Robots and Global Value Chains

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

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Abstract

In this paper, we study the relationship between a country’s exposure to robots and reshoring activities that unfolded in the past 25 years. We employ country-industry-year data for the period 1995-2018 and eight European countries. We test for the Granger causality between robots and GVC participation, and we use a panel vector autoregression approach and impulse response functions to assess the impact of the former on the latter. Our regressions show that higher exposure to industrial robots corresponded to an average higher offshoring intensity. We also find, however, that from 2011 robotization led to an increasing near-shoring from other European countries.

Keywords: backshoring, global value chains, nearshoring, panel VAR, robots
JEL: F23;O33

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'. One of the underlying reasons for observing such a trend is that firms started to transfer production closer to home countries through a process defined as reshoring, nearshoring, or backshoring. The international business literature has provided some theoretical and empirical evidence on the factors that can push or pull the processes of backshoring (e.g. Di Mauro et al. 2018; Strange and Zucchella 2017). Connected with this point, another global trend has rapidly emerged, that refers to the installation of automation technologies within production processes. 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.

The literature so far provides ambiguous predictions on this topic as growing robot adoption may generate both a displacement and productivity effect that may impact both negatively and positively on reshoring activities. The literature has adopted only an indirect measure of reshoring as opposed to offshoring finding ambiguous results but mainly using firm level data 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 but without considering which is the geographical sourcing of value added that it is than used in exports.

Therefore, our aim is that of connecting the two fields of research such as the one about GVC dynamics and that of impact of robot adoption that has evolved quite independently so far.

From an empirical point of view, we study the robot-GVC relation by focusing on eight 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 making it possible to distinguish whether the impact of robots passes through backshoring or nearshoring.

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 relationship varies across the available industries, with special attention to the transport industry.

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 1993 to 2019 at the country and sector level only for the eight 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, from 1995 to 2018.

The rest of the paper is organized as follows: in Section 2 is provided an overview of the two literatures dealing with the robot adoption and GVC evolution and how the two are interconnected. 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. 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 concept 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).

Indeed, the share of trade passing through GVC backward or forward linkages has evolved at a high pace since the beginning of the'90s: the expanding trend has had quite relevant impact on development as the breaking up of different part 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 unfold mainly because of the eruption of the global financial crisis with this trend continuing nowadays because of several reasons such as trade wars, the Covid pandemic but also the way the production process is carried out, such as the role played by the adoption of new technologies (Javorick 2020; Antras 2020).

Over the period of fast globalization firms' decisions of where to local their production were 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 was also one of the ways to remain competitive on the market by having access to new resources not available at home, such as skilled workforce or natural resources. 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.

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 expanding trend 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.

Platanesi and Araunzo Carod (2019) describe this new trend according to which firms are partially relocating their production processes back to the home countries on the impulse of some drivers. They point out that they can be related mainly to the geographical and institutional distance as well as 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. 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).

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 among the determinants what 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. 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 idea 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 considered as determinants of slowdown, while the role of adoption of Industry 4.0 is not clear-cut. Using a gravity approach, they also find confirmation using panel data of these trends. 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 and globalization of its domestic value added.

Krenz et al. (2021) consider from a theoretical point of view the opposing choices of offshoring and reshoring proposing 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 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. 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. 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.

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.

What seems to be quite common is that the motivation related to costs is among the most important factor that may impact on the decision to reshore. Therefore, we investigate what is the impact that robot adoption that may generate on them and whether some sectors specific trends are at work.

The literature on automation adoption has mainly evolved staring with sector level works that found contrasting results on employment but especially negative with respect to the shrinkage of the amount 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. However, the literature about robot adoption has been rarely put in connection with GVC literature except for the attempts by Krenz et al. (2021) and Krenz and Strulik (2021), 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.

The impact of automation on trade can be considered to mirror partially the channels that are at work in the relationship between automation and employment.

On the one side, like 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. This may largely decrease the amount of time to get products to the

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

markets (Dachs 2019) thus enhancing domestic productivity and contributing to also decrease labour costs.

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

Which of the two effect 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).

