Robots and Global Value Chains

*** PRELIMINARY VERSION: NOT TO BE QUOTED ***

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Abstract

In this paper, we study whether, and to what extent, the exposure to industrial robots for a set of advanced European countries leads to the regionalization of their global value chains. We employ country-industry-year data for the period 1995-2018 from OECD-ICIO and we merge it with robot data from the IFR. To assess the non-spurious long run relationship between robots and GVC dynamics, we adopt a panel cointegration approach and dynamic OLS. Our results suggest that sectoral heterogeneity matters: on average, a higher exposure to robotization Granger causes a lower degree of GVC regionalization, but we also find many sectors for which GVC become more regional. Specifically, these sectors are those characterized by a higher degree of upstreamness, in which robots tends to substitute more intensively for routinary tasks and labour.

Keywords: global value chains, industrial robots, panel cointegration, regionalization

1. Introduction

Since the 2007 global financial crisis, countries' participation in global value chains (GVC) started slowly and steadily decreasing. This trend became even more pronounced in the early 2020s with the deployment of COVID-19 on a global scale, leading the Economist to formulate the term 'slowbalization'. While in the 80s' and '90s when reached its peak the main trend was characterized by process of production delocalization thanks to the unfolding ICT revolution, a relocation back to home countries has been recently observed. A quite large amount of international business literature has provided some theoretical and empirical evidence on the factors that can push or pull the processes of relocation (e.g. Di Mauro et al. 2018; Strange and Zucchella 2017, Pinheiro 2023). Although these motivations can be many and heterogenous one of the first that is considered to have triggered the progressive delocalization of production is cost advantage of low wage countries. As the cost difference among countries is progressively eroding, further motivations such as the searching for better quality control, lower coordination costs and a strategical correction of previous offshoring decisions has started to play their role as well. In the description of the evolution of the GVC dynamics, the literature has started to question about the transformation of the way they organize. This happened mainly in response to the pandemics (e.g. Pla-Barber et al. 2021), but it started to be a point of investigation also in previous years as the GVC geography and its alternative trend of tightening and widening called for further interest (e.g, Hernández and Pedersen, 2017).

At the same time, another global trend that has rapidly emerged refers to the installation of automation technologies within production processes. The technologies implied are all those related to the Industry 4.0 (e.g. Ancarani et al. 2019), but, in this work, we refer in particular to the role played by robot installations. The increasing propensity of firms to invest in automated technology is the outcome of three factors: the declining price of robots, the declining interest rates, and the rising uncertainty generated by the financial crisis (Graetz and Michels, 2018 Marin, 2018; IFR, 2020; Fernàndez-Macias et al., 2021). This last aspect might have led companies in advanced economies to use robots to replace routine jobs and reduce labor costs (Acemoglu and Restrepo, 2018, 2019, 2020) instead of transferring production to low-wage countries.

Theoretical predictions about both positive and negative linkages between the two trends have been proposed: on the one side higher levels of robot adoptions can generate a process of relocation of production back to home countries, thus acting towards a process of GVC regionalization, as an increase in productivity may occur, fostering competitive production that does not rely only on cost advantages. On the other side, the same productivity increase may generate greater offshoring, because of the greater need of intermediate inputs, that through ICT can be easily handled. In this case, the mechanisms act in the opposite direction that is a further GVC spreading (Artuc et al. 2022). The empirical literature so far provides ambiguous predictions on this topic as growing robot adoption has generated both a displacement and a productivity effect. A recent meta-analysis provides evidence of a quite significant effect of reshoring (Pinheiro et al., 2023) even though has been found that the level of analysis and structure of data may play a role as well. Indeed, the micro-level literature has adopted only an indirect measure of reshoring as opposed to offshoring finding ambiguous for different countries (e.g., Faber, 2020; Stapleton and Webb 2021).

Only Krenz et al. (2021) and Krenz and Strulik (2021) adopt a macro-perspective (country-sector) which is like the one we adopt: however, the do not consider the role played by geography as the country/region of sourcing of the value added that it is used in exports is not provided. Moreover, they just focus on the process of offshoring without considering whether through this channel GVC breadth is going to be affected.

Our perspective is a bit different as it implies the consideration of the fact that the GVC dynamics may have changed recently due to the likely impact of automation, in particular by spurring a process of GVC shrinkage that has occurred especially after the stagnation in international trade following the financial crisis, but also because of other determinants at the country/sector level. These two fields of research have not been examined in connection so far.

From an empirical point of view, we study the robot-GVC relationship by focusing on seven developed economies in Europe for which we have detailed information at country-industry-year level. We test whether industries most exposed to industrial robots are also those for which a lower share of the gross value-added of exports originates from out-of-region low-wage countries distinguishing among different geographical areas according to their distance from Europe. In this way, we are able to track the GVC dynamics over the years making it possible to understand whether the impact of robots has been a driver of GVC regionalization.

We expect that higher exposure to robots reduces the contribution of both peripheral and neighboring low-wage countries to the gross value added of exports. In the latter, instead, we should find that higher robot exposure per employee corresponds to a lower contribution to the gross value added of exports of the periphery, and a higher contribution of the neighborhood. In this way, we try to understand whether the robot upheaval is an explanation for the lower GVC participation of countries in the last decade (Antras and Chor 2018, 2021; Bontadini et al., 2022).

On top of this, we also run a sectoral analysis by testing whether the robot-GVC dynamics varies across the available industries. Indeed, the participation of countries and sectors to GVC can be affected by many determinants that can depict an heterogenous framework (Fernandes et al. 2022).

Our empirical analysis relies on two main data sources. To measure robot exposure, we use data on industrial robots installations and operational stocks from the International Federation of Robots (IFR). Data on robots are available from 1995 to 2018 at the country and sector level only for the seven European countries mentioned above. We combine these data with information on countries and industries' participation in GVC come from the OECD-ICIO database and the underlying input-output tables. We get to a dataset made up of 10 manufacturing sectors available in each country in 8 countries for 24 years.

The rest of the paper is organized as follows: in Section 2 we provided an overview of the streams of literature dealing with the robot adoption and GVC evolution.

Section 3 provides description of the data used and some descriptive evidence of the variables at stake. Section 4 considers the methodology and section 5 presents the results and discussion. Section 6 concludes.

2. Related literature

The concept of GVC has come into light several years ago when it became important to describe in detail the process that was unfolding in international markets due to the increasing fragmentation of production. Indeed, the focus on specific tasks to be carried out rather than just final product (Gereffi, 1994) was the idea underlying the multifold concept of GVC for which the back-and-forth trade of intermediates across at least two countries is considered as the core idea (Antras 2021; Amador and Cabral, 2016).

The share of trade passing through GVC backward or forward linkages has evolved at a high pace since the beginning of the'90s moved by several causes and, among them the most relevant are the role of falling trade barriers as well as that of ICT adoption (Alcácer et al. 2016) this expanding trend has had quite relevant impact on growth of firms and countries as the breaking up of different parts of the production process to the highest extent has also led firms and countries to achieve progressively higher efficiency (World Bank 2020).

However, a decreasing trend started to become visible over the years 2007-2009 mainly because of the eruption of the global financial crisis that impacted the production networks to a large extent. This shift is partly continuing nowadays because of several reasons such as trade wars, the Covid pandemic but also the way firms are modifying their production processes due to the adoption of new technologies (Javorick 2020; Antras 2020). In describing the evolving trend of GVC transformation, Zhan (2021) evidenced that the dynamics is going toward a regionalization rather than a further globalization of value chains. This is in line with a literature that revolves around the investigation of the drivers of GVC reconfiguration (Hernández and Pedersen, 2017).

