Robots and global value chains

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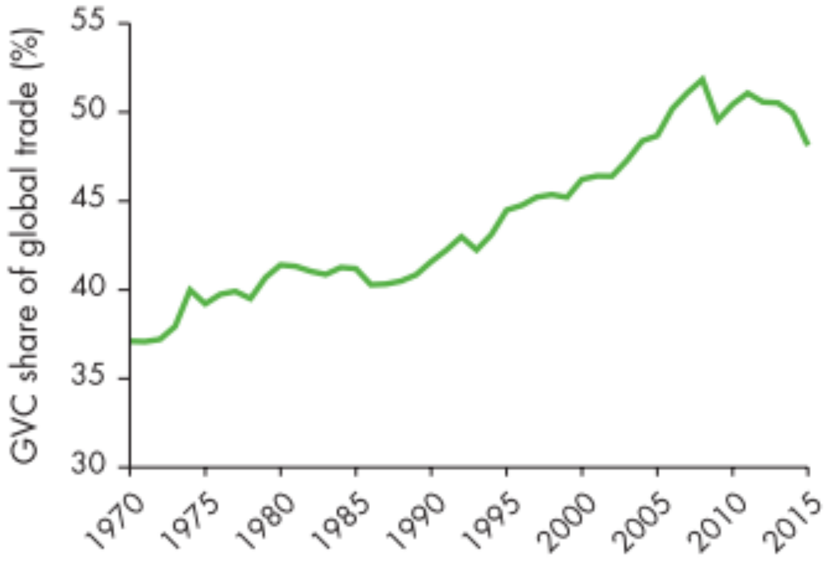
Stylised facts #1

- Rise in GVC participation that started in the 90's (favoured by ICT) is progressively declining (Los et al., 2015; Antras, 2020)

- **Slowering** of offshoring + rise of reshoring/backshoring/nearshoring (Krenz and Strulik, 2021, Marvasi 2023; Pinheiro et al. 2023)
- **Heterogeneous** motivations behind this trend → cost advantage of low-wage countries … but **cost differences** among countries are progressively eroding

