imports (Guide to OECD's Trade in Value Added indicators, 2022). It varies at the country-industry-year level and, again, it captures the importance of intermediate imports (and their role as a source of international competitiveness) to produce goods and services for export.

Forward participation in GVCs refers to the extent to which a country's exports incorporate value added into their trade partners' exports. In other words, it measures how much a country produces and ships inputs that are further re-exported. A measure is given by domestic value added embodied in foreign exports as a share of gross exports (OECD, 2022). It varies at the country-industry-year.

Fig. 3 presents the evolution of average backward and forward participation in GVCs (left axis) and robot adoption (right axis) across the 56 countries included in the analysis.**Include Table with list of countries in the appendix** Participation in GVCs is normalized to 1 in 1995 and weighted by country-industry output. Robot adoption corresponds to the global stock of robots per thousand workers (adding all countries together). The shaded area corresponds to the years of the global financial crisis, which severely affected trade patterns. Forward participation in GVCs grows all over this period, except for the years 2000–2002 and 2008–2009; and it is highly correlated with the upward trend in robot adoption (0.84). Backward participation in GVCs grows until 2008, and declines thereafter. The bottom figure depicts the same trends but calculated for two mutually exclusive samples (of 28 countries each): OECD and non-OECD. The trends are similar for OECD countries. And the correlations between forward and backward participation in GVCs and robot adoption are higher (0.97 and 0.75, respectively) than in top figure. In contrast, non-OECD countries exhibit a much faster increase (than OECD countries) in backward and forward participation in GVCs until the global financial crisis, almost no robot adoption during this sub-period, and a sharp decline in GVCs integration in the following years, with robot adoption that begins to grow steadily. This divergent patterns motivate us to conduct robustness exercises that separate OECD vs. non-OECD countries, and the pre-crisis vs. post-crisis periods.

Fig. 5 in the appendix presents these trends separately for each of the 22 industries included in the analysis.

Add descriptive figure for BW and FW participation in GVCs by country (in the appendix)

Other industry outcomes: output, employment, average wage and labor's share of value added. We also include value added per worker and trade intensity (i.e. imports plus exports as a fraction of output) as control variables.

III Results

III.1 The effects of robot adoption on industry outcomes

To estimate the causal effects of robot adoption on industry outcomes we run the following regression:

$$Y_{jct} = \beta_0 + \beta_1 Robot\ Adoption_{jct} + \alpha_j + \gamma_c \times \delta_t + X'_{jc0}\theta + \varepsilon_{jct} \quad (1)$$

Y_{jct} correspond to backward participation in GVCs, forward participation in GVCs, log output, log employment, log average wage and labor's share of value added; α_j, γ_c, δ_t are industry, country and year fixed effects. The vector X_{jc0} includes control variables measures in the baseline year (1995) and interacted with year dummies: value added per worker, trade intensity (imports and exports divided by output). The preferred specifications also control for initial differences in backward and forward participation in GVCs and robot adoption, and include $\gamma_c \times \delta_t$ (country x year) fixed effects to control for country-specific temporal shocks. These regressions capture within country variation in robot adoption and outcomes across industries and time.

Two-way clustered standard errors that are robust against heteroskedasticity and correlation within countries and industries are in parentheses. Estimates are robust to alternative clustering (countries, industries, country-industry pairs).

Robot adoption is endogenous because industry shocks affect automation decisions and industry outcomes simultaneously.

IV design: we use demographic change as a source of exogenous cross-country variation in the incentives to automate; that we combine with global industry trends in robot adoption that aim to capture advances in technology, availability and prices, acting as exogenous supply shifters for robot adoption in each industry-country pair. The IV is constructed as follows:

$$Robot\ Adoption_{jct}^{WORLD} = Aging_c \times Robot\ Adoption_{jt}^{World} \tag{2}$$

where $Aging_c$ represents the 1990-2020 change in the ratio of old-age population (+56 years) to middle-age population (21–55 years old), following Acemoglu and Restrepo (2022). And $Robot\ Adoption_{jt}^{World}$ is the (simple) average industry robot adoption across the world (i.e. across the 57 countries included in the analysis). Fig. 1 shows that there is a positive and significant correlation between the average annual increase in robot adoption during 1995–2020 and population aging between 1990 and 2020.

Next step: add cross–industry variation in the incentives to automate: (i) replaceability index (Graetz and Michales, 2018), and/or (ii) share of old-age to middle-age workers (Acemoglu and Restrepo, 2022). Both constructed using microdata from US industries in 1990 (US Census). **Potential improvement:** use information for other countries as well (using Census data from IPUMS; at least for one country from each region: Europe, LA, EAP, MEA, NA).