Over the period of fast globalization firms' decisions of where to locate their production was quite easy to make as the cost minimizing choice led them to offshore their production where the costs, and especially labour costs, were lower. This choice, favoured by the large labour costs differences among countries, was also one of the ways to remain competitive on the market. Having access to new resources not available at home, such as skilled workforce or natural resources, were also a relevant strategic decision to improve efficiency. From an organizational point of view, this led to the global expansion of production driving the rise of FDI from North to the South. This trend of geographical enlargement of GVC was also due to the rising efficient of the ICT and lower transport cost (Amador and Cabral, 2016). Fernandes et al. (2022) has put into evidence the many different country/sectors drivers are at work when considering GVC participation, thus introducing a relevant degree of heterogeneity in the way GVC dynamics may evolve.

Both theoretical perspective (Kano et al. 2020) as well as measurement issues of GVC has been quite intensively investigated (Johnson, 2018; Antras and Chor 2021). In this respect, to account for the abovementioned decreasing trend, that is to understand whether a process of GVC regionalization is occurring, some accounting of a possible backshoring\reshoring process is starting to develop. This stream of literature can be considered at the intersection between International Business literature (IB) and economics as both examines drivers and consequences of the shrinkage of GVC's length.

In general, the IB literature has expanded in trying to study more in depth those determinants also drawing on case studies and different empirical approaches (Di Mauro et al. 2018; Johansson et al. 2019) as a part of the stream of literature dealing with the relationship between technology and location of foreign activities (e.g. Hannibal and Knight 2018).

Some of most common drivers that are put into evidence are related mainly to the geographical and institutional distance encompassing some pull factors of sending countries (related to the importance of regaining the so called "Made in" effect) and the push factors of destination countries with specific reference to the dynamics of labour markets (Platanesi and Araunzo-Carod, 2019).

While reshoring decisions can be also interpreted more broadly as a way to correct a previous offshoring decision that is no longer working (Gray et al. 2017), Dachs et al. (2019) put into evidence that is lacking is a closer look at those new production technologies, such as those related to Industry 4.0 or the internet of things, that allowed production manufacturing to relocate back home. Within the theoretical framework of the Dunning paradigm, they put into evidence that backshoring is still a rare phenomenon mainly driven by the motivation of gaining higher flexibility and favoured by the adoption of Industry 4.0 technologies. Similarly, Ancarani et al. (2019) point to the competitive priorities that can represent import factors of backshoring such as cost priorities but also flexibility, delivery and quality priorities finding that the adoption of Industry 4.0 is associated with gaining high quality and to reduce some kind of costs, especially those related to non-conformance. Blázquez et al. (2023) evidence that digital services, and in particular their contribution to generate value added that is exported, is favouring the backward participation in GVC, inside an evolving trend of a new kind of globalization type. However, the impact of adoption of new technologies is not that unanimous, as for example, De Backer and Flaig (2017) reveal that the use new technology may reduce the attraction of low distance locations. In the same way, Kamp and Gibaja (2021) find evidence that the impact of Industry 4.0 adoption is not so relevant like other location specific factors or some kind of uncertainties like the occurrence of other pandemic events.

In the same way, from an economics point of view, the literature is progressively acknowledging the idea that revolves around the fact that a deglobalization trend is unfolding (Antras 2021; Van Bergeijk 2019).

Some recent descriptive evidence is given by Cigna et al. (2022) finding that protections policies, the increasing volatility of transport costs, the decline in FDI trend but also the rising labour costs in emerging countries are all determinants of slowdown, while the role of adoption of Industry 4.0 is not clear-cut. In trying to account for specific GVC dynamics, Bontadini et al. (2022) analyse the global vs regional trend in GVC with respect to Europe and Asia: their descriptive evidence point out that Europe is characterised by a specific integration pattern which implies a progressive regionalization of its foreign value added but also a globalization of its domestic value added. Going more in depth into the relationship between labor market and GVC dynamics, Fontagné et al. (2023) using a country/industry perspective, evidence that it is the combination of both the position of the country/sector inside the GVC as well as the rate of adoption of robots that automate some tasks this may impact on the employment share. The motivation is that moving backward or forward the GVC implies a different degree of repetitive tasks to be performed and then a different risk of being automated. This can be considered as an indirect effect that technology may have through GVC. Nevertheless, the impact of technology can also be a direct one, that is of substitution or complementarity. They find that for a sample of European manufacturing sectors, robot adoption contributes to reduce the labour share through the GVC position of the sector/country because they favour a kind of upstream specialization[1]. In contrast to this result no direct impact of robot is detected.

This macro perspective, which is close to the one we adopt, is used also by Krenz et al. (2021) who consider, from a theoretical point of view, the opposing choices of offshoring and reshoring. They propose a new reshoring intensity measure taking into account the increase of the ratio of domestic inputs related to foreign inputs. The focus of the paper is on the impact on workers revealing a patterns

[1] As the authors evidence, this kind of specialization is influenced by the role of China's amount of robotization.

of increasing wage inequality between high skill and low skill workers. The role automation adoption is taken into considering finding a positive impact on the increased reshoring activity. Nevertheless, this perspective only takes into consideration the relocation of production without a geographical perspective[2]. What is emerging in the literature about GVC, despite the perspective used, is that technology can not only favour disruption of production processes but also provide incentives for backshoring\nearshoring events.

The second kind of literature we take into consideration is about automation adoption: it has evolved staring with sector level works that found contrasting results on employment but especially negative with respect to the shrinkage of the number of unskilled workers even though a quite high variability depends on the countries and period analysed (Graetz and Michaels 2018, Acemoglu and Restrepo 2020, Klenert et al. 2023). While the studies on the impact on the labour market dynamics have mainly involved developed countries, much less evidence has been provided on the impact they may represent for the developing countries. Using a country/sector perspective, Gravina and Pappalardo (2022) find that robots in developed countries, by spreading their exposure to developing countries, may adversely impact the labour market of developing countries decreasing the labour share therein. According to this perspective, GVC linkages may play important role in affecting the relationship between robot adoption and employment. However, the literature about robot adoption has been rarely put in connection with GVC literature, but a growing literature has started to investigate whether robot adoption and trade are connected as this may indeed in influence on the sourcing decisions and economies of trading partners. In this respect, the impact of automation on trade can be considered to partially mirror the channels that are at work in the relationship between automation and employment. On the one side, acting as a sort of displacement effect we see that because of the narrowing gap of labour costs, the demand of goods produced abroad is lower and, following a process of reshoring, jobs in trading partners are at risk. However, on the other side the robot adoption may stimulate productivity and improve the demand for intermediates thus affecting the sourcing decisions positively. This productivity effect is contrary to the displacement effect by generating also higher job demand. Robots are indeed devices that may save time in building customised product by also increasing the degree to which is it possible not to deliver some tasks to suppliers that being quite geographically distant are difficult to supervise (e.g. Artuc et al. 2022; Bontadini et al. 2022; Stapleton and Webb 2021). This may largely decrease the amount of time to get products to the markets (Dachs 2019) thus enhancing domestic productivity and contributing also

[2] Krenz and Strulik (2021) corroborates this first empirical evidence by studying the same relationship also for Eastern European and emerging countries and finding a similar positive impact on reshoring intensity

to decrease labour costs[3]. Which of the two effects is going to prevail is an empirical matter. The evidence gathered so far is ambiguous: Stemmler (2019) for Brazil, Faber for Mexico (2020) and Kugler for Colombia (2020) using a local labour market approach find that robot adoption in the North generates negative impact on employment and exports.

Artuc et al. (2022), Stapleton and Webb (2021) for Spain, Baur et al. (2022) for Latin America find that robot adoption increase total sourcing activities. However, they mainly use a firm level perspective. DeBacker et al. (2018) only evidence small effects of robotics on forward participation in GVC while Carbonero et al. (2020) find a decrease in the international sourcing of intermediates but no effect on reshoring. From a sectoral point of view, there are some case studies that can add some complexity to this picture. In particular, the apparel and textile sector may represent a case in point as it is characterised by a frequent change in the way the product is manufactured generating difficulties in programming robots to carry out always new tasks. Secondly, the large investment need is a barrier that may negatively impact on robot adoption. (Barca de Mattios, 2021).