3. Data

To test our main hypotheses, we build a dataset at the country-industry-year level. Our sample is made up of eight European countries (i.e., *home* countries): Finland, France, Germany, Italy, Norway, Spain, Sweden, and the UK. We focus on them because are those for which we have information on robot installations and stocks at the country and industry level from the whole period under investigation.

To measure a country's industry's robot exposure, we use data on industrial robots' installations and operational stocks provided by the International Federation of Robotics (IFR). To compute our measure of robot density, we combine IFR data with data on the number of employees in each country and industry provided by OECD STAN.

Countries' and industries' participation in GVC is measured through the OECD Inter-Country Input-Output (ICIO) 2021 database. For each of the 10 manufacturing sectors available in each country, we consider the share of gross value added of exports (FVA) originating from low-wage countries. Specifically, we distinguish low-wage foreign countries into two groups that are different according to their distance from home countries. One group refers to countries located close to home, i.e., within the EU-28 area outside the eight focal economies: this group captures the neighborhood of our home

economies. We also define a special subset of these neighboring countries which is represented by Eastern European countries (i.e., *near East*). The second group is given by all the other countries located outside Europe, at a higher distance (i.e., the periphery). Among them, we define a second sub-sample made by Asian economies (i.e., the *far East*).
In line with Krentz and Strulik (2021), we define a measure of reshoring that is given by the domestic-foreign input ratio. Specifically, the numerator corresponds to the gross value added of exports originating from the eight home economies, while the denominator corresponds to the gross value added of exports originating from, respectively, neighboring European countries (with a focus on Eastern European countries) and the other economies located outside Europe (with special focus on far East, Asian, countries). Distinguishing between neighboring and peripheral countries helps to unpack reshoring into its two main components: back-shoring and near-shoring. The former corresponds to the relocation at the home (Europe) of activities previously accomplished abroad (either in the neighborhood or in the periphery), and the latter to the relocation of activities from the periphery to the neighborhood. Specifically, we use five measures:

$\frac{home}{periphery}$, which is used to measure back-shoring from peripheral countries to home Europe

$\frac{home}{far\ East}$, which is used to measure back-shoring specifically from Asian countries to home Europe

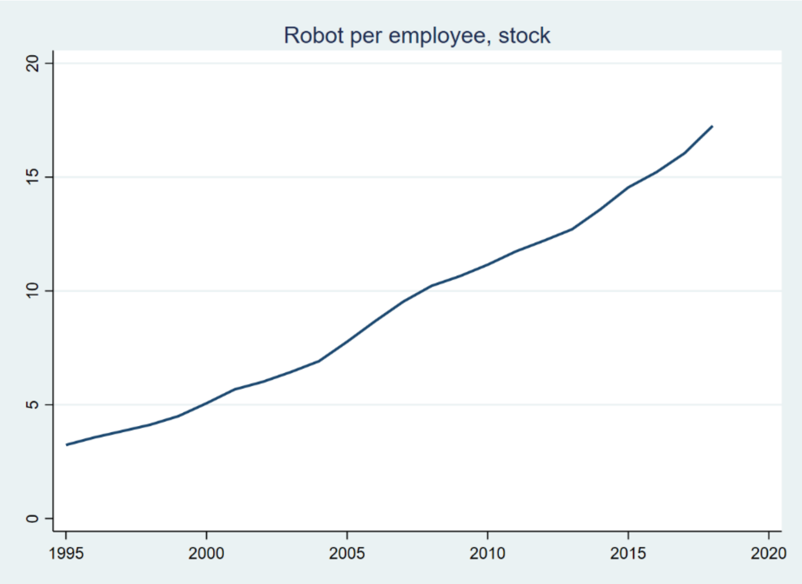
$\frac{home}{neighborhood}$, which is used to measure near-shoring from neighboring countries to home Europe

$\frac{home}{near\ East}$, which is used to measure near-shoring from peripheral countries to neighboring countries

$\frac{far\ East}{near\ East}$, which is used to measure near-shoring from Asian countries to Eastern European countries