Table 1 presents the results. Columns 1: OLS. Columns 2-8: 2SLS. Columns 3-6 subsequently control for initial differences in VA per worker, trade intensity, backward and forward participation in GVCs, robot adoption and country x year FE. Columns 7 and 8 restrict the sample to manufacturing industries only, and column 8 excludes the automotive industry.

Threat to identification: if there are business-stealing effects across countries induced by capital investments (Aghion et al., 2024) part of results could be driven by relative expansions of output and employment in countries adopting more robots. To partially address this concern we control for time-varying import/output and export/output ratios.

III.2 Integration into GVCs and employment growth

To estimate the relation between participation in GVCs and employment we run the following regression:

$$Log(Employment)_{jct} = \beta_0 + \beta_1 GVC_{jct} + \alpha_j + \gamma_c \times \delta_t + X'_{jc0}\theta + \varepsilon_{jct} \tag{3}$$

We separately use both measures of backward and forward participation in GVCs. In the first-stage we run GVC_{jct} on $Robot\ Adoption_{jct}^{WORLD}$; which corresponds to the reduced-form regressions in Panels B and C of Table 1. The second-stage would capture the effects of automation on employment that occur through a greater integration (backward or forward) into GVCs.

Table 2 presents the results. Columns 1: OLS. Columns 2-8: 2SLS. Different columns correspond to the same specifications as in Table 1. **COMMENT RESULTS**

III.3 Integration into GVCs and robot adoption

To estimate the relation between *past* participation in GVCs and robot adoption we run the following regression:

$$Robot\ Adoption_{jct} = \beta_0 + \beta_1 GVC_{jct-1} + \alpha_j + \gamma_c \times \delta_t + X'_{jc0}\theta + \varepsilon_{jct} \quad (4)$$

We separately use both measures of *lagged* backward and forward participation in GVCs. In the first-stage we run GVC_{jct-1} on $Robot\ Adoption^{WORLD}_{jct-1}$; which is very similar to the reduced-form regressions in Panels B and C of Table 1. The second-stage would capture the effects of *past* participation in GVCs on *current* robot adoption; driven by global industry automation trends.

Table 3 presents the results. Columns 1: OLS. Columns 2-8: 2SLS. Different columns correspond to the same specifications as in Tables 1 and 2. **COMMENT RESULTS**

III.4 Robot adoption among trade partners

To estimate the relation between robot adoption among trade partners and domestic robot adoption we run the following regression:

$$Robot\ Adoption_{jct} = \beta_0 + \beta_1 RA^{SC}_{jct} + \beta_2 RA^{DC}_{jct} + \alpha_j + \gamma_c \times \delta_t + X'_{jc0}\theta + \varepsilon_{jct} \quad (5)$$

Where RA^{SC}_{jct} (RA^{DC}_{jct}) is robot adoption in source (destination) countries, calculated as a weighted average of global industry trends combined with cross-country variation in aging across source (destination) countries in each industry, with weights that correspond to the 1995's industry import (export) share of each country.

Table 4 presents the results. Columns 1-7: OLS. Columns 1-7 correspond to specifications 2-8 in Tables 1, 2 and 3. **COMMENT RESULTS**

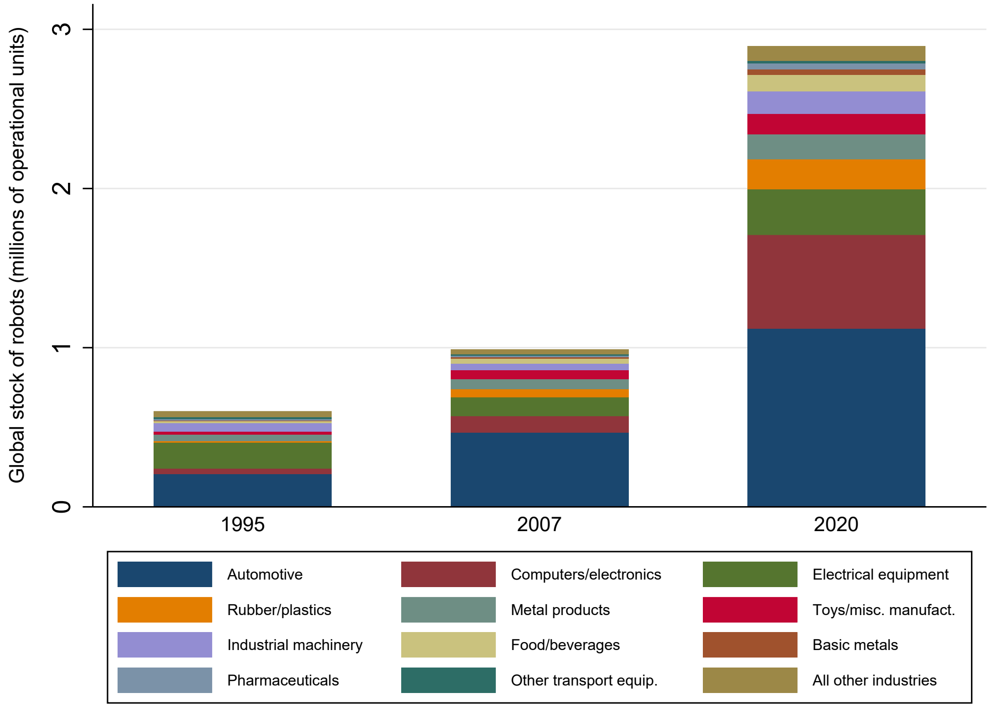
III.5 Robustness exercises (TBC)