Due to lack of studies that, at the macrolevel, analyse the connection between GVC dynamics and automation adoption, our purpose is thus to dig deeper into the relationship between these two literature by adopting a perspective which takes into account sectoral heterogeneity.

3. Data and variables

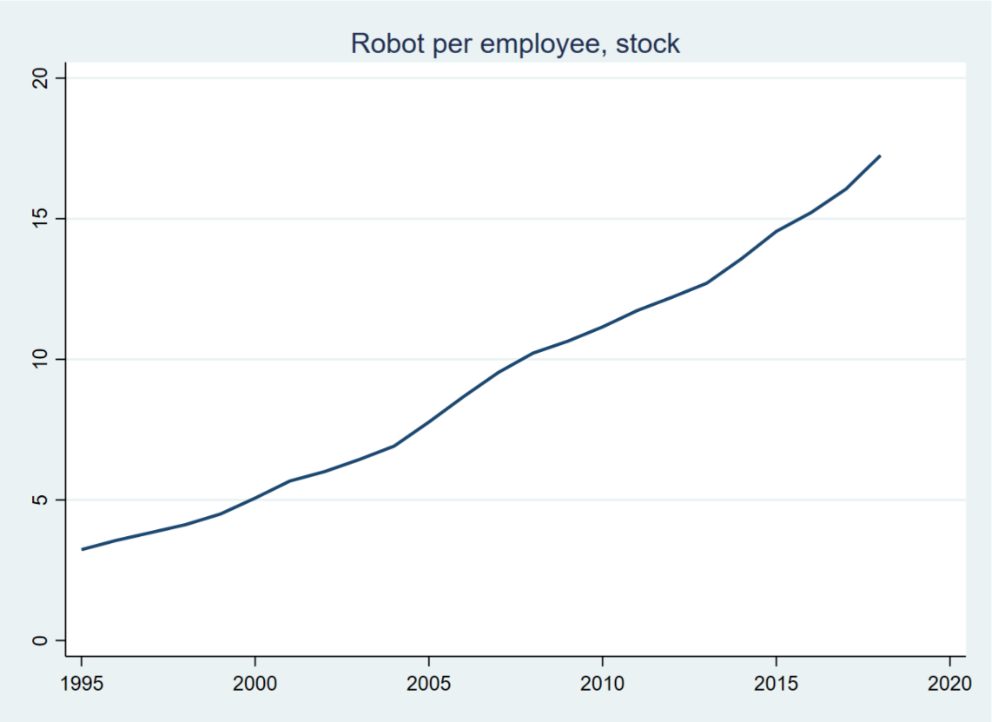
To test our main hypotheses, we merge different data sources that provide information at the country-industry-year level. The final dataset is made up of ten manufacturing sectors at the two-digit level and seven European countries (i.e., *home* countries, H): Finland, France, Germany, Italy, Spain, Sweden, and the UK. The decision to focus only on these countries is because they are the only ones for which we have information on robot installations and stocks at the country and industry level from the whole period under investigation, 1995-2018.

To measure the exposure to robotization, we use data on industrial robots provided by the International Federation of Robotics (IFR). Our indicator of a country-industry's exposure to robots per employee (ROBOT) is computed by combing 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. To reduce the risk of endogeneity between robot exposure and employment, we fix the denominator at the beginning of our sample period, i.e., 1995. For the empirical analysis, we transform the variable into a natural logarithm (*ln*ROBOT). We further proceed to harmonize the two-digit sectors across

[3] In this respect Rodrik (2018) evidences that the comparative advantage of developing countries may change as the low labour costs are not anymore, a source that may sustain it.

the different data sources. Figure 1 shows the increasing trend in the average robot exposure from 1995 to 2018 for our seven home countries taken together.

Figure 1. Average robot exposure, trend 1995-2018



Source: authors' elaborations from IFR data

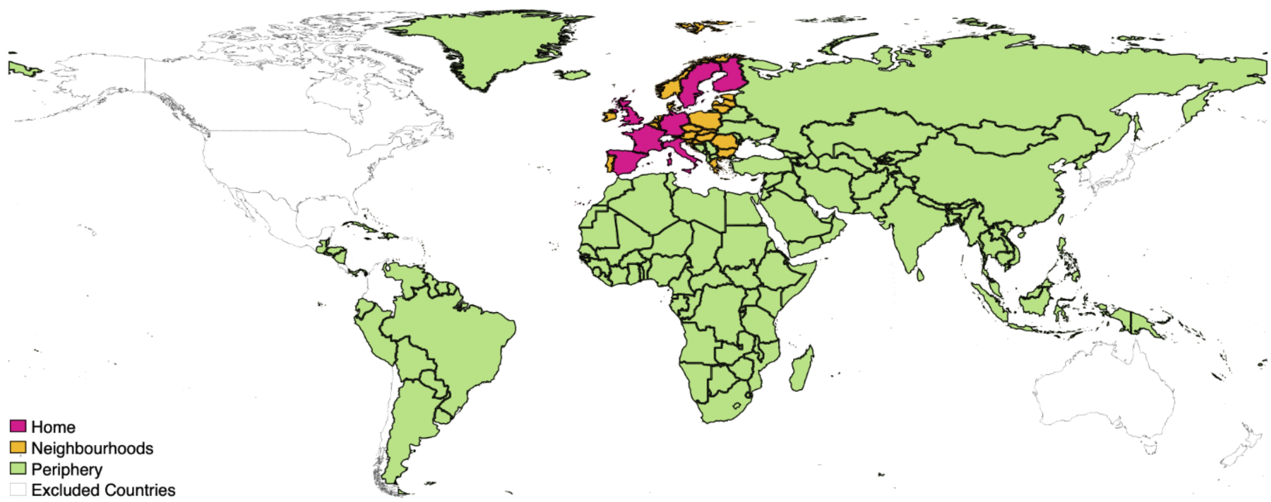
Countries' and industries' participation in GVCs is measured through the OECD Inter-Country Input-Output (ICIO) database, 2021 edition. For each of the ten manufacturing sectors available in each country, we consider the share of gross value added of exports originating from foreign countries (FVA), focusing on low-wage countries, i.e., countries with an average hourly wage rate lower than that of our home countries[4]. Initially, we distinguish low-wage countries into two groups according to their distance from home countries H. One group refers to the 'neighbourhood' (N), i.e., countries located within the same region of H countries, namely the European Union-28. This group includes countries that share a common trade and currency area with our home economies, thus minimizing transport and transaction costs during trade and subcontracting relationships. The second group is given by low-wage countries located outside the European Union, at a higher geographical and

[4] This choice leads us to drop the following advanced non-EU economies from the database: USA, Canada, Japan, Australia, New Zealand, Switzerland, South Korea, and Israel.

institutional distance than N. We define this group as 'the periphery' (P) without any distinction about the region of the world. Managing trade and subcontracting relationships with economic agents located in these countries should imply higher transport and transaction costs, but higher savings in labour costs.

As a robustness check, we also define two alternative subsets of neighboring and peripheral countries represented by, respectively, Eastern European countries belonging to the EU-28 region (i.e., *near East*) and extra-UE Asian economies (i.e., the *far East*). Figure 2 shows the three regions, H, N, and P, and the two sub-regions, near East and far East.

