Global Value Chains, functional specialization and technology adoption *

Lionel Fontagné

Bank of France, CEPII & PSE.

Ariell Reshef

CNRS, Université Paris 1 Panthéon-Sorbonne, PSE, and CEPII

Gianluca Santoni

CEPII

Giulio Vannelli

CNRS, Université Paris 1 Panthéon-Sorbonne

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Abstract

We study the direct and indirect effects of ICT adoption and robotization on labor shares and business function specialization in a sample of 14 manufacturing industries in 14 European countries in 1999-2011. Our main contribution is to study the indirect effect of technology adoption via global value chain (GVC) participation, i.e., changes in geographical location of production stages. We develop methodology to separately account for robots in the total capital stock. Increases in forward GVC participation reduce labor shares and result in a shift in functional specialization away from fabrication towards other business functions: management, marketing and R&D. ICT adoption increases labor intensity through complementarity with labor, in particular in fabrication and marketing functions. We do not find any direct effects of robot adoption. In contrast, robots affect labor via their impact on forward GVC participation. In order to better understand the indirect effect, we build gravity-based measures of productivity in upstream and downstream activities. We find that robots increase productivity only in upstream activities, which is consistent with data robot applications. ICT adoption exhibits equally positive effects on both types of productivity, which explains why we find no impact of ICT on GVC participation.

Keywords: labor share, global value chains, technological change

JEL Codes: E25, F14, F16, 033

*Lionel Fontagné: lionel.fontagne@banque-france.fr; **Ariell Reshef**: ariell.reshef@psemail.eu; **Gianluca Santoni**: gianluca.santoni@cepii.fr; **Giulio Vannelli**: giulio.vannelli@univ-paris1.fr. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101004703 (PILLARS). We wish to thank the participants in the PILLARS Econpol Conference, for their comments and suggestions.

1 Introduction

Countries and industries that integrate into Global Value Chains (GVCs) gain by specializing in activities in which they have a comparative advantage, while offshoring other stages of the chain. These changes may manifest both in specializing in activities closer to final demand, i.e. more downstream, as well as further away, i.e. more upstream. Beyond affecting trade and ownership patterns at the global level, these movements also affects payments to domestic factors. First, the specialization in a new activity might require new tasks whose relative use of labor vs capital is different, thus affecting the remuneration of these factors; secondly, increasing integration implies that a greater share of the value added embodied in a single unit of final good accrues to foreign factors, and similarly the output of domestic factors increasingly accrues to final good production abroad; all in all, this induces a geographical reallocation of payments to primary factors.

Against this background, technological change also plays a role. On the one side, it has a direct effect by complementing or substituting labor. On the other side, it impacts the specialization pattern by allowing to perform a wider array of activities and/or increasing the productivity of the different productions. Therefore, it directly affects the position along GVCs and through that further impacts payments to labor.

In this article, we study both the direct impact of technology and GVCs on labor outcomes as well as their combined impact, disentangling the three single channels. Explicitly, we first investigate which is the direct impact of a variation in GVCs position on labor outcomes. In so doing, we examine several measures that focus on different aspects of GVCs position. As concern labor outcome, we first focus on the labor share and further examine the impact on different groups of labor occupations. Looking at the within labor payment variation is paramount. Specialization within GVCs allows indeed to change the activities and the tasks performed and therefore to vary labor requirements: thus, we expect the general effect on total payments to labor to be heterogeneous across the occupations that are replaced vs introduced.

At the same time, we examine how adoption of new technologies contribute to shape these patterns. As above discussed, in the first place we examine the direct impact of technological change on labor outcomes. This impact is parallel to that of GVCs. Then, we add to this standard channel, an indirect impact that propagate through the variation in GVCs position. Technological change may indeed allow firms to perform new activities thus changing the position within GVCs. We provide a comprehensive assessment by analyzing the specific impact of distinct categories of technologies, which we argue may have a heterogeneous effect. Machinery, ICT and automation potentially require divergent skills, as well as they substitute for different types of occupation. In addition, their impact on specialization may also vary: for instance, while ICT may support a better management of the currently performed tasks, investments in automation may induce further specialization.