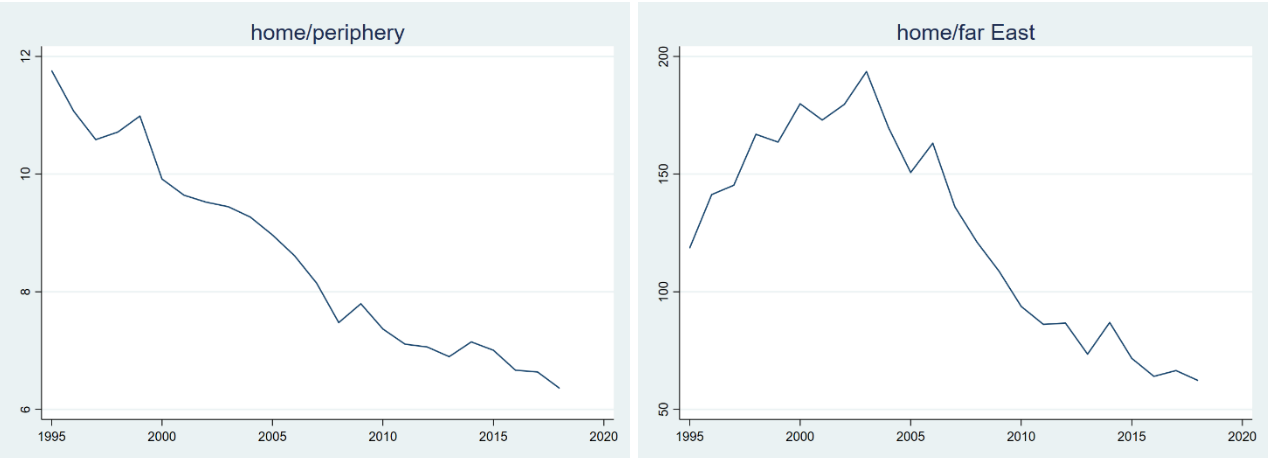
Figure 1 shows the increasing trend in the average robot exposure (i.e., operational stock per employee) from 1995 to 2018 in our eight focal countries. Figure 2 shows the trend in the average GVC participation through back-shoring from peripheral (and Asian) regions to home Europe. Figure 3, instead, shows the trends in the average GVC participation through near-shoring from peripheral to neighboring regions.

Figure 1. Average robot exposure, trend 1995-2018



Source: authors' elaborations from IFR and EU-KLEMS data

Figure 2. GVC participation trend: home/periphery and home/far East



Source: authors' elaborations from OECD-ICIO data

Figure 3. GVC participation trend: home/neighbor, neighbor/far East, near East/far East

Source: authors' elaborations from OECD-ICIO data

From Figure 2, left panel, we note that, across more than two decades, our eight European economies continuously tended to offshore their activities to peripheral regions. From the right panel, instead, we note the increasing tendency to relocate activities to Asian economies from 2002, i.e., after the entrance of China into the WTO.

Figure 3, top panels, also shows the increasing propensity of our eight European countries to offshore production activities in neighboring regions, such as Eastern Europe. The bottom panel, interestingly, shows that, on average, Asian economies started attracting larger shares of production activities after 2006, somehow replacing neighboring Eastern European countries.

In the next section, we test whether these trends are correlated with the increasing exposure to robotization of production processes. To do so, we adopt a Granger causality approach based on panel VAR.

4. Empirical methodology

The empirical analysis is carried out through the following steps. First, we test for the stationarity of our variables using a series of unit root tests. Second, we adopt a panel VAR approach to assess the Granger causality between robot exposure and reshoring. Finally, we use Impulse Response Functions to show the impact of robots on GVC participation for country-industry pairs over time.

The basic model that we estimate is the following:

(1) $Y_{it} = \alpha Y_{it-1} + \beta ROBOT_{it-1} + \gamma_i + \delta_t + \varepsilon_{it}$

where *i* refers to the country-industry pair, *t* to the years from 1995 to 2018, and *ROBOT* is our focal measure of robot exposure given by the (natural log +1) operational stock per employee, this latter measured in the year 1995 to avoid possible endogeneity between robot stocks and employment. The dependent variable *Y* corresponds to the (natural log of) five measures of GVC participation that differ according to the regions of the world considered:

$\frac{home}{periphery}$, $\frac{home}{far\ East}$, $\frac{home}{neighborhood}$, $\frac{home}{near\ East}$, and $\frac{far\ East}{near\ East}$.