Figure 2. Distinguishing Home, Neighbourhood, and Periphery: world map



Source: authors' elaborations

To measure both the country-industry's participation in GVC and the possible regionalization of such GVCs over time, we proceed by defining a series of indicators which measure the FVA originating from home, or neighbouring countries with respect to the FVA originating from the periphery, in the spirit of Krentz and Strulik (2021). Specifically, we define a series of ratios where the numerator corresponds to the gross value added of exports originating from either the seven home countries (FVA-H), or alternatively from the neighbourhood (FVA-N). The denominator corresponds to the gross value added of exports originating from the peripheral economies located outside the EU28 (FVA-P). Distinguishing between neighboring and peripheral countries helps to understand the dynamics of regionalization of the GVCs over time. A more regional GVC corresponds to the following two scenarios: (i) 'strong' regionalization, that is the relocation at home of activities previously accomplished in the periphery (i.e., from P to H); (ii) 'weak' regionalization, that is the relocation in the neighbourhood of activities previously accomplished in the periphery (i.e., from P to N).

As a robustness test, we use two alternative indicators to detect neighbouring and peripheral countries. One corresponds to the ratio between FVA-H and FVA-EASTEU, that is the FVA originating from Eastern European countries belonging to the EU28 region. The other corresponds to the ratio between FVA-H and FVA-ASIA, namely the FVA originating from Asian economies located in the far East. These two subgroups represent two relevant markets for the relocation of manufacturing activities of our home European countries. As shown in Table 1, on average, almost 38% of the FVA originating from neighbouring countries come from the near East, while the share of peripheral FVA originating from Asia is roughly the 25%.

Table 1. Sources of FVA

Source region	FVA (mln USD, current prices)
FVA-H	31244.5
FVA-N	2978.93
FVA-(H+N)	34223.4
FVA-EASTEU	1124.38
FVA-P	2345.61
FVA-ASIA	590.507

Source: authors' elaborations on OCED-ICIO data

To capture GVC regionalization/globalization dynamics, we use the following five measures:

$\frac{FVA-H}{FVA-P}$, which is used to measure the 'strong' regionalization/globalization dynamics, i.e., from the periphery to the home region, or viceversa;

$\frac{FVA-N}{FVA-P}$, which is used to measure the 'weak' regionalization, i.e., from the periphery to the neighbourhood, or viceversa;

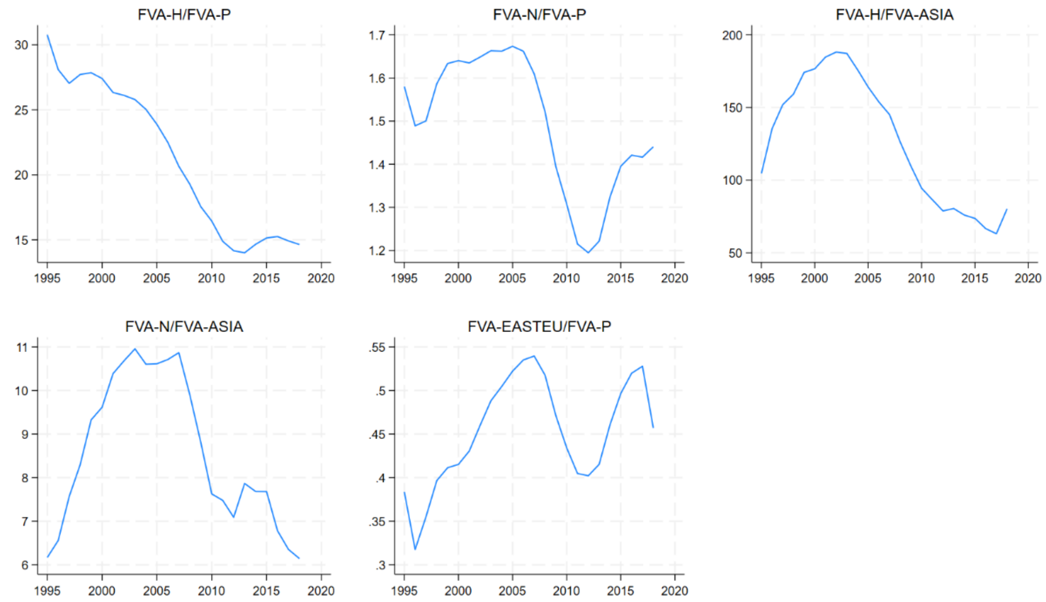
$\frac{FVA-H}{FVA-ASIA}$, which is used to measure the 'strong' regionalization/globalization towards (or from) Asia, i.e., from Asian countries to the home region, or viceversa;

$\frac{FVA-N}{FVA-ASIA}$, which is used to measure the 'weak' regionalization towards (or from) Asia, i.e., i.e., from Asian countries to the neighbourhood, or viceversa;

$\frac{FVA-EASTEU}{FVA-P}$, which is used to measure an alternative version of the 'weak' regionalization/globalization, which occurs from the periphery to the near East region, or viceversa.

To mitigate their volatility and make their distributions less erratic, we reformulate each of the five indicators above as three-year moving averages. Then, we proceed by transforming each variable in a natural logarithm. Figure 3 shows the trend of the five GVC indicators (before log transformation).

Figure 3. GVC participation trends



Source: authors' elaborations from OECD-ICIO data

From the top-left graph, we observe a declining trend in $\frac{FVA-H}{FVA-P}$, especially during the late 1990s and until 2011, a few years after the financial crises of 2007-08 and 2011-12. This trend is also documented by Los et al. (2015) and Bontadini et al. (2022) and refers to the geographical expansion of GVCs occurred in the era of hyper-globalization (Baldwin, 2016), followed by a more recent period of deceleration in GVC participation. A similar trend characterizes the variable $\frac{FVA-N}{FVA-P}$, where the increase in the value in the last eight years calls for a 'weak' regionalization of GVCs that is even more pronounced than the 'strong' one. The top-right and bottom-left charts show the trends for $\frac{FVA-H}{FVA-ASIA}$ and $\frac{FVA-N}{FVA-ASIA}$ respectively. In both cases, we observe an initial period of regionalization during the 1990s, followed by a strong globalization of GVCs, probably due to the entry of China in the WTO and the period of strong economic upturn in many Asian economies. The final chart on the bottom-right documents an increasing regionalization of GVC from the periphery to the near East.

In the following, we will try to assess whether the increasing robotization of manufacturing processes can explain the dynamics of GVC participation of countries and sectors.

4. Empirical methodology

The empirical analysis is targeted at assessing whether there is a non-spurious long-run relationship between the exposure to robotization of our home countries and sectors and their GVC participation dynamics. To do so, we carry out a panel cointegration analysis which involves the following steps. First, we test for the stationarity of all our variables using a series of second-generation unit root tests. Second, we test for panel cointegration using the second-generation test developed by Westerlund (2007). Third, we assess the strength of the relationship using dynamic OLS, and, finally, we test for the direction of causality using a panel vector error correction model (PVECM).

The use of a panel cointegration analysis has a series of important advantages. First, using standard panel regressions with non-stationary variables would lead to spurious estimates in the absence of panel cointegration (Herzer and Donaubauer, 2018). Second, linear regressions involving cointegrated variables are not subject to the omitted variables bias, and the cointegration property does not vary with the inclusion of additional variables. Third, it allows estimating long-run coefficients which are robust to endogeneity. This property is also known as super-consistency and characterizes the estimates of long-run coefficients through dynamic Ordinary Least Squares (DOLS) which are consistent, asymptotically unbiased, and normally distributed. Fourth, with the use of PVECM models, it is possible to assess the direction of short and long-run causality between the variables of interest. Therefore, the use of a panel cointegration approach allows assessing whether robot exposure of countries and sectors is related with GVC participation in a meaningful, non-spurious, way.