We relate to different strands of literature. First we contribute to the studies on the relationship between GVCs integration and labor. Sposi, Yi & Zhang (2021) extend a model of sequential GVCs production proposed by Antràs & De Gortari (2020) to include Heckscher-Ohlin forces, and show that declines in trade barriers cause relocation of relatively capital-intensive upstream stages to relatively capital abundant countries. Reshef & Santoni (2022) study the evolution of labor shares with respect to GVCs integration: they find that the declines of labor shares are driven by forward GVCs integration, i.e. exporting of intermediate goods, coinciding with China's rapid integration into international production networks. Timmer, Miroudot & de Vries (2019) study the contribution of different type of occupations within the labor shares to GVCs integration. They show that value added exports denote wide heterogeneity across countries in the use of business functions, thus suggesting countries' specialization in different stages of the chain.

We also relate to the literature that has studied the relationship between technology adoption and labor outcomes. Several studies have focused on the polarizing role of ICT technologies according to the skills' level (Goos & Manning 2007, Autor, Katz & Kearney 2008, Michaels, Natraj & Van Reenen 2014, Harrigan, Reshef & Toubal 2021). More recently, a rapidly growing literature has focused on robots and automation providing theoretical frameworks to interpret their impact on labor outcomes as well as first empirical estimates (Graetz & Michaels 2018, Acemoglu & Restrepo 2018, 2019, 2020). A different strand of the literature has focused on the role of technology sophistication for resilience to shocks: Comin, Cruz, Cirera, Lee & Torres (2022) show that more technologically sophisticated firms experienced higher sales in the first phase of the pandemic, disentangling a direct and an indirect impact of technology.

Finally, we relate to the literature studying the impact of technology on GVCs integration. In so doing, we are among the first to study the impact of automation. In a seminal work, Artuc, Bastos & Rijkers (2020) develop a Ricardian model encompassing robots adoption, and provide evidence that robotization fosters GVCs integration by increasing trade between South and North in both directions.

We contribute to these strands of literature by focusing on the industry-level variations in labor, technology and GVCs positions for 14 European countries in the manufacturing sector. We find that an increase in GVCs integration is associated with a reduction of the labor share, which is mainly absorbed by occupations related to fabrication. We also show that the impact manifests only for upstream movements, i.e. moving further from final demand. On the contrary, we do not find a similar effect for increasing downstreamness, i.e. moving further from primary inputs. These results seem consistent with previous evidence in Sposi et al. (2021) and Reshef & Santoni (2022). We also detect an impact on labor outcomes due to technology adoption, although this is heterogeneous across different categories of technology: while machinery and ICT have a direct impact, the effect of robots propagates only through the variation in GVCs position. Disentangling the direct vs indirect effect of technology is one of the contribution of this paper. Moreover, we develop a procedure to measure the stock of robots value, thus allowing for a direct comparison of the investments across technology types.

Finally, in estimating the indirect impact through GVCs, we also provide evidence of a robust relationship between technology adoption and GVCs position. In particular, we find that investments in robots increase distance to final demand by increasing the relative productivity in intermediate goods production vis à vis final good production.