- Separate OECD from non-OECD; and 1995–2008 from 2010–2020.
- Control for time-varying import/output and/or export/output ratios.
- Exclude outliers (top 5% countries, top 5% obs).
- Exclude years of global crisis (2008–2010).
- Inclusion of unspecified robots.
- Use some kind of weights in the regressions (?)

IV Conclusions (TBA)

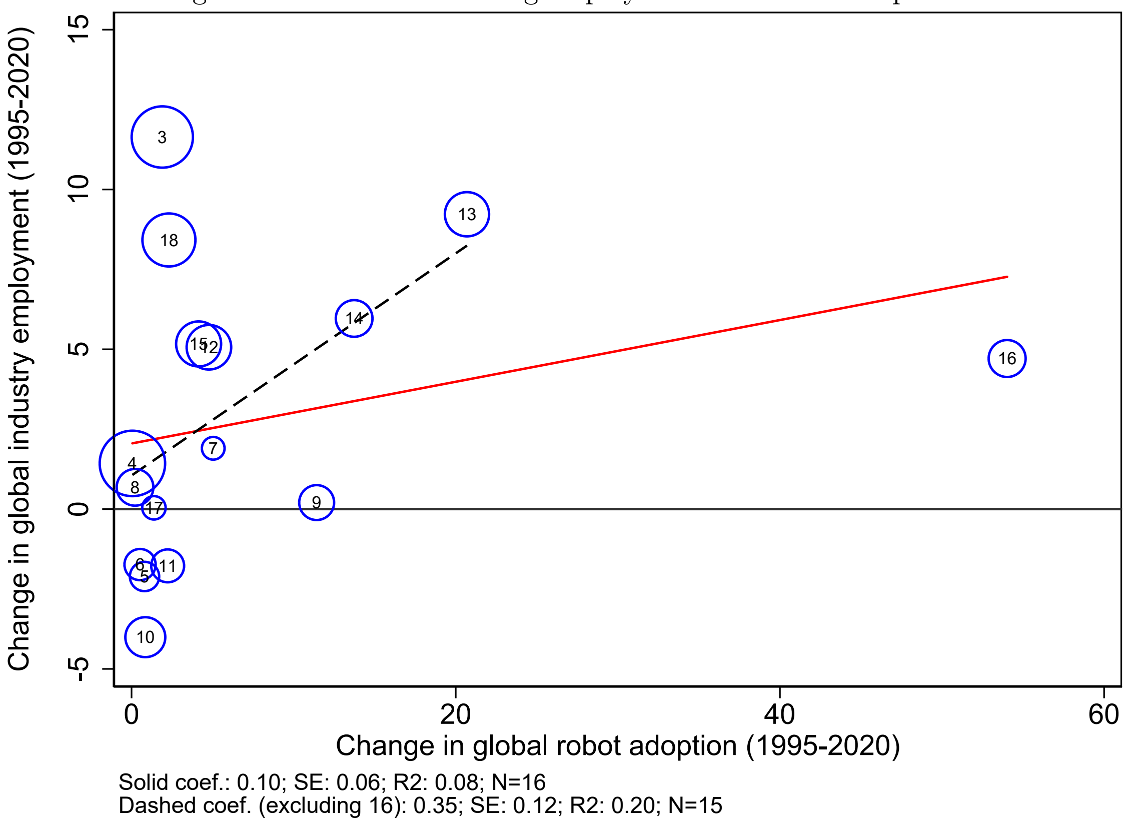
V Figures and tables

Fig. 1: Global stock of robots, by industry



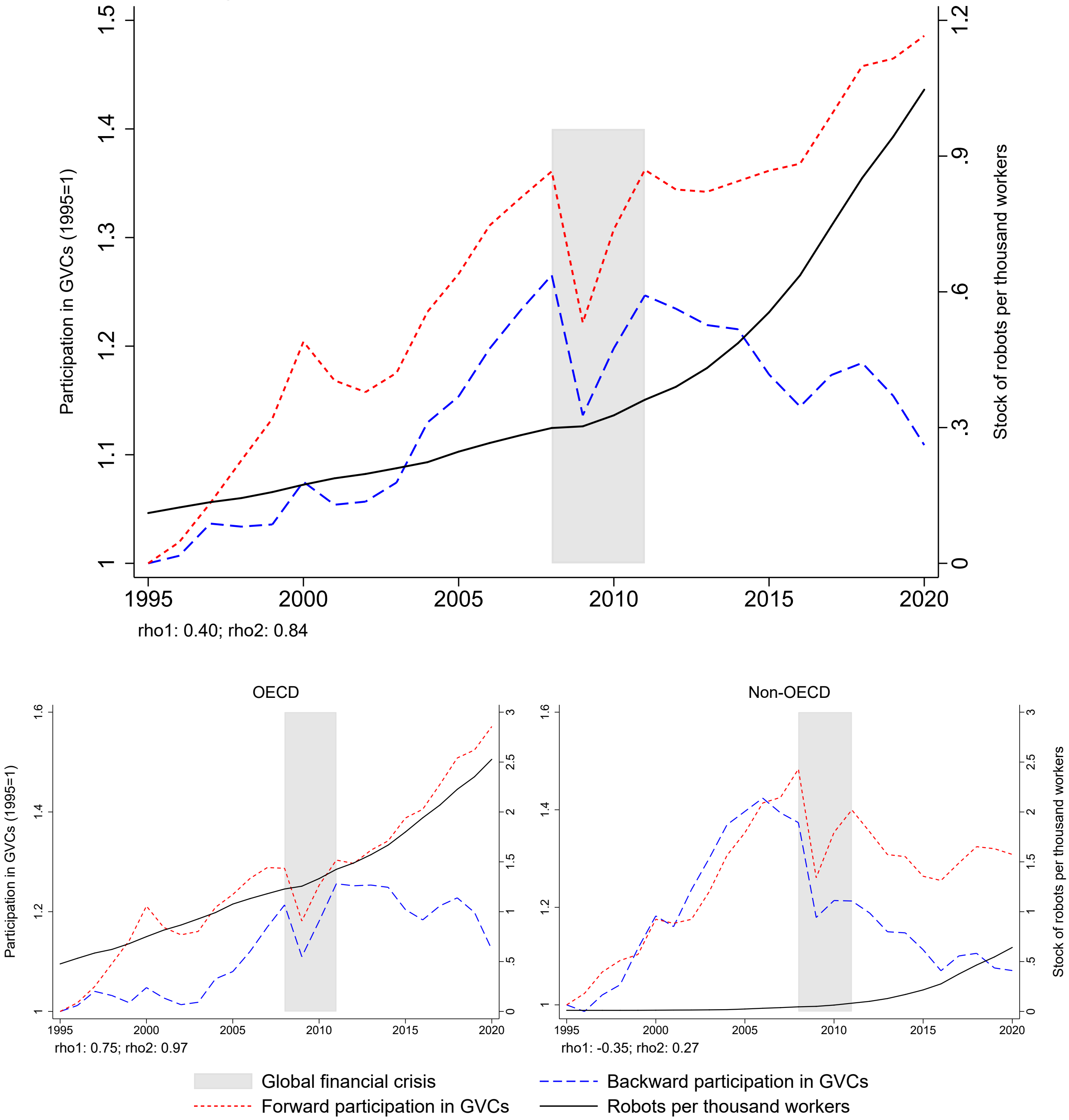
Notes. The figure presents the global stock of robots (expressed in million operational units) in 1995, 2007 and 2020. Source: International Federation of Robotics (IFR).