4.1. Unit root tests

As a first step of our econometric analysis, we test for the presence of a unit root in our main variables. Although the first-generation panel unit root tests are a common practice, they are also sensitive to the presence of cross-sectional dependence that emerges because of the existence of common shocks within groups of observations, or because of spillovers across countries and sectors. The asymptotic convergence to the normal distribution of the estimators of the first-generation panel unit root tests assumes that all the units of the panel are independent; therefore, if cross-section dependence exists, these first-generation tests are not reliable. To avoid this problem, we use a second-generation panel unit root test developed by Pesaran (2007), based on the Im, Pesaran and Shin (2003) unit root test. To detect the presence of a unit root the following equation is estimated:

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

which consists in extending the individual augmented Dickey-Fuller (ADF) regressions with the cross-sectional means of the lagged levels and first differences of the individual regressor *y* that are used as proxy for the unobserved common factors. The null hypothesis is that β_i=0, which is tested by averaging the t_i statistics corresponding to β_i in equation 1 (Pesaran, 2007; Burdisso and Sangiacomo, 2016). The alternative hypothesis, instead, is that β_i<0 for i=1, 2,…,M and β_i=0 for i=M+1, M+2,…, N (with $M<N$). The test is called the cross-sectional Im, Pesaran and Shin (CIPS) test and is based on the null hypothesis that the variable under investigation has a unit root. We first test for the presence of a unit root in our focal variables in levels, and then in their first differences. If the test does not reject H_0 when variables are in levels but rejects it when they are in first differences, then we conclude that they are integrated of order 1, that means they are non-stationary.
Table 2 shows the results of the CIPS tests for all our variables (log transformed).

Table 2. Panel unit root test

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*)	
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***

Notes: *** significant at the 1% level; ** significant at the 5% level. All the tests with variables in levels include an intercept and a linear trend. All the tests with variables in first differences include only a constant. The 10%, 5%, and 1% critical values are -2.58, -2.65, and -2.77, with an intercept and a trend, and -2.08, -2.16, and -2.3 with only a constant.

From Table 2 we find that all our variables are non-stationary, or I(1). The t statistics of all the variable in levels are never statistically significant, while those for the variables in first difference are always significant at the 1% level. With robot and GVC variables having a unit root, we proceed by testing whether they are also cointegrated.

4.2. Panel cointegration

To be sure that the relationship between *ln*ROBOT and our GVC variables is not spurious, we test whether the variables are cointegrated. We use the four second-generation tests proposed by Westerlund (2007), which, differently from the first-generation panel cointegration tests, have good small sample properties and allow controlling for cross-sectional dependence. Differently from residual-based cointegration tests, usually requiring that the long-run parameters for the variables in their levels are equal to the short-run parameters for the variables in their differences, Westerlund (2007) proposes a series of tests which are based on structural dynamics and the possibility that an error correction (EC) term in a panel error-correction model is equal to zero. In doing so, the tests allow also controlling for cross-sectional dependence as well as panel-specific trend and slopes (Persyn and Westerlund, 2008).

The tests rely on the following EC equation:

$$(2)\ \Delta y_{it} = \delta_i' d_t + \alpha_i (y_{it-1} - \beta_i' x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=-q_i}^{p_i} \Delta x_{it-j} + u_{it}$$

where i refers to the country-industry pair, and d_t to the deterministic component, that can be equal, respectively, to zero (absence), one (like having a constant term), or to $(1, t)'$ which means having both a constant and a trend. The most important parameter is α_i, as it represents the speed to which the system corrects back to the equilibrium relationship $y_{i,t-1} - \beta'_i x_{i,t-1}$ after a shock. An error correction occurs when $\alpha_i<0$, so that we can say that the variables y and x are cointegrated. If, instead, $\alpha_i=0$, no cointegration occurs because there is no error correction. The Westerlund (2007) test works on testing the null hypothesis H_0: $\alpha_i=0$ for all i. The alternative hypotheses, instead, are two. One is that $\alpha_i<0$ for at least one panel unit, or group G, while the other is that $\alpha_i=0$ for the whole panel P. The test produces four statistics, namely two group-mean (G_α and G_τ) and two panel statistics (P_α and P_τ) that are used to test the null hypothesis of absence of cointegration. Moreover, the test allows to account for cross-sectional dependence across the groups by bootstrapping the p values (with 500 replications).

In running the tests, we initially use Δ*ln*ROBOT as the explanatory variable x and, alternatively, the five GVC indicators (in first difference) as dependent variable. However, one of the main underlying assumptions is that x is weakly exogenous (Westerlund, 2007). To test for this, we follow Herzer and Donaubauer (2018) and we perform the Westerlund test for the reverse regression, where we use *ln*ROBOT as dependent variable and, alternatively, our five GVC indicators (in first difference) as explanatory variables. This idea is inspired by Hall and Milne (1994), who show that weak exogeneity in a cointegrated system implies non-causality in the long run. If the test does not reject the null hypothesis of weak exogeneity of our GVC indicators, it means that they do not have any causal effect on *ln*ROBOT in the long run. Therefore, the long-run causality runs from robot exposure to GVC participation, and not viceversa. Table 3 shows the results of the four panel cointegration tests. Due to the limited number of years available, we keep the number of lags equal to 1.

Table 3. Panel cointegration test

Panel A	G_τ	G_α	P_τ	P_α
Δ*ln*ROBOT→Δ*ln*H/P	-2.073***	-5.541**	-17.43**	-4.949**
Δ*ln*ROBOT→Δ*ln*N/P	-2.486***	-6.209**	-20.94***	-6.361***
Δ*ln*ROBOT→Δ*ln*H/Asia	-1.662	-6.484***	-8.361	-6.798***
Δ*ln*ROBOT→Δ*ln*N/Asia	-2.493***	-5.601*	-18.69***	-5.130***
Δ*ln*ROBOT→Δ*ln*EASTEU/P	-2.180**	-5.072	-20.18***	-6.672***

Panel B	G_τ	G_α	P_τ	P_α
Δ*ln*H/P → Δ*ln*ROBOT	-1.061	-2.824	-6.769	-2.062
Δ*ln*N/P → Δ*ln*ROBOT	-1.883	-4.823	-13.44	-4.597
Δ*ln*H/Asia →Δ*ln*ROBOT	-1.259	2.885	4.485	-1.403
Δ*ln*N/Asia → Δ*ln*ROBOT	-1.017	2.504	5.104	-1.039
Δ*ln*EASTEU/P → Δ*ln*ROBOT	-1.198	-2.564	-8.298	-1.527

Notes: Number of panels: 70; number of periods 24. The test statistic for panel cointegration be computed using, first, the alternative hypothesis that at least one panel is cointegrated, and second, that all the panels are cointegrated. Cross-sectional means have been subtracted from all variables. The p-values are obtained by bootstrap with 500 replications. *** significant at 1% level; ** significant at 5% level; * significant at the 10% level.

Panel A reports the outcome of the direct test of cointegration between the regressor *ln*ROBOT and the GVC-related dependent variable (in first difference). In almost all the cells, the statistics rejects the null hypothesis of absence of cointegration. Panel B, instead, reports the results of the Westerlund test for the reverse regressions, where, on the contrary, we find that all the statistics do not reject H_0. From these results we conclude that robot exposure and the participation to GVC by countries and sectors are cointegrated and that *ln*ROBOT is weakly exogenous.

4.3. Assessing the long-run relationship between robots and GVC dynamics

As a third step, we estimate the long-run cointegration relationship between robots and participation in GVC by countries and sectors using the dynamic OLS (DOLS) approach developed by Kao and Chang (2000). In presence of cointegrated variables, the use of DOLS is recommended because standard OLS would produce biased estimates of the coefficients in presence of serial correlation and endogeneity. We estimate the following regression:

$$(3)\ y_{it} = \mu_i + \gamma f_t + \beta lnROBOT_{it} + \sum_{j=-k}^{k} \lambda_{ij}\, \Delta lnROBOT_{it} + \epsilon_{it}$$

where y stands for the five GVC-related indicators, p represents the number of lags, that we set equal to 1 because of the limited number of years available, and where we include a linear time trend f_t and a series of panel-specific intercepts μ_i. To mitigate cross-sectional dependence due to the presence of unobserved common factors, we demean each variable. However, this does not eliminate the problem if, for example, countries and sectors react to common shocks in a different, and idiosyncratic, way. For this reason, we also compute Pesaran's (2004) cross-sectional dependence CD test by computing the CIPS panel unit root test for the residuals. The idea is that if the residuals are stationary, it can be concluded that the estimates are not spurious.