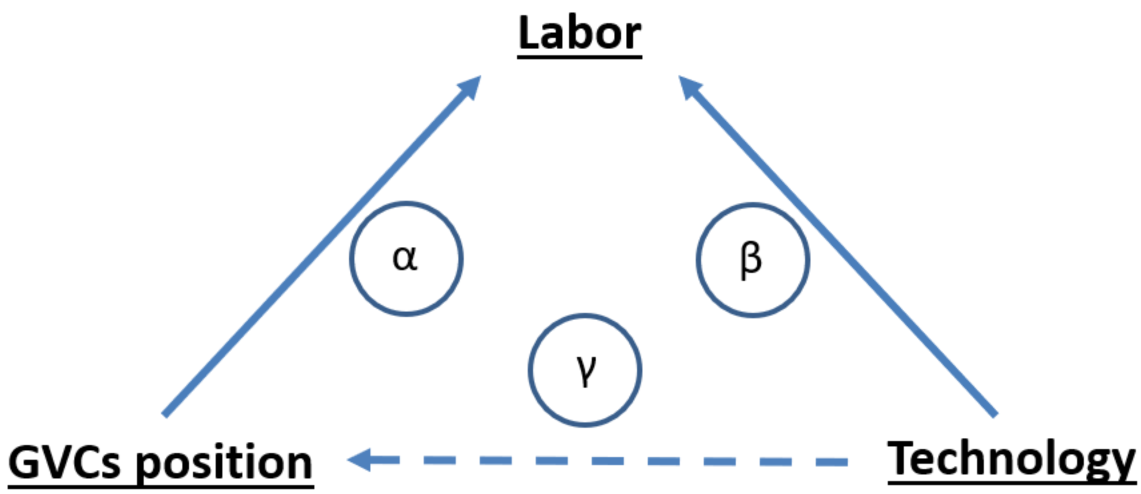
The remainder of this paper is structured as follows: Section 2 depicts our theoretical framework and provides the related empirical specifications; Section 3 presents the data and in-sample descriptive statistics; Section 4 describes the results; Section 5 discusses next steps and Section 6 concludes.

2 Theoretical framework and empirical specification

This section develops the conceptual framework guiding the empirical analysis and provides the theoretical foundations of the econometric approach.

We argue that GVCs position and technology adoption impact labor along different directions, Figure 1. A change in GVCs position affects labor through a direct impact, denoted by α, that is related to the variation of payments between primary factors due to the change in the tasks performed. The effect of investments in technology manifests instead along two separate impacts: a direct impact on labor, denoted by β, due to substitution or complementarity with employment, and an indirect impact, denoted by γ, through the change in GVCs position, which propagates to labor with magnitude $\alpha\gamma$. Therefore, the overall effect of technological change on labor can be estimated as $\beta + \alpha\gamma$, where $\alpha\gamma$ is the combined effect of technology and GVCs.

Figure 1: The impact of GVCs position and technological change on labor



Notes: We discuss how we estimate α, β, and γ in the dedicated subsections below. The econometric specifications are reported in Equations 1 and 10.

Our conceptual framework refines the estimation of the impact of GVCs and technology on labor with respect to standard representations in the literature. The introduction of the indirect impact of technology on GVCs allows indeed to estimate an extra effect that is usually overlooked. Neglecting this channel, not only silences an additional effect on the labor shares, but also leads to biased estimates for the impact of technological change when investigating the role of specific types of technologies.

Despite its virtues, it is worth stressing the challenges related to the estimation of this framework. Taking into account such a complex interaction of different effects entails facing severe endogeneity concerns. To address these issues we perform a two steps estimation procedure. In the first step we estimate the direct impact of GVCs position and technology on labor, respectively α and β, adopting a theory consistent estimator. In this step we care to purge the endogeneity from the position within GVCs using an instrumental variable approach. In the second step, we estimate the impact of technology on GVCs, γ, by developing an alternative measure of GVCs position that exploits the virtue of the Gravity framework to purge endogenous shocks contemporaneously impacting technology adoption and variation in GVCs position.

In the following subsections we discuss the theoretical foundations underlying the two step estimation procedure.