Fig. 2: Global manufacturing employment and robot adoption



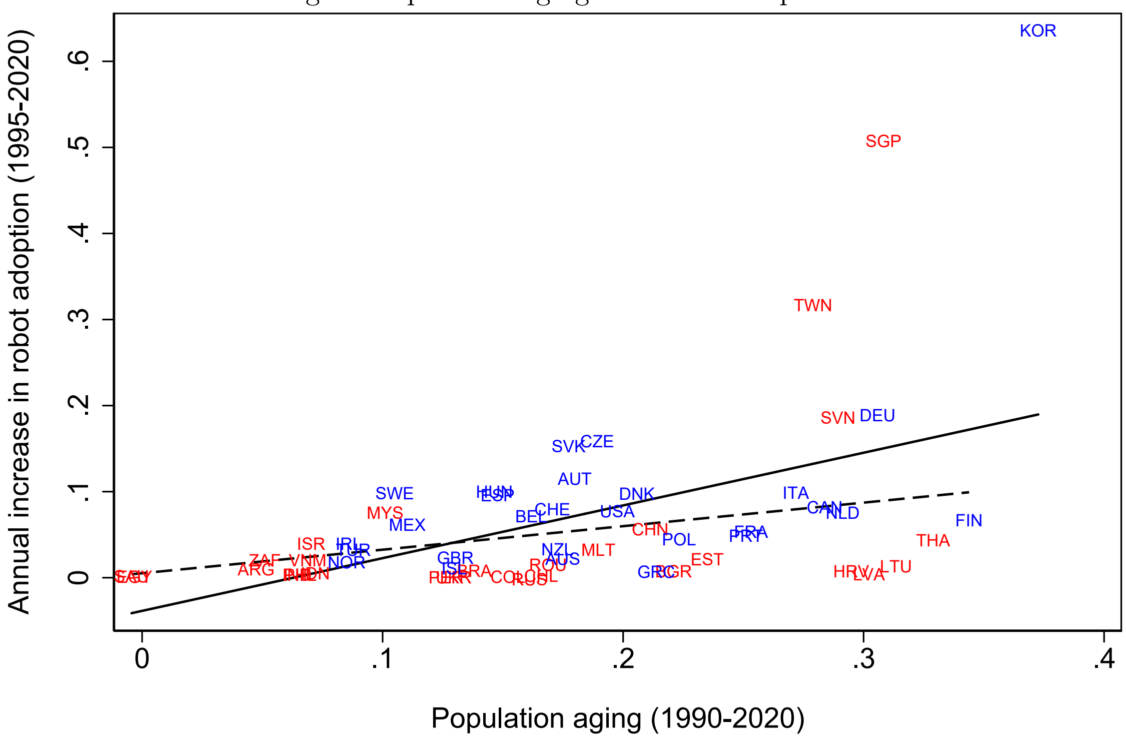
Notes. Notes. The figure depicts the correlation between the 1995–2020 change in global industry employment and the 1995–2020 change in robot adoption, for manufacturing industries only. The sample includes 56 countries. The red solid and black dotted lines correspond to the unweighted correlations between both variables (the latter excludes the automotive industry). Bubble size represents industry employment in 2020. Number correspond to: 3 Food/beverages; 4 Textiles; 5 Wood/furniture; 6 Paper/printing; 7 Pharmaceuticals/cosmetics; 8 Other chemicals; 9 Rubber/plastics; 10 Mineral products; 11 Basic metals; 12 Metal products; 13 Computers/electronics; 14 Electrical equipment; 15 Industrial machinery; 16 Automotive; 17 Other transport equipment; 18 Toys/misc. manufacturing. Sources: International Federation of Robotics (IFR) and OECD Employment statistics.

Fig. 3: Participation in GVCs and robot adoption, 1995–2020



Notes. The top figure presents the evolution of average backward and forward participation in GVCs (left axis) and robot adoption (right axis) across the 56 countries included in the analysis. Participation in GVCs normalized to 1 in 1995 and weighted by country-industry output. Robot adoption corresponds to the global stock of robots per thousand workers (in all countries). *rho1* (*rho2*) is the temporal correlation between backward (forward) participation in GVCs and robot adoption. The bottom figure depicts the same trends but calculated for two mutually exclusive samples of 28 countries each: OECD and non-OECD. Sources: International Federation of Robotics (IFR) and OECD Employment and Trade in Value Added datasets (2023 edition).

Fig. 4: Population aging and robot adoption



Solid coef.: 0.61; SE: 0.24; R2: 0.24; N=56
Dashed coef. (excludes KOR and SGP): 0.27; SE: 0.10; R2: 0.15; N=54

Notes. The figure depicts the correlation between the average annual increase in robot adoption during 1995–2020 and population aging between 1990 and 2020 (measured as the change in the ratio of old-age workers (+56) to middle-age workers (21–55)). Blue (red) labels correspond to OECD (non-OECD) countries. Sources: International Federation of Robotics (IFR), OECD Employment statistics and United Nation's World population prospects.