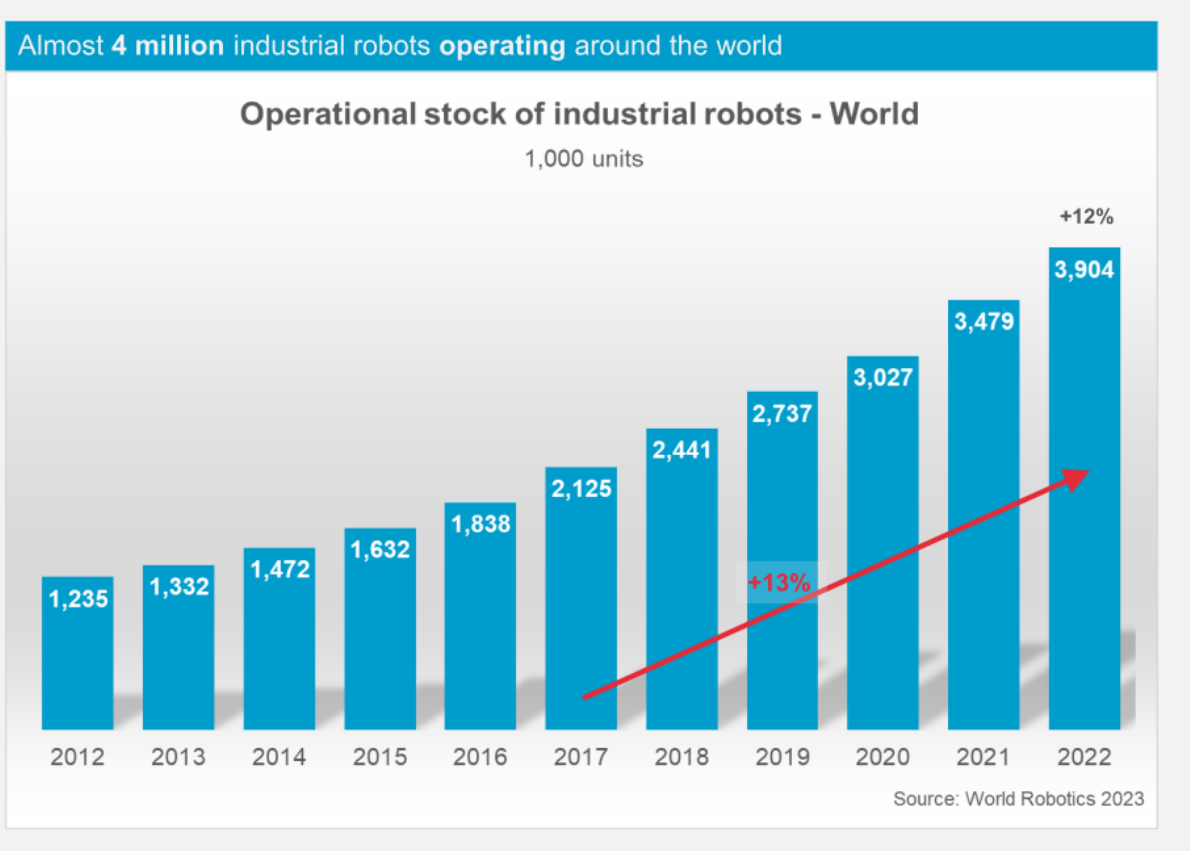


Source: World Bank, 2020

Stylised facts #2

- **Increasing** investments of firms/sectors in automation technology, especially **industrial robots** and I4.0

- Driven by **many** motivations (e.g. decline of production costs of robots)



Research question

What is the linkage between these two trends?

- Higher levels of robot adoption can drive the relocation of production back home → productivity gains from automation → **lower** need to save on labour costs via offshoring
- Higher robot-induced productivity → **greater** offshoring due to a higher demand for intermediate inputs and components
- Empirical literature thus far provides **ambiguous** evidence → job displacement and productivity effects

The two streams of literature (GVC dynamics and effects of automation adoption) have evolved quite **independently**

GVC dynamics

- **Main research questions analyzed**:
  - What are the factors that generated the **expanding trend** of GVC and **their impacts** ?(e.g. Alcácer et al., 2016; Buckley and Strange, 2015) → **theoretical** perspectives and **measurement** issues (e.g Kano et al. 2020; Antras and Chor, 2021)
  - Drivers of GVC reconfiguration and **regionalization process** (Bontadini et al. 2022; Zhan 2021; Bolea et al. 2022) → push and pull factors of backshoring\reshoring (Di Mauro et al. 2018; Platanesi and Araunzo-Carod,2019)

- Scant attention given to the consideration that **new technologies** can alter **the determinants** of global production favouring reshoring (e.g. Dachs 2019; Ancarani et al. 2019; De Backer et al. 2018; Kamp an Gibaja, 2021)
- Investigated the role of Industry 4.0 in **changing the geographical configuration of GVC** (e.g. Dachs et al. 2019; Ancarani, 2019; Kinkel et al. 2023) but not clear consensus (e.g. Blázquez et al. 2023, Cigna et al. 2022)

Robot literature: impact through GVC/trade

Channels at work:

1. **Displacement** effects → lower demand for goods produced abroad (production reshoring)
2. **Productivity** effects → increased demand for intermediates
   - Expedite production avoid outsourcing of tasks to geographically distant suppliers that are challenging to monitor

Results ambiguous :

- Stemmler (2023) for Brazil, Faber for Mexico (2020) and Kugler for Colombia (2020) find that robot adoption in the North **generates negative impact on employment and exports (LLM approach)**

- Cilekogu (2024), Stapleton and Webb (2021) for Spain, Baur et al. (2022) for Latin America find that **firm level** robot adoption **increase total sourcing activities → Artuc et al. (2023) the same from country/sector perspective**

- DeBacker et al. (2018) small effect on forward GVC participation, Carbonero et al. (2020) find **decrease** in the international sourcing of intermediates and employment in emerging countries but **no effect on reshoring (country-sector)**

- Krenz et al. (2021) & Krenz and Strulik (2021): **positive effect on reshoring (cross-country/sector data) but no role of GVC dynamics** (see also Gravina and Pappalardo, 2022)

Our contribution

- Assess the causal nexus between robots and GVC boundaries at the macroeconomic level → Analysis of the long-run relationship between robot exposure and the dynamics of GVC participation

- Certain key characteristics of the sectors may play a relevant role in shaping the relationship between robots and GVCs → macro-meso level perspective