2.1 The direct impact of GVCs and technology on the labor share

We can derive a specification for the direct impact of GVCs and technology from the theoretical expression of the cost function. By Shephard's lemma, the labor share, LS equals the elasticity of the cost function with respect to the price of labor. After some manipulations, and augmenting for the position in GVCs, we can rewrite in changes as follows[1]:

$$\Delta LS_{ckt} = \kappa + \alpha \Delta GVC_{ckt} + \beta \Delta \ln(K/VA)_{ckt} + \mathrm{FE}_c + \mathrm{FE}_k + \varepsilon_{ckt} \tag{1}$$

We run stacked differences regressions with Δ periods equal to 2011-2007, 2007-2003, 2003-1999. $\ln(K/VA)$ is the log of capital over value added ratio; we further split to account for the stock value of machinery, $\ln(Mach/VA)$, ICT, $\ln(ICT/VA)$, and robots, $\ln(Robots/VA)$. To measure GVCs position we use the distance from final demand, *Ups*, the distance from primary inputs, *Dwn*, and total length of the chain, *Length*, that corresponding to the sum of the two (Antràs, Chor, Fally & Hillberry 2012, Miller & Temurshoev 2017). FE_c and FE_k are respectively country and industry fixed effects to absorb relative wages and time invariant factors.

To address endogeneity we instrument GVC with a measure of market access adapting Antràs & De Gortari (2020). We instrument *Ups* with market access, MA^g_{ckt} for intermediate goods, $g = int$, *Dwn* with final goods, $g = fin$, and *Length* with the sum of the two, $g = int + fin$. We construct the instrument at the country-industry-year level as the weighted sum of the expenditure E by each foreign country d for good type $g = \{int, fin, int + fin\}$ produced by a given industry k, with weights equal to the distance between the two countries, $dist_{ck}$:

$$MA^g_{ckt} = \sum_{d=1}^{D} \frac{E^{d,g}_k}{dist_{cd}} \tag{2}$$

[1] The full derivation is reported in Appendix A.2.

2.2 The indirect impact of technology through GVCs

We study the impact of technology adoption on GVCs position by investigating whether different types of technologies are associated more with variation in intermediate input production (and exporting) or with final goods assembly. To detect such impact we need to address endogeneity issues: for instance, foreign demand shock may affect both output and the propensity to invest in technology, thus leading to estimate a biased relationship between the two.

For this purpose, we develop a measure of position that is purged from demand shocks by exploiting the virtue of a gravity based framework. To do so we estimate a measure of relative productivity as the log ratio of productivity in intermediate goods production – associated with a more upstream position – over productivity in final goods production – associated with a more downstream position. To estimate these two elements, we exploit the Leontief structure $X = Z + Y = AX + Y$ and split the matrix of intermediate input shipments, Z, from that of final goods shipment, Y. Consider the case of productivity in intermediate inputs and matrix $Z = [z^{kj}_{cd}]$, where c is a source country, d is a destination country, and k and j denote industries. We are not interested in the using industry dimension j, so we sum over j to get $z^k_{cd} = \sum_j z^{kj}_{cd}$. Import shares are given by $\pi^k_{cd} = z^k_{cd} / \sum_c z^k_{cd}$. We model these along the lines of Eaton & Kortum (2002),

$$\begin{aligned}
\pi^k_{cd} &= \frac{T^k_c (C^k_c)^{-\theta_k} \left(\tau^k_{cd}\right)^{-\theta_k}}{\sum_{c',k} \left(T^k_{c'}/C^k_{c'}\right)^{\theta_k} \left(\tau^k_{c'd}\right)^{-\theta_k}} \\
&= \exp\left\{ \ln \frac{T^k_c (C^k_c)^{-\theta_k} \left(\tau^k_{cd}\right)^{-\theta_k}}{\sum_{c',k} \left(T^k_{c'}/C^k_{c'}\right)^{\theta_k} \left(\tau^k_{c'd}\right)^{-\theta_k}} \right\} \\
&= \exp\{ \underbrace{\ln T^k_c (C^k_c)^{-\theta_k}}_{\alpha^k_c} + \underbrace{[-\ln \sum_{c',k} \left(T^k_{c'}/C^k_{c'}\right)^{\theta_k} \left(\tau^k_{c'd}\right)^{-\theta_k}]}_{\beta^k_d} + \underbrace{\ln \left(\tau^k_{cd}\right)^{-\theta_k}}_{\epsilon^k_{cd}} \} \ ,
\end{aligned} \tag{3}$$