The terms γ_i and δ_t represent, respectively, country-industry-specific unobserved fixed effects and time-specific fixed effects, while ε is the stochastic error component.

Preliminary to the panel VAR causality analysis, we test for the stationarity of *Y*, and *ROBOT*. The so-called first-generation panel unit root tests are the most used, but they are sensitive to the presence of cross-sectional dependence that emerges because of the existence of common shocks within groups of countries and industries or because of spillovers across countries-industries. 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, we estimate the following equation:

(2) $\Delta y_{it} = \beta_i y_{it-1} + \gamma_i \overline{\Delta y_{it}} + \delta_i \overline{y_{it-1}} + \mu_i + \epsilon_{it}$

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 2 (Pesaran, 2007; Burdisso and Sangiacomo, 2016). The alternative hypothesis, instead, is that β_i <0 for i=1,2,…,M and βi=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 difference, we conclude that they are integrated of order 1, or non-stationary. Otherwise, if the test rejects the null hypothesis both when the variables are in levels and when they are in first difference, we conclude that they are integrated of order 0, or stationary. Table 1 shows the results of the CIPS tests, where we include a linear trend and an intercept.

After establishing the stationarity of our variables, we proceed to estimate the relation between robot exposure and GVC participation using a panel vector autoregression (PVAR) estimator. We estimate equation 1 by first differencing each variable to remove the country-industry-specific fixed effects, and then we subtract the cross-sectional mean to remove time-specific fixed effects. Then, we applied the panel GMM approach suggested by Holtz-Etkin, Newey and Rosen (1988) where we use lagged values (i.e., up to the third lag) of *ROBOT* and *Y* as instruments to obtain consistent estimates of the coefficients. We also provide the bi-directional Granger causality Wald test, based on the null hypothesis that the explanatory variable *X* (*ROBOT*, *Y*) does not Granger cause the dependent variable *Y* (respectively *Y*, *ROBOT*).

Starting from our PVAR model, we also look at the impulse-response functions (IRF), which describe the reaction of *Y* to a one-standard-deviation (orthogonalized) shock in robot exposure per capita over a period of five years, and where standard errors and confidence intervals are computed using 200 Monte Carlo simulations.

5. Results

Table 1 reports the results of the PVAR regressions when we consider the entire 1995-2018 period. Table 2, instead, shows the PVAR estimates when we restrict the sample to years 2011-18. From Table 1, Columns 1-3, we find that higher exposure to robots Granger causes a higher offshoring intensity, regardless of the region of destination. The Wald test confirms that the direction of the causality runs from robots to GVC, and not vice-versa.

Table 2, Columns 1 and 2, interestingly shows that, after 2011, such an effect of robotization vanishes, especially when referring to peripheral regions. Instead, in Column 3 we find a positive and statistically significant coefficient of ROBOT, meaning that, after 2011, a higher robotization induced our home European countries to nearshore production from other neighboring economies.

Table 1. Panel VAR estimates: all years

	(1)	(2)	(3)
DEP. VAR. Y =	Δln(Home/Periphery)	Δln(Home/Far East)	Δln(Home/Neighbor)
$\Delta\ln(Y)_{t-1}$	-0.192***	-0.328***	-0.139***
	(0.028)	(0.036)	(0.037)
$\Delta\ln(\text{ROBOT})_{t-1}$	-0.127***	-0.674***	-0.082***
	(0.040)	(0.089)	(0.017)
N	1760	1760	1760
GC Wald test			
Robot → GVC	9.544***	56.78***	21.84***
GVC → Robot	1.820	0.957	2.081

GMM-robust weight matrix. Instruments: 1 to 3 years lagged ln(Y) and ln(ROBOT). *** significant at the 1% level.