- Geography of GVC: Home Vs Neighborhood Vs Periphery

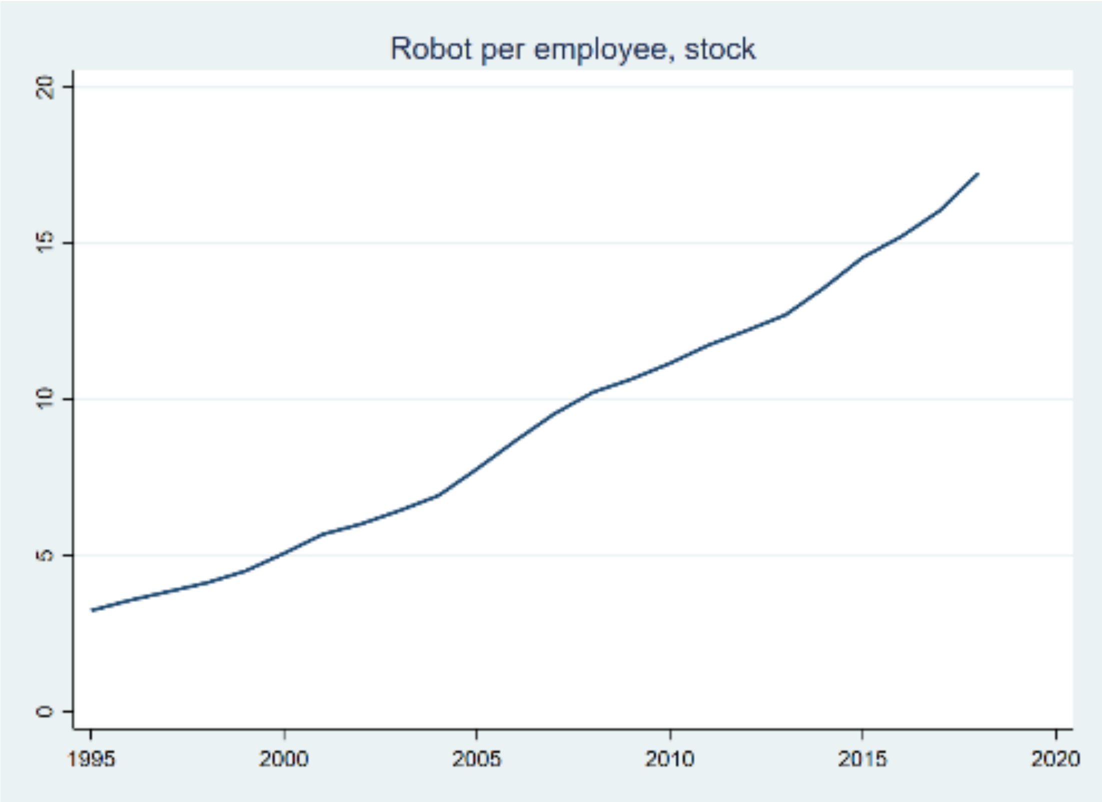
Technology can not only disrupt production processes but also provide incentives for backshoring/nearshoring events, thereby causing both regionalization and further globalization

Data

7 European countries: **Finland, France, Germany, Italy, Spain, Sweden, UK**

- Robot exposure ➔ **International Federation of Robots (IFR)**
  - An **industrial robot** is defined as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR, 2020, p. 23)
  - Data available from 1995 to 2018 at the **country** and **sector** level (10 2-digit)
  - Combine IFR data on operational stocks with data on the number of employees in each country and two-digit industry provided by the OECD STAN database (1995)
- Countries and sectors' **participation in GVC**: **OECD Inter-Country Input-Output (ICIO) 2021 release** ➔ sectors' harmonization with IFR and OECD-STAN
- For each of the 10 manufacturing sectors we consider the **gross value added of exports** originating from **low-wage countries (FVA)**

Average robot exposure, trend



Increasing trend in the average robot exposure from 1995 to 2018 for our seven **home countries**

Geography of GVC (1)

- Home (H): FVA from Finland, France, Germany, Italy, Spain, Sweden, UK
- Neighbourhood (N): FVA from **close countries** in the same region (EU27+UK)