Another related problem with DOLS regressions is the implicit assumption of homogeneous slope coefficients, that is estimating one single parameter β for all i. In other words, pooled estimators may yield biased estimates of the sample mean of the individual coefficients when the true slope coefficients are heterogeneous. We suspect that our case can be of this type, as we observe both countries and sectors, which can adapt their GVC participation to automation in a different way.

To allow the slope coefficients to vary between countries and sectors, we use the group-mean DOLS (DOLS-GM) estimator developed by Pedroni (2001). In this case, we estimate 70 separate country-sector-specific DOLS regressions, and we average the individual coefficients β_i to produce one single final impact. Although cointegration implies that the long-run relationship between robots and GVC is not influenced by omitted variables, we test for the robustness of the DOLS coefficients by including two other relevant variables that can affect the regionalization/globalization of GVCs of countries and sectors: Information and Communication Technology capital (ICT) and other machinery and equipment (MACH).

The results of the DOLS regressions are shown in Tables 4-8. In each table, Columns 1 and 2 show the results of the DOLS and DOLS-GM regressions in which the main regressor is only lnROBOT, while the corresponding results of the augmented regressions are shown in Columns 3 and 4.

Table 4. The long-run relationship between robots and GVC: DOLS and DOLS-GM

DEP. VAR. $ln(\frac{FVA-H}{FVA-P})$	(1) DOLS	(2) DOLS-GM	(3) DOLS	(4) DOLS-GM
lnROBOT	-0.070**	0.084*	-0.082**	0.062*
	(0.031)	[3.622]	(0.034)	[3.486]
lnICT			-0.209***	0.632**
			(0.079)	[19.45]
lnMACH			0.122	-0.411**
			(0.106)	[-10.07]
Demeaned data	Yes	Yes	Yes	Yes
R^2	0.151		0.447	
CD test	140.9***		120.7***	
N. countries	70	70	70	70
N. obs.	1470	1470	1470	1470

Notes: DOLS: pooled DOLS estimator developed by Kao and Chiang (2000);.CD is the cross-sectional dependence test proposed by Pesaran (2004). DOLS-GM: t-statistics are reported in squared brackets. *** significant at 1% level; ** significant at 5% level.

Table 5. The long-run relationship between robots and GVC: DOLS and DOLS-GM

DEP. VAR. $ln(\frac{FVA-N}{FVA-P})$	(1) DOLS	(2) DOLS-GM	(3) DOLS	(4) DOLS-GM
lnROBOT	0.019	0.161**	-0.003	0.178**
	(0.023)	[17.01]	(0.025)	[11.5]
lnICT			-0.018	0.105**
			(0.057)	[7.92]
lnMACH			0.049	-0.114
			(0.077)	[-2.502]
Demeaned data	Yes	Yes	Yes	Yes
R^2	0.031		0.178	
CD test	91.23***		85.31***	
N. countries	70	70	70	70
N. obs.	1470	1470	1470	1470

Notes: DOLS: pooled DOLS estimator developed by Kao and Chiang (2000);.CD is the cross-sectional dependence test proposed by Pesaran (2004). DOLS-GM: t-statistics are reported in squared brackets. *** significant at 1% level; ** significant at 5% level.

Table 6. The long-run relationship between robots and GVC: DOLS and DOLS-GM

	(1)	(2)	(3)	(4)
DEP. VAR. $ln(\frac{FVA-H}{FVA-ASIA})$	DOLS	DOLS-GM	DOLS	DOLS-GM
lnROBOT	-0.090**	0.039	-0.065	0.069**
	(0.044)	[2.841]	(0.047)	[-9.355]
lnICT			-0.242***	0.712**
			(0.109)	[14.22]
lnMACH			0.060	-0.571**
			(0.147)	[-6.671]
Demeaned data	Yes	Yes	Yes	Yes
R^2	0.432		0.699	
CD test	113.7***		109.6***	
3N. countries	70	70	70	70
N. obs.	1470	1470	1470	1470

Notes: DOLS: pooled DOLS estimator developed by Kao and Chiang (2000);.CD is the cross-sectional dependence test proposed by Pesaran (2004). DOLS-GM: t-statistics are reported in squared brackets. *** significant at 1% level; ** significant at 5% level.

Table 7. The long-run relationship between robots and GVC: DOLS and DOLS-GM

	(1)	(2)	(3)	(4)
DEP. VAR. $ln(\frac{FVA-N}{FVA-ASIA})$	DOLS	DOLS-GM	DOLS	DOLS-GM
lnROBOT	-0.007	0.123**	0.007	0.092
	(0.033)	[12.69]	(0.036)	[-0.015]
lnICT			-0.052	0.213
			(0.083)	[1.393]
lnMACH			-0.012	-0.280*
			(0.111)	[-4.145]
Demeaned data	Yes	Yes	Yes	Yes
R^2	0.327		0.412	
CD test	122.6***		104.2***	
N. countries	70	70	70	70
N. obs.	1470	1470	1470	1470

Notes: DOLS: pooled DOLS estimator developed by Kao and Chiang (2000);.CD is the cross-sectional dependence test proposed by Pesaran (2004). DOLS-GM: t-statistics are reported in squared brackets. *** significant at 1% level; ** significant at 5% level.

Table 8. The long-run relationship between robots and GVC: DOLS and DOLS-GM

Dep. Var. $ln(\frac{FVA-EASTEU}{FVA-P})$	(1) DOLS	(2) DOLS-GM	(3) DOLS	(4) DOLS-GM
*ln*ROBOT	0.121^{***}	0.085^{*}	0.119^{***}	0.098^{**}
	(0.028)	[5.888]	(0.031)	[7.293]
*ln*ICT			-0.133^{*}	0.153^{**}
			(0.071)	[9.091]
*ln*MACH			0.082	0.167
			(0.096)	[2.749]
Demeaned data	Yes	Yes	Yes	Yes
R^2	0.180		0.194	
CD test	76.40^{***}		81.22^{***}	
N. countries	70	70	70	70
N. obs.	1470	1470	1470	1470

Notes: DOLS: pooled DOLS estimator developed by Kao and Chiang (2000);.CD is the cross-sectional dependence test proposed by Pesaran (2004). DOLS-GM: t-statistics are reported in squared brackets. *** significant at 1% level; ** significant at 5% level.

The results from Tables 4 to 7 show an interesting scenario. From Columns 1 and 3 in each table, we find almost always a negative (and sometimes significant) coefficient for assessing the link between robots and GVC participation. When using a pooled estimator, the main result is that an increasing exposure of manufacturing sectors in our seven EU countries to robotization corresponds to an extension of GVCs beyond the regional boundaries. This result is robust to the inclusion of ICT and other fixed capital assets.

However, the CD tests always reject (at the 1% level) the null hypothesis of no cross-sectional dependence, meaning that these results can be contaminated by unobserved common shocks to which countries and sectors react in a different way. To get such a heterogeneity, Columns 2 and 4 report the results of the DOLS-GM regressions, where the reported estimated coefficient is the average of 70 individual DOLS coefficients. Interestingly, in all the tables, this averaged coefficient is positive and (almost always) statistically significant, implying that the average negative effect of Columns 1 and 3 is driven by a few large negative outliers and thus is not representative of most country-sector pairs.

The results from Table 8, instead, are robust across all the four columns: a higher exposure to robotization implies a higher regionalization of GVCs running from the periphery to the near East.

Combining the results from all the five tables, we draw two conclusions: (i) a higher robotization of manufacturing processes is responsible for the higher regionalization of GVCs; (ii) sectoral heterogeneity matters, as this nexus holds for most of the sectors under examination.