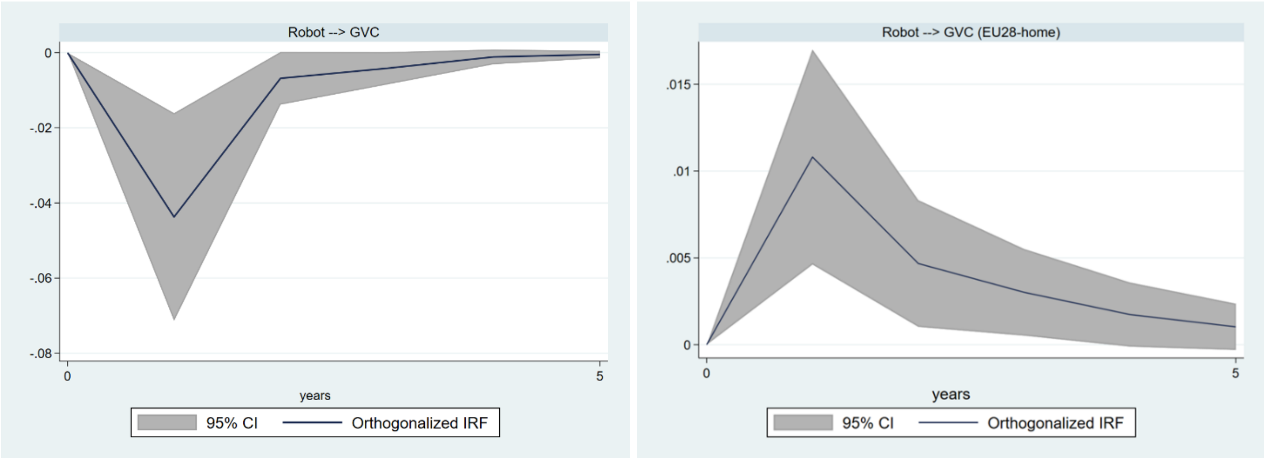
Table 2. Panel VAR estimates: after 2011

	(1)	(2)	(3)
DEP. VAR. Y =	Δln(Home/Periphery)	Δln(Home/Far East)	Δln(Home/Neighbor)
$\Delta\ln(Y)_{t-1}$	-0.246***	-0.324***	-0.160***
	(0.048)	(0.086)	(0.061)
$\Delta\ln(\text{ROBOT})_{t-1}$	0.030	-0.272	0.154***
	(0.108)	(0.211)	(0.049)
N	560	560	560
GC Wald test			
Robot → GVC	0.075	1.667	9.743***
GVC → Robot	0.662	0.079	0.188

GMM-robust weight matrix. Instruments: 1 to 3 years lagged ln(Y) and ln(ROBOT).). *** significant at the 1% level.

Figure 4 shows the IRF related to the estimates of Table 1, Column 1, and Table 2, Column 3. The graphs refer to a one-standard-deviation shock in robot exposure and the corresponding effect on GVC participation across five years. The left graph shows the negative relationship between *ROBOT* and *home/periphery* while the right one shows the positive relationship with respect to *home/neighbor* after 2011. These figures show that nearshoring is a relatively recent phenomenon that is significantly related to robotisation.

Figure 4. Impulse response functions



6. Conclusions

In this paper we have investigated whether robots and reshoring activities can be two related economic trends in the global scene. On the one side, the GVC literature has shown an increasing trend toward the relocation of production activities back home, without properly consider the role of new technologies such as robots. Instead, the role of higher investment in ICT has been considered mainly as way to further fragment production. On the other side, the literature about robot adoption has mainly concentrated on the examination of the impacts on the dynamics of jobs and labour market, without giving enough attention has been given to the consideration that new technologies (such as those related to industry 4.0) can alter the determinants of global production favouring reshoring (e.g. Dachs et al. 2019).

Among the reshoring\backshoring motivations one of the most relevant, that both IB and economics literature point out is that of the narrowing labour costs between countries.

To bridge the gap between the two streams of literature dealing respectively with the determinants of reshoring and the impacts of robot adoption at the macroeconomic level, in this paper we have contributed to the literature by examining whether robot adoption in 8 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. Using a PVAR approach, we test whether the value added of exports coming from other countries that we split according to different geographical areas is related to their exposure to robotization. Our regressions show that the increased robotization of production processes corresponded to a higher average offshoring of production activities, both to the neighbouring and peripheral regions. When restricting the analysis to 2011-18, however, we find evidence of an increasing near-shoring intensity related to robot exposure. We can not show a unique path of evolution of GVC geography but according to the period analysed we see diverging trends.

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