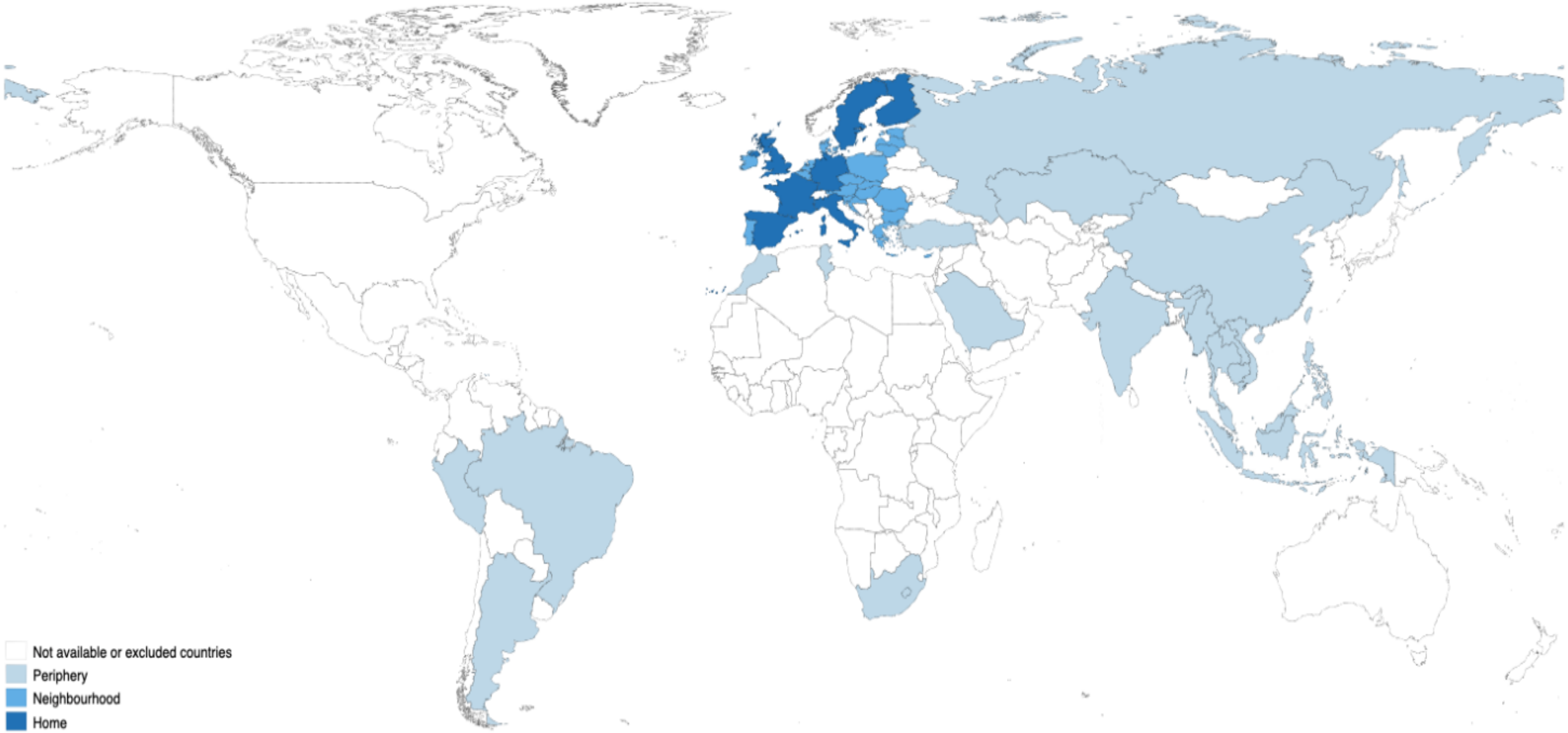
[focus on East-EU]

- Periphery (P): FVA from **other countries outside the EU-28 region**

[focus on Asia]

Source region	FVA 1995	FVA 2018	% $\Delta FVA_{1995\text{-}2018}$	FVA 1995-2018
Home (H)	25413.6	33455.3	31.64	31244.5
Neighbourhood (N)	1645.27	4487.09	172.7	2978.93
Periphery (P)	1153.73	3305.99	186.5	2345.61
East-EU	277.248	2040.11	635.8	1124.38
Asia	546.874	1632.94	985.9	1120.29

Geography of GVC (2)