As a final step, we test for the direction of causality. Since panel cointegration does not per se clarify the direction of causality between robots and GVCs, we follow Herzer and Donaubauer (2018) and estimate a panel vector error correction model (PVECM) and we provide a series of test for weak and strong exogeneity. In a first step, the EC is computed starting from the DOLS estimated coefficient, while in a second step the lagged EC is included as a regressor in a PVECM, together with (one year) lagged robot and GVC-related regressors, both in first difference. The inclusion of the lagged difference allows testing for (Granger) causality in the short-run, whereas the inclusion of the EC allows testing for causality in the long-run. To capture the direction of such a causality, we run two regressions, one where $\frac{FVA-H}{FVA-P}$ (and $\frac{FVA-N}{FVA-P}$) is used as dependent variable and one reverse regression where the same variable is used as the main explanatory variable.

Specifically, we start from the following two equations:

$$(4)\ \Delta ln\frac{FVA-H}{FVA-P}_{it} = \mu_{1i} + \alpha_1 EC_{it-1} + \varphi_{11}\Delta ln\frac{FVA-H}{FVA-P}_{it-1} + \varphi_{12}\Delta lnROBOT_{it-1} + \varepsilon_{it}$$

$$(5)\ \Delta lnROBOT_{it} = \mu_{2i} + \alpha_2 EC_{it-1} + \varphi_{21}\Delta lnROBOT_{it-1} + \varphi_{22}\Delta ln\frac{FVA-H}{FVA-P}_{it-1} + \epsilon_{it}$$

And we provide three tests. First, we test for the weak exogeneity of the main explanatory variable by testing whether the EC coefficient is equal to zero (Hall and Milne, 1994). If the test does not reject the null hypothesis of weak exogeneity then the variable under observation has no causal effect on the dependent variable. In our case, if α_1 is different from zero and α_2 is equal to zero, then the long run causality runs only from robots to GVC and not viceversa. If the first test is about the long run causality, the second concerns the identification of a causal link between robots and GVC dynamics in the short run. To do so, we directly test for the joint significance of the lagged differences of the explanatory variables, that is φ_{12}=0 in Equation 4 and φ_{21}=0 in Equation 5. Third, we test for strong exogeneity by testing the joint significance of both the lagged differenced explanatory variables and the EC term. Testing for strong exogeneity in a system of two cointegrated variables means that a variable (e.g., GVC regionalization) is not Granger caused by another one (e.g., robots) neither in the short nor in the long run. Table 9 reports the results of the causality tests concerning our two main GVC-related variables: $\Delta ln\frac{FVA-H}{FVA-P}$ in panel A, and $\Delta ln\frac{FVA-N}{FVA-P}$ in panel B.

Table 9. Causality tests between robots and GVC dynamics

A. Dependent variable: $\Delta ln\frac{FVA-H}{FVA-P}$	
Weak exogeneity test	
Coeff EC = 0	49.87*** [0.000]
Short-run Granger non-causality test	
Coeff ΔlnROBOT=0	0.50 [0.481]
Strong exogeneity test	
Coeff EC= coeff ΔlnROBOT = 0	49.88*** [0.000]
Dependent variable: ΔlnROBOT	
Weak exogeneity test	
Coeff EC = 0	1.04 [0.307]
Short-run Granger non-causality test	
Coeff ΔlnH/P=0	0.97 [0.324]
Strong exogeneity test	
Coeff EC= coeff ΔlnH/P = 0	1.45 [0.484]

B. Dependent variable: $\Delta ln\frac{FVA-N}{FVA-P}$	
Weak exogeneity test	
Coeff EC = 0	82.50*** [0.000]
Short-run Granger non-causality test	
Coeff ΔlnROBOT=0	0.26 [0.607]
Strong exogeneity test	
Coeff EC= coeff ΔlnROBOT = 0	85.20*** [0.000]
Dependent variable: ΔlnROBOT	
Weak exogeneity test	
Coeff EC = 0	5.53** [0.019]
Short-run Granger non-causality test	
Coeff $\Delta ln\frac{FVA-N}{FVA-P}$ =0	0.03 [0.863]
Strong exogeneity test	

Coeff EC= coeff $\Delta ln\frac{FVA-N}{FVA-P}$ = 0	5.96 [0.061]

From Panel A we find that the null hypothesis of weak exogeneity is rejected for $\Delta ln\frac{FVA-H}{FVA-P}$ whereas it is not rejected for ΔlnROBOT, in line with the panel cointegration tests of Section 4.2. This means that, in the long run, the Granger causality runs from robots to GVC and not viceversa. Interestingly, we also find that the short run Granger causality test fails to reject the null hypothesis, implying that robotization and GVC dynamics do not affect each other in the short run. Combined with the strong exogeneity test, this means that the link between GVC and robots is a long term one.

These results are almost confirmed in Panel B for the case of weak GVC regionalization. The only difference is that, in this case, we cannot exclude a mutual influence of $\Delta ln\frac{FVA-N}{FVA-P}$ on ΔlnROBOT in the long run. In conclusion, we find robust evidence that a higher exposure to robotization Granger causes a higher (strong and weak) regionalization of GVCs in countries and sectors.

5. Discussion

Once confirmed the direction of causality, we now come back to the role of sector heterogeneity in explaining the robot-GVC nexus. Tables 10 and 11 report the sign of the 70 coefficients from the DOLS-GM regressions for the following two main dependent variables: $ln\frac{FVA-H}{FVA-P}$ and $ln\frac{FVA-N}{FVA-P}$.

We observe that, in both tables, most of the reported signs is positive (57% in Table 10 and 71% in Table 11).

Table 10. Sign of the DOLS-GM coefficients: $\frac{FVA-H}{FVA-P}$

	10-12	13-15	16-18	19	20-21	22-23	24-25	26-27	28	29-30
Finland	-	-	+	+	+	+	-	-	+	+
France	+	-	+	+	+	+	-	+	-	+
Germany	-	+	+	-	+	-	+	+	-	+
Italy	-	+	+	-	+	-	+	+	-	+
Spain	+	+	+	-	+	-	-	+	-	+
Sweden	-	-	+	+	+	+	-	-	+	-

UK	-	-	-	+	-	+	+	-	-	+

Notes: Number of +: 40/70=57%. Legenda: 10-12 Food & beverages; 13-15 Textile; 16-18 Wood, paper, printing;19 Coke; 20-21 Chemicals, pharmaceuticals; 22-23 Rubber, plastics, non-metallic mineral products; 24-25 Basic metals, fabricated metal products; 26-27 Computer, electrical equipment; 28 Machinery & Equipment; 29-30 Motor vehicles & Transport Equipment.

Table 11. Sign of the DOLS-GM coefficients: $\frac{FVA-N}{FVA-P}$

	10-12	13-15	16-18	19	20-21	22-23	24-25	26-27	28	29-30
Finland	-	+	+	+	+	+	-	-	+	+
France	+	+	+	+	+	+	+	+	-	+
Germany	+	+	+	+	+	+	+	+	-	-
Italy	+	+	+	-	+	+	-	+	+	+
Spain	+	-	+	+	+	-	-	+	-	-
Sweden	+	+	+	-	+	-	+	-	+	-
UK	-	-	+	+	-	+	+	+	+	+

Number of +: 50/70=71%. Legenda: 10-12 Food & beverages; 13-15 Textile; 16-18 Wood, paper, printing;19 Coke; 20-21 Chemicals, pharmaceuticals; 22-23 Rubber, plastics, non-metallic mineral products; 24-25 Basic metals, fabricated metal products; 26-27 Computer, electrical equipment; 28 Machinery & Equipment; 29-30 Motor vehicles & Transport Equipment.