T denotes the level of technology; τ denotes bilateral trade barriers that we account for with distance, a dummy for international trade flows and a residual component ψ; the unit cost terms C may include inputs (both domestic and imported) and domestic primary factors, as in Caliendo & Parro (2015); we allow different elasticities θ by industry. We do not need to consider cross-industry effects as long as the share of inputs used by destination industries is fixed (Cobb-Douglas aggregator over all inputs), as in Caliendo & Parro (2015). We estimate (3) by PPML in cross sections in some periods t, industry k by industry k including source and destinations fixed effects, along with distance and a dummy for international trade flows to control for bilateral factors in $\tau^k_{c'd}$:

$$\pi^{(kt)}_{cd} = e^{dist_{cd} + International_{cd} + \alpha^{(kt)}_c + \beta^{(kt)}_d + \varepsilon^{(kt)}_{cd}} . \tag{4}$$

Using the estimates we can construct

$$\text{Source} : \widehat{T}^{(kt)}_c (\widehat{C}^{(kt)}_c)^{-\theta_k} = e^{\widehat{\alpha}^{(kt)}_c} \tag{5}$$

$$\text{Destination} : \sum_{c'k} \widehat{T}^{(kt)}_{c'} (\widehat{C}^{(kt)}_c)^{-\theta_k} [\widehat{\tau}^{(kt)}_{cd}]^{-\theta_k} = \widehat{\Phi}^{(kt)}_{cd} = e^{-\widehat{\beta}^{(kt)}_d} \tag{6}$$

$$\text{Bilateral} : [\widehat{\tau}^{(kt)}_{cd}]^{-\theta_k} = e^{\widehat{\varepsilon}^{(kt)}_{cd}} \tag{7}$$

In practice, the source and destination fixed effects are identified only up to a constant. Since π^d_{ck} are shares and we estimate (4) by PPML, we can easily deal with this normalization. Therefore, we define our measure of productivity in intermediate goods production (a) as

$$\varphi^a_{ck} = \frac{e^{\widehat{\alpha}^{(kt)}_c}}{\max_k [e^{\widehat{\alpha}^{(kt)}_c}]} \tag{8}$$

Estimation of productivity in final goods production, φ^y_{ck} follows the same procedure considering the matrix Y.

We can finally define our alternative measure of GVCs position as

$$\varphi^{ay}_{ck} = \ln \left[\frac{\varphi^a_{ck}}{\varphi^y_{ck}} \right] \tag{9}$$

The following table provides correlations between upstreamness and our measures of productivity. Results are coherent with theoretical predictions: higher productivity in intermediate goods production is associated with a more upstream position (Col. 1). On the contrary, we find a negative coefficient for productivity in final goods production. The estimation controls for yearly and industries' trends: the latter are required due to the within industry-year normalization of $e^{\widehat{\alpha}^{(kt)}_c}$. Results are robuts to the addition of country fixed effects, Col. (2). In Col. (3) and (4) we disentangle Ups between distance to final goods production abroad, Ups^{for}, and domestically, Ups^{dom}. Consistent with the geographical fragmentation of production due to GVCs, the coefficient of $\ln(\varphi^a)$ is found to be larger for foreign upstreamness (Col. 3). Finally, Column (5) to (7) shows that the relationship is not driven by specific years, while it is constant throughout our period.