Indicators: strong vs weak GVC regionalization

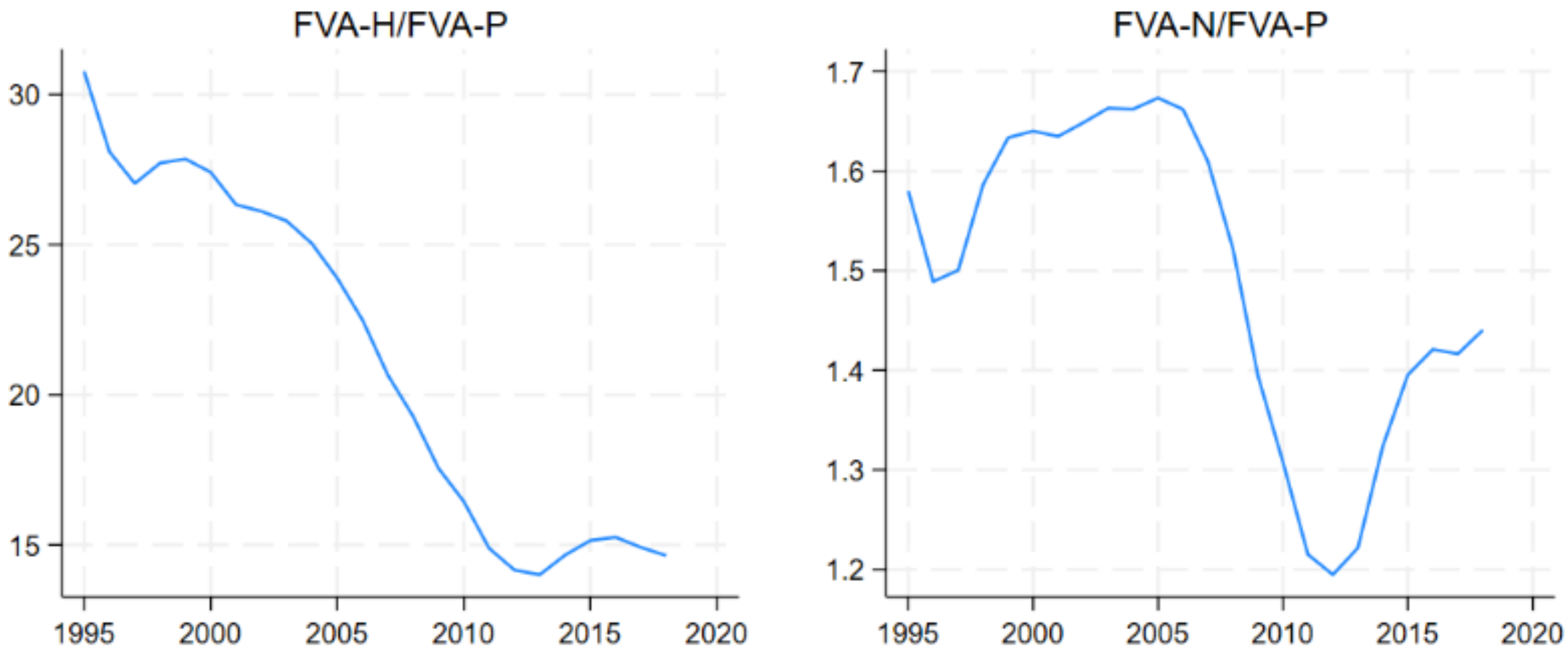
- We consider the share of gross value added of exports (FVA) originating from home, or neighbouring countries, with respect to the FVA originating from peripheral countries (Krenz and Strulik, 2021):

- $\frac{\mathrm{H}}{\mathrm{P}}$ → *«Strong»* regionalization: from the periphery to the home regions

- $\frac{\mathrm{N}}{\mathrm{P}}$ → *«Weak»* regionalization: from periphery to neighbourhood

Sector	Nace Rev. 2	*ROBOT*	*H/P*	*N/P*
Food & Beverages	10-12	4.478	59.14	2.226
Textile & Clothing	13-15	0.435	12.60	1.837
Wood & Paper	16-18	1.854	44.98	2.034
Coke	19	21.94	17.28	1.693
Chemicals, Pharma	20-21	0.051	7.990	0.963
Rubber & Plastics	22-23	7.393	21.18	1.513
Basic metals	24-25	8.931	17.93	1.287
Computer & Electronics	26-27	5.196	10.03	1.098
Machinery & Equipment	28	5.844	8.318	0.840
Motor vehicles	29-30	45.76	12.67	1.411

GVC trends


FVA-H/FVA-P
30
25
20
15
1995
2000
2005
2010
2015
2020
FVA-N/FVA-P
1.7
1.6
1.5
1.4
1.3
1.2
1995
2000
2005
2010
2015
2020

Empirical strategy in 4 steps

1. Second generation **unit root tests** (CIPS) (Pesaran, 2007)

2. Second generation **cointegration** tests (Westerlund, 2007)

3. **Dynamic OLS (DOLS)** regressions + **FMOLS** (Kao and Chang 2000; Pedroni 2000)