Table 1: The effects of robot adoption on GVC, output, employment and wages

	OLS	2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. First-stage: Robot adoption							
Robot adoption (world)		4.791***	4.917***	4.842***	3.357***	3.248***	3.233***	4.450***
		(0.823)	(0.838)	(0.814)	(0.327)	(0.312)	(0.272)	(0.883)
R-squared		0.39	0.40	0.42	0.60	0.58	0.57	0.37
KP F-stat		32.2	32.6	33.4	99.1	102.9	130.2	24.0
	Panel B. Backward linkages in GVCs							
Robot adoption	0.099***	0.090***	0.094***	0.116***	0.172***	0.135**	0.140**	0.033
	(0.023)	(0.030)	(0.030)	(0.036)	(0.055)	(0.056)	(0.057)	(0.109)
	Panel C. Forward linkages in GVCs							
Robot adoption	0.010***	0.005***	0.006***	0.007***	0.009***	0.009***	0.009***	0.010**
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
	Panel D. Log output							
Robot adoption	0.011***	0.004	0.007***	0.007***	0.009***	0.008**	0.010***	0.016***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
	Panel E. Log employment							
Robot adoption	0.009***	0.007**	0.008***	0.008***	0.011***	0.010***	0.011***	0.018***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
	Panel F. Log average wage							
Robot adoption	0.000	−0.004**	−0.002	−0.002	−0.003	−0.003	−0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
	Panel G. Labor's share of value added							
Robot adoption	−0.000***	−0.000	−0.001	−0.001	−0.001	−0.001	−0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Number of countries	56	56	56	56	56	56	56	56
Number of industries	22	22	22	22	22	22	16	15
Observations	20927	20927	20927	20927	20927	20927	15219	14280
Covariates:								
VA per worker			✓	✓	✓	✓	✓	✓
Trade intensity			✓	✓	✓	✓	✓	✓
Log output			✓	✓	✓	✓	✓	✓
Backward part. GVC				✓	✓	✓	✓	✓
Forward part. GVC				✓	✓	✓	✓	✓
Robot adoption					✓	✓	✓	✓
Country x Year FE						✓	✓	✓
Sample:								
Manufacturing only							✓	✓
Excl. Automotive								✓

The table presents estimates of the effects of robot adoption on integration into GVCs (panels D and C), output (E), employment (F), average wage (G) and labor's share in value added (H) during 1995–2020. In columns 2 to 8, robot adoption is instrumented with global industry trends combined with cross-country variation in aging. Control variables subsequently added in colums 3-5 (and maintained in columns 6-8) are measured in 1995 and interacted with year dummies. Column 6-8 control for country × year fixed effects. Columns 7 and 8 restrict the sample to manufaturing industries only, and column 8 excludes the automotive industry. Two-way clustered standard errors that are robust against heteroskedasticity and correlation within countries and industries are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table 2: Integration into GVCs and employment growth

	OLS	2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. First-stage: Backward participation in GVCs								
Robot adoption (world)		0.420***	0.444***	0.553***	0.576***	0.437***	0.408**	−0.029
		(0.143)	(0.135)	(0.142)	(0.163)	(0.166)	(0.172)	(0.499)
R-squared		0.73	0.74	0.82	0.82	0.62	0.64	0.64
KP F-stat		8.2	10.2	14.4	11.9	6.6	5.2	0.0
Second-stage: Log employment								
Backward participation in GVCs	0.025***	0.089**	0.086***	0.072***	0.066***	0.074**	0.056**	−0.836
	(0.006)	(0.039)	(0.033)	(0.026)	(0.021)	(0.030)	(0.028)	(15.315)
Panel B. First-stage: Forward participation in GVCs								
Robot adoption (world)		0.023***	0.027***	0.034***	0.029***	0.029***	0.031***	0.045**
		(0.007)	(0.005)	(0.009)	(0.007)	(0.008)	(0.008)	(0.021)
R-squared		0.48	0.50	0.83	0.84	0.83	0.82	0.82
KP F-stat		9.8	22.2	15.2	14.9	11.9	12.4	4.3
Second-stage: Log employment								
Forward participation in GVCs	0.349***	1.648***	1.429***	1.162***	1.297***	1.117***	0.739**	0.532
	(0.096)	(0.606)	(0.498)	(0.370)	(0.378)	(0.379)	(0.293)	(0.805)
Number of countries	56	56	56	56	56	56	56	56
Number of industries	22	22	22	22	22	22	16	15
Observations	20988	20988	20988	20988	20927	20927	15219	14280
Covariates:								
VA per worker			✓	✓	✓	✓	✓	✓
Trade intensity			✓	✓	✓	✓	✓	✓
Log output			✓	✓	✓	✓	✓	✓
Backward part. GVC				✓	✓	✓	✓	✓
Forward part. GVC				✓	✓	✓	✓	✓
Robot adoption					✓	✓	✓	✓
Country x Year FE						✓	✓	✓
Sample:								
Manufacturing only							✓	✓
Excl. Automotive								✓