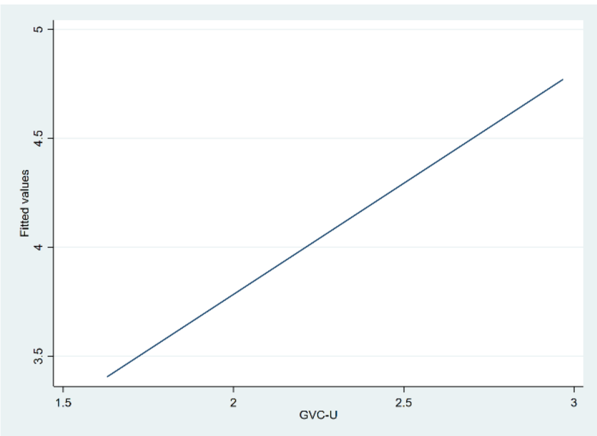
In the following, we try to test whether there is a sectoral pattern that drives these results, and we try to provide a possible explanation which combines on the idea of a upstreamness/downstreamness of sectors proposed by Antras and Chor (2013) and the idea of functional specialization in GVCs analyzed by Fontagnè et al. (2023). The degree of upstreamness of a sector in a country captures the distance, in terms of production stages, of the output of a sector from final demand. Sectors characterized by high degrees of upstreamness are sectors that often produce intermediate goods that are used by downstream industries for further processing. According to Fontagnè et al. (2023), robots play a key role in raising the degree of a sector's upstreamness because they rise productivity in upstream sectors and complement their complex tasks and skills, while reducing the weight of manual tasks and the total labour share. On the contrary, robots do not have an impact on productivity in downstream industries and contribute to decreasing their degree of downstreamness.

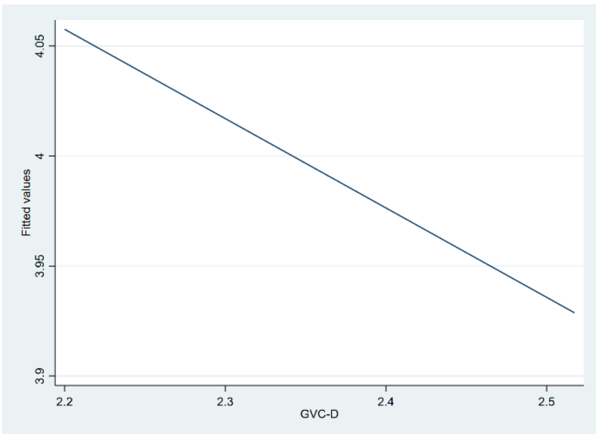
Taking stock from these two contributions, we posit that the number of cases for which a higher exposure to robots induces GVC to become more regional might depend on the level of upstreamness of the manufacturing sectors in our dataset. We do expect that the more a sector is upstream, the more robots will contribute complementing high-level tasks and skills while replacing low-skill, or fabrication, ones. Hence, the need to relocate production towards locations beyond the EU28 region decreases, and we should expect GVC to become more regional.

To test this idea, we proceed as follows. First, we extract the data on countries and sectors' level of upstreamness and downstreamness from Antras and Chor (2021). Since the two indicators are available at the three-digit level, we compute their corresponding average at the two-digit level and for our seven home countries. To mitigate the risk of endogeneity with respect to robots, we consider the keep the value of upstreamness (GVC-U) and downstreamness (GVC-D) in the year 1995. Then, for each of the ten manufacturing sectors available, we count the number of positive signs (+) emerging from the DOLS-GM regressions, as shown in Tables 10 and 11. Finally, we plot the linear relationship between this number and GVC-U and GVC-D respectively.

Figure 4. The relationship between GVC regionalization and upstreamness/downstreamness

Strong regionalization: $\frac{FVA-H}{FVA-P}$





Weak regionalization: $\frac{FVA-N}{FVA-P}$

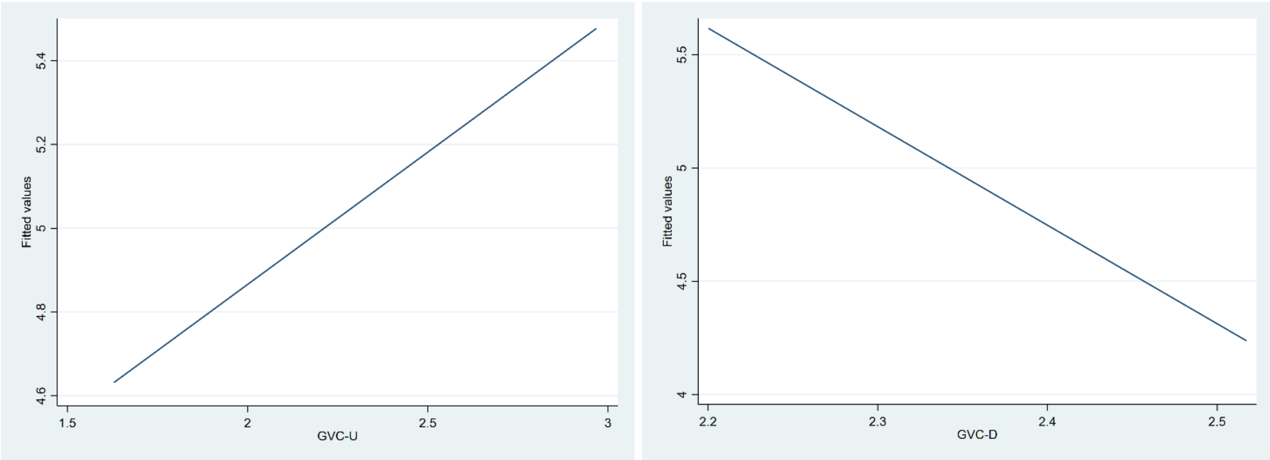


Figure 4 reports the four graphs, two for the strong regionalization and two for the weak regionalization case. Both the top and the bottom panel provide the same result: a clear positive correlation between GVC-U and the number of positive signs (i.e., a more regional GVC), and a clear negative correlation of this latter with GVC-D, confirming our expectations.

6. Conclusions

In this paper, by connecting two different pieces of research, we have investigated whether robot adoption and GVC historical dynamics may be related. The GVC literature has shown that, after a period of hyper globalization in the early ‘90s, an increasing trend toward the relocation of production activities back home, thus feeding a process of GVC regionalization. So far, the role of higher investment in ICT has been considered mainly as way to further fragment production (Alcácer et al. 2016). The framework can become different when considering the impact of new technologies, such as those implied in the automation processes. In particular, the literature about robot adoption has mainly concentrated on the examination of the impacts on the dynamics of jobs and labour market (e.g., Klenert et al. 2023), without giving enough attention to its likely influence on the reconfiguration of the geography of GVC. Indeed, the adoption of new technologies, such as those related to Industry 4.0 can alter the determinants of global production in some cases favouring reshoring (e.g. Dachs et al. 2019). The case of robots affecting reshoring processes has been investigated also at the macrolevel (Krenz et al. 2021; Krenz and Strulik. 2021), which is our perspective as well, but without considering whether the geography play any role.

To bridge the gap between the two streams of literature dealing respectively with the determinants of GVC reconfiguration and the impacts of robot adoption, in this paper we have contributed to the literature by examining whether robot adoption in seven European countries has contributed to this trend of reconfiguration of the global economy over the years 1995-2018 using data at the country-industry level. Employing panel-time series techniques such as a cointegration and dynamic OLS approach, we test whether the value added of exports coming from other countries that we split according to different geographical areas, respectively 'neighbourhood' and 'perifery', is related to their exposure to robotization. The results we obtain report that a process of GVC regionalization can be at work due to robot adoption. A relevant point is that we find that a quite important role is played by sectoral heterogeneity, as in some sectors GVC regionalization can be the outcome of higher robot exposure, in particular for those sectors characterised by a higher degree of upstreamness. We therefore evidence that global and innovation dynamics are strictly interconnected, but causality runs in one direction, that is from robot adoption to GVC regionalization. In this way we also prove that not only the "history" of GVC evolution but also its geographical dynamics may be affected by automation.

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