Table 1: Correlation between *Ups* and φ

Var.	(1) Ups	(2) Ups	(3) Ups^{for}	(4) Ups^{dom}	(5) Ups	(6) Ups	(7) Ups
$\ln(\varphi^a)$	0.242^a	0.209^a	0.136^a	0.073^a	0.199^a	0.224^a	0.264^a
	(0.010)	(0.009)	(0.012)	(0.011)	(0.036)	(0.042)	(0.042)
$\ln(\varphi^y)$	-0.259^a	-0.191^a	-0.100^a	-0.091^a	-0.181^a	-0.207^a	-0.235^a
	(0.010)	(0.010)	(0.012)	(0.012)	(0.032)	(0.039)	(0.041)
Obs	2,545	2,545	2,545	2,545	196	196	196
R^2	0.935	0.952	0.885	0.862	0.964	0.957	0.960
FEs	y k	y c k	y c k	y c k	c k	c k	c k
Year	all	all	all	all	1999	2003	2007

Notes: Robust standard errors in parentheses. "*a*" $p < 0.01$, "*b*" $p < 0.05$, "*c*" $p < 0.1$. Weighted regressions using country-industry VA in 1999 as weight.

Armed also with an alternative measure for GVCs position, we estimate the impact of technology on GVCs as follows:

$$\Delta GVC_{ckt} = \kappa + +\beta \Delta \ln(K)_{ckt} + \text{FE}_c + \text{FE}_k + \varepsilon_{ckt} \tag{10}$$

Also in this case we run stacked differences regressions with periods equal to 2011-2007, 2007-2003, 2003-1999. GVC_{ckt} is either Ups or φ^{ay}_{ck} and $\Delta \ln(K)_{ckt}$ is the variation in the stock of technology, as above split between machinery, ICT and robots.

3 Data and descriptive statistics

We construct our estimation sample combining different sources. Labor data come from Timmer et al. (2019), who report the labor share, and the share accrued to different business functions for countries and industries in WIOD 2013 industry classification. They define 4 broad groups of occupations: Fabrication (FAB), R&D, Management (MGT), and Marketing (MAR).[2]

GVCs positioning is measured using international input-output tables using WIOD 2013 release. We follow the methodologies and definitions proposed by Antràs et al. (2012) and Miller & Temurshoev (2017) to estimate distance from final demand, *Ups*, distance from primary factor, *Dwn*, and total length of the chains, $Length = Ups + Dwn$. To construct the instrument we source gravity variables from the CEPII gravity dataset (Head & Mayer 2014).

To gather information for technology stocks, we combine two different sources. EU KLEMS provides data on capital stock at the country-industry level disaggregated for ten different categories. First, we match the EU-KLEMS to the WIOD industry nomenclature. Then, for each country-industry we define the stock in ICT vs non-ICT capital. The former comprises IT (computer and hardware), CT (communication technologies) and Software and Databases; the latter the rest of capital. Being interested in the role of robots, a crucial challenge is to estimate their value and remove it from the total of non-ICT capital. To do so, we source information on stock and investments of units of robots from the International Federation of Robotics (IFR). Matching the IFR with the WIOD nomenclature and exploiting the standardization of robots capabilities and prices (Acemoglu & Restrepo 2020), we converted stock of units in stock of values using unit prices series from IFR. This procedure allows, first, to have the stock of robots in value terms, thus comparable to that of ICT and non-ICT capital in EU-KLEMS; secondly, to clean the EU-KLEMS non-ICT aggregate from robots, thus avoiding double counting. Therefore, combining these different sources we end up with three categories of technology: *ICT*, *Robots*, and the rest of technology, which we refer to us *Machinery*.

Given the coverage of the different data sources we end up with a balanced panel comprising 14 European countries and 14 manufacturing sectors in the period 1999-2011. Included countries are: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, UK, Greece, Italy, Netherlands, Slovakia and Sweden. Included industries are (in parentheses NACE rev.1 code): Food, Beverages & Tobacco (15-16), Textiles & Apparel (17-18), Leather & Footwear (19), Wood & Cork (20), Pulp, Paper, Printing & Publishing (21-22), Coke, Refined petroleum and Nuclear (23), Chemicals (24), Rubber & Plastics (25), Other non-metallic mineral (26), Basic metals and Fabricated metals (27-28), Machinery

[2] Table A.2 provide the ISCO-88