4. Test of the direction of causality – **short run and long run (PVECM)**

Step 1: Unit root test (2nd generation Pesaran 2007)

$$\Delta y_{it} = \beta_i y_{it-1} + \gamma_i \overline{\Delta y}_{it} + \delta_i y_{t-1} + \mu_i + \varepsilon_{it}$$

- Individual ADF equation augmented with cross-sectional averages of lagged levels and first dif of the series, as proxy for unobserved common factors
- CIPS test: the variable has a **unit root** under the null

Panel A: robot exposure	CIPS
Levels (c, t)	
*ln*ROBOT	-1.439
First differences (c)	
Δ*ln*ROBOT	-3.379***
Panel B: GVC variables	CIPS
Levels (c, t)	
*ln*H/P	-2.221
*ln*N/P	-2.084
*ln*H/Asia	-2.155
*ln*N/Asia	-2.475
*ln*East/P	-2.517
First differences (c)	
Δ*ln*H/P	-2.588***
Δ*ln*N/P	-2.780***
Δ*ln*H/Asia	-2.855***
Δ*ln*N/Asia	-3.450***
Δ*ln*East/P	-3.387***

The CIPS tests reveal that all our variables **are non-stationary**, or I(1)

Step 2: Cointegration test (2nd generation Westerlund, 2007)

- $\Delta y_{it} = \delta_i' d_t + \alpha_i(y_{it-1} - \beta_i' x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=-q_i}^{p_i} \Delta x_{it-j} + u_{it}$

Panel A	G_τ	G_α	P_τ	P_α
*ln*ROBOT→*ln*H/P	-2.073***	-5.541**	-17.43**	-4.949**
*ln*ROBOT→*ln*N/P	-2.486***	-6.209**	-20.94***	-6.361***
*ln*ROBOT→*ln*H/Asia	-1.455	-2.616	-9.515	-1.572
*ln*ROBOT→*ln*N/Asia	-3.595***	3.929	-1.560*	2.261
*ln*ROBOT→*ln*EastEU/P	-2.180**	-5.072	-20.18***	-6.672***
*ln*ROBOT→*ln*EastEU/Asia	-2.522***	-5.768*	-15.84**	-5.540**

Panel B	G_τ	G_α	P_τ	P_α
*ln*H/P → *ln*ROBOT	-1.061	-2.824	-6.769	-2.062
*ln*N/P → *ln*ROBOT	-1.883	-4.823	-13.44	-4.597
*ln*H/Asia → *ln*ROBOT	-0.965	-3.240	-2.819	-0.723
*ln*N/Asia → *ln*ROBOT	-1.058	-2.610	-9.623*	-2.100
*ln*EastEU/P → *ln*ROBOT	-1.198	-2.564	-8.298	-1.527
*ln*EastEU/Asia →*ln*ROBOT	-1.036	-2.369	-7.393	-1.294

H_0: α_i=0
H_1: α_i<0 ➔ EC at work

Cointegration: the null Ho tests the absence

X (Robots) should be weakly exogenous → long run causality

- No omitted I(1) variables
- Robust to omitted I(0) var: invariant to model extensions

Step 3: Dynamic OLS (Kao and Chang, 2000)

$$y_{it} = \mu_i + \gamma f_t + \beta lnROBOT_{it} + \sum_{j=-k}^{k} \lambda_{ij} \Delta lnROBOT_{it} + \epsilon_{it}$$

- **Robust** to **omitted** variables but we include ICT and Machinery
- **De-meaned** data to control for unobserved common factors
- But…pooled estimators **may yield biased estimates** of the sample mean of the individual coefficients when the true slope coefficients are heterogeneous
- Group-Mean panel DOLS and FMOLS (Pedroni 2000) **to account for heterogeneous slope coefficients ➔** estimate separate country-sector DOLS/FMOLS regressions and average the individual βs

Results: Home Vs. Periphery

DEP. VAR. *ln*(H/P)	(1) DOLS	(2) DOLS-GM	(3) FMOLS	(4) FMOLS-GM	(5) DOLS	(6) DOLS-GM
*ln*ROBOT	-0.015***	0.08**	-0.011***	0.09**	-0.029***	0.06**
	(0.004)	[10.18]	(0.001)	[14.42]	(0.004)	[8.20]
lnK_{IT}					0.128***	0.63**
					(0.012)	[23.46]
lnK_{MACH}					-0.019	-0.41**
					(0.013)	[-10.84]
Demeaned data	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.936		0.852		0.939	
CD test Pesaran (2015)	-3.004***		-3.038***		-3.061***	
N. countries-sectors	70	70	70	70	70	70
N. obs.	1677	1677	1679	1679	1677	1677