The table presents estimates of the relation between participation in GVCs and employment during 1995–2020. Both backward participation in GVCs (panel A) and forward participation in GVCs (panel B) are instrumented with global industry trends combined with cross-country variation in aging. Specifications in columns 1 to 8 are the same as in Table 1. Two-way clustered standard errors that are robust against heteroskedasticity and correlation within countries and industries are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table 3: Lagged integration into GVCs and robot adoption

	OLS	2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. First-stage: Lagged backward participation in GVCs								
Lagged robot adoption (world)		0.471***	0.462***	0.579***	0.600***	0.468***	0.443**	−0.033
		(0.153)	(0.140)	(0.146)	(0.163)	(0.175)	(0.181)	(0.487)
R-squared		0.73	0.74	0.82	0.82	0.63	0.66	0.65
KP F-stat		9.3	11.4	14.7	12.7	6.8	5.6	0.0
Second-stage: Robot adoption								
Lagged backward part. in GVCs	0.2*	10.9***	11.0***	8.9***	6.2***	7.7**	8.1**	−141.3
	(0.1)	(3.4)	(3.3)	(2.6)	(1.8)	(3.0)	(3.4)	(2104.1)
Panel B. First-stage: Lagged forward participation in GVCs								
Lagged robot adoption (world)		0.027***	0.029***	0.032***	0.028***	0.028***	0.029***	0.038*
		(0.007)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)	(0.020)
R-squared		0.48	0.50	0.84	0.84	0.84	0.83	0.83
KP F-stat		14.8	37.1	19.1	17.5	14.7	14.6	3.3
Second-stage: Robot adoption								
Lagged forward part. in GVCs	5.1*	193.8***	172.7***	159.7***	131.9***	128.7***	122.1***	121.5**
	(2.8)	(34.6)	(24.5)	(32.8)	(26.9)	(29.4)	(28.7)	(56.2)
Number of countries	56	56	56	56	56	56	56	56
Number of industries	22	22	22	22	22	22	16	15
Observations	20751	20751	20751	20751	20751	20751	15091	14160
Covariates:								
VA per worker			✓	✓	✓	✓	✓	✓
Trade intensity			✓	✓	✓	✓	✓	✓
Log output			✓	✓	✓	✓	✓	✓
Backward part. GVC				✓	✓	✓	✓	✓
Forward part. GVC				✓	✓	✓	✓	✓
Robot adoption					✓	✓	✓	✓
Country x Year FE						✓	✓	✓
Sample:								
Manufacturing only							✓	✓
Excl. Automotive								✓

The table presents estimates of the relation between lagged participation in GVCs and robot adoption during 1995–2020. Both lagged backward participation in GVCs (panel A) and lagged forward participation in GVCs (panel B) are instrumented with lagged global industry trends combined with cross-country variation in aging. Specifications in columns 1 to 8 are the same as in Tables 1 and 2. Two-way clustered standard errors that are robust against heteroskedasticity and correlation within countries and industries are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