- 10% increase in exposure to industrial robots corresponds to an average 0.15% decrease in *H/P* → decrease in the strong regionalization of GVCs…but **the presence of outliers** may impact the results

- Results turns positive with GM estimators (70 separate country-specific DOLS regressions) → regionalization **increase**

Results: Neighborhood Vs. Periphery

DEP. VAR. *ln*(N/P)	(1) DOLS	(2) DOLS-GM	(3) FMOLS	(4) FMOLS-GM	(5) DOLS	(6) DOLS-GM
*ln*ROBOT	0.109***	0.17***	0.106***	0.16***	0.104***	0.18**
	(0.001)	[36.26]	(0.002)	[49.16]	(0.002)	[24.50]
lnK_{IT}					0.101***	0.10**
					(0.007)	[6.83]
lnK_{MACH}					-0.057***	-0.11
					(0.008)	[-2.11]
Demeaned data	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	No	Yes	No	Yes	No
R^2	0.895		0.760		0.899	
CD test Pesaran (2015)	-1.887*		-1.887*		-2.002**	
N. countries-sectors	70	70	70	70	70	70
N. obs.	1677	1677	1679	1679	1677	1677

10% increase in the robot stock per employee corresponds to an average 1-1.8% increase in (weak) GVC regionalization in the long run

Results: alternative indicators

Dep. Var. *ln*(N/Asia)	(1) DOLS	(2) DOLS-GM	(3) FMOLS	(4) FMOLS-GM	(5) DOLS	(6) DOLS-GM
*ln*ROBOT	0.305***	0.27***	0.284***	0.29***	0.246***	0.27***
	(0.006)	[78.33]	(0.002)	[92.85]	(0.005)	[40.69]
lnK_{IT}					0.174***	-0.25
					(0.014)	[-2.07]
$\ln K_{MACH}$					0.316***	0.48**
					(0.015)	[22.63]
Demeaned data	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	No	Yes	No	Yes	No
R^2	0.968		0.908		0.971	
N. countries-sectors	70	70	70	70	70	70
N. obs.	1677	1677	1679	1679	1677	1677

Higher exposure to automation yields a decrease in the FVA originating from peripheral regions

Dep. Var. *ln*(EastEU/P)	(1) DOLS	(2) DOLS-GM	(3) FMOLS	(4) FMOLS-GM	(5) DOLS	(6) DOLS-GM
*ln*ROBOT	0.011**	0.09**	0.003	0.10***	-0.002	0.10**
	(0.005)	[12.33]	(0.003)	[33.51]	(0.0097	[10.20]
lnK_{ICT}					-0.033	0.15**
					(0.022)	[16.67]
$\ln K_{MACH}$					0.086***	0.17*
					(0.025)	[4.34]
Demeaned data	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	No	Yes	No	Yes	No
R^2	0.903		0.788		0.904	
N. countries-sectors	70	70	70	70	70	70
N. obs.	1677	1677	1679	1679	1677	1677

Direction of causality: PVECM

- **Short-run** and **long-run** causality tests (Hall and Milne 1994; Herzer 2012; Herzer et al. 2018)
- To capture the direction of such a causality, we run two regressions
  - **Direct** regression: H/P (and N/P) as dependent variables
  - **Reverse** regression: ROBOT as dependent variable
- Testing for strong exogeneity of ROBOT in a system of two cointegrated variables means that ROBOT **is not Granger caused** by GVC variables in the **short** and in the **long** run
- Two-step procedure
  - Compute the EC from the DOLS regression: $EC_i = GVC_i - (c_i - \beta_{DOLS} ROBOT_i)$
  - Estimate two separate ECM regressions:

- $\Delta ln\left(\frac{H}{P}\right)_{it} = \mu_{1i} + \alpha_1 EC_{it-1} + \varphi_{11} \Delta ln\left(\frac{H}{P}\right)_{it-1} + \varphi_{12} \Delta lnROBOT_{it-1} + \varepsilon_{it}$
- $\Delta lnROBOT_{it} = \mu_{2i} + \alpha_2 EC_{it-1} + \varphi_{21} \Delta lnROBOT_{it-1} + \varphi_{22} \Delta ln\left(\frac{H}{P}\right)_{it-1} + \epsilon_{it}$

Weak exogeneity test: $\alpha_{1,2}=0$

Short-run Granger non-causality test: $\varphi_{11,21}=0$

Strong exogeneity test: $\varphi_{11,21}=\alpha_{1,2}=0$

Results: PVECM

- Null hypothesis of weak exogeneity **is rejected** for $\Delta ln\frac{H}{P}$ whereas **it is not rejected** for ΔlnROBOT
- Robotization affects GVC dynamics **also in the short run**, but not vice versa
- **Strong exogeneity test**: the direction of causality **runs from robotization to GVC regionalization**, and not vice-versa

A. Dependent variable: ΔlnH/P		Coefficient
Weak exogeneity test		
Coeff EC = 0	180.8***	
	[0.000]	
Short-run Granger non-causality test		
Coeff ΔlnROBOT=0	3.80*	0.023*
	[0.051]	(0.012)
Strong exogeneity test		
Coeff EC= coeff ΔlnROBOT = 0	90.80***	
	[0.000]	
Demeaned data	Yes	
Adjusted R^2	0.280	
Nr. Countries	70	
Nr. Obs.	1,540	

B. Dependent variable: ΔlnROBOT		Coefficient
Weak exogeneity test		
Coeff EC = 0	2.78	
	[0.096]	
Short-run Granger non-causality test		
Coeff ΔlnH/P=0	1.53	0.061
	[0.216]	(0.050)
Strong exogeneity test		
Coeff EC= coeff ΔlnH/P = 0	2.49*	
	[0.085]	
Demeaned data	Yes	
Adjusted R^2	0.048	
Nr. Countries	70	
Nr. Obs.	1,540	

Regionalisation and sectoral heterogeneity

The results achieved can be driven by **two** characteristics of the manufacturing sectors:

- **Labour intensity:** sectors where labour is used more intensively than capital, **are those where investments in robots have more scope to substitute for labour →** spurring the regionalization of GVCs
- **Upstreamness: average distance from final use →** captures the extent to which a sector is positioned at the beginning of the production process
  - The regionalization of the European GVCs **involves the upstream stages of production** rather than the downstream ones (Bontadini et al. 2023)
  - Sectors characterized by high degrees of upstreamness are those that often produce **intermediate goods demanding complex tasks and skills and substituting low-skill, routinary, standardized ones** (Fontagnè et al., 2023)
  - The more a sector is upstream, the higher will be the propensity to relocate close to the home region

- **Labour** intensity: L/K
- Indicator of **upstreamness** (GVC_{UP}) is computed from Antras and Chor (2013, 2018): weighted average position of a country-(three-digit) industry's gross output in GVCs **relative to final demand**
- The impact of lnROBOT on lnN/P is estimated in the two subperiods, 1995-2008 and 2009-18 (following the results of structural break test)

A. *ln*H/P	DOLS-GM	GVC_{UP} High	GVC_{UP} Low
L/K	High	0.25**	0.04
	Low	-0.06	-0.02

B. *ln*N/P	1995-2008 DOLS	GVC_{UP} High	GVC_{UP} Low
L/K	High	0.218***	0.038
	Low	-0.046	0.091

C. *ln*N/P	2009-2018 DOLS	GVC_{UP} High	GVC_{UP} Low
L/K	High	0.556***	-0.111***
	Low	-0.730***	0.086

The long-run effect of automation on the regionalization of GVC holds **where there is more room for robots to replace** unskilled/routine labour and **complement** knowledge-intensive functions

Conclusions

- **Evidence of long-run (non-spurious) relationship running from robot exposure to GVC regionalization**
  - Higher exposure to industrial robots of countries and sectors → higher contribution to foreign value added from neighbouring European countries than from peripheral extra-European economies.
  - Even stronger when we restrict the neighbouring countries to Eastern Europe and the peripheral countries to South and Eastern Asia
- Country-sector **heterogeneity matters** → Pattern more evident for high-upstreamness sectors and labour intesive
- Automation, together with ICTs, played a significant role in keeping the European value chains mostly **regional,** at least from the input sourcing side.
  - EU labour markets → the increasing exposure to industrial robots did not generate wide phenomena of job losses or mass unemployment (Dachs et al. 2019).