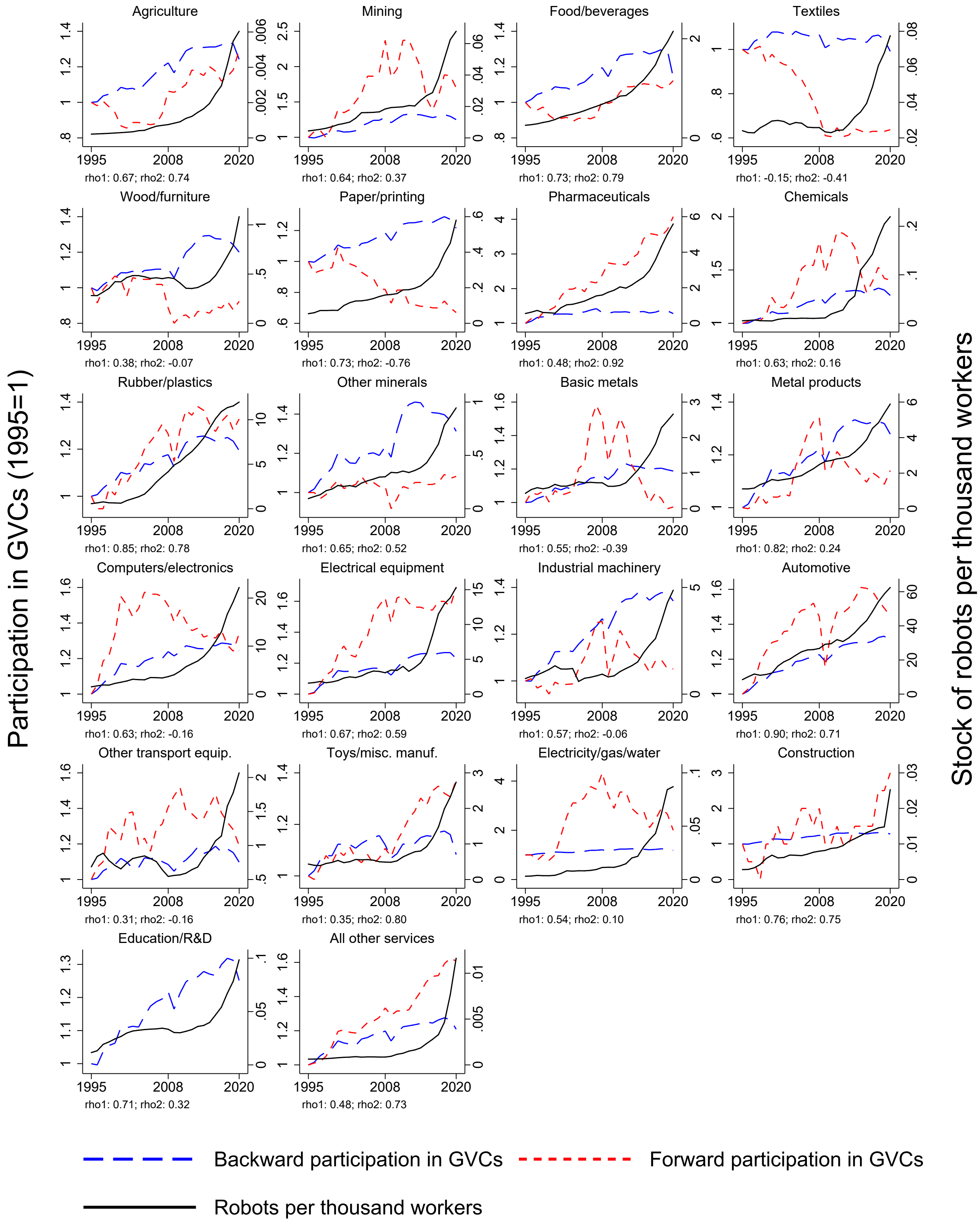
Table 4: Robot adoption among trade partners

	OLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Robot adoption						
Robot adoption in source countries	−0.753	−0.538	−0.504	−0.242	−0.255	−0.154	−4.139
	(1.291)	(1.329)	(1.198)	(0.934)	(0.899)	(0.893)	(2.555)
Robot adoption in destinations	6.855***	6.732***	6.440***	3.537***	3.454***	3.369***	7.353***
	(1.114)	(1.084)	(0.949)	(0.630)	(0.662)	(0.691)	(2.277)
R-squared	0.42	0.42	0.44	0.63	0.61	0.61	0.39
Number of countries	56	56	56	56	56	56	56
Number of industries	22	22	22	22	22	16	15
Observations	20927	20927	20927	20927	20927	15219	14280
Covariates:							
VA per worker		✓	✓	✓	✓	✓	✓
Trade intensity		✓	✓	✓	✓	✓	✓
Log output		✓	✓	✓	✓	✓	✓
Backward part. GVC			✓	✓	✓	✓	✓
Forward part. GVC			✓	✓	✓	✓	✓
Robot adoption				✓	✓	✓	✓
Country x Year FE					✓	✓	✓
Sample:							
Manufacturing only						✓	✓
Excl. Automotive							✓

The table presents estimates of the relation between robot adoption in source and destination countries and domestic robot adoption during 1995–2020. Robot adoption in source (destination) countries is a weighted average (of global industry trends combined with cross-country variation in aging) across source (destination) countries in each industry, with weights that correspond to the 1995's industry import (export) share of each country. Specifications in columns 1 to 7 are the same as in columns 2 to 8 of Tables 1, 2 and 3. Two-way clustered standard errors that are robust against heteroskedasticity and correlation within countries and industries are in parentheses. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Additional figures and tables

Fig. 5: Participation in GVCs and robot adoption, by industry



Notes. The figures present the evolution of average backward and forward participation in GVCs (left axis) and robot adoption (right axis) across the 56 countries included in the analysis during 1995–2020, by industry. Participation in GVCs are normalized to 1 in 1995. Robot adoption corresponds to the global industry stock of robots per thousand workers (in all countries). *rho1* (*rho2*) is the temporal correlation between backward (forward) participation in GVCs and robot adoption. Sources: International Federation of Robotics (IFR) and OECD Employment and Trade in Value Added datasets (2023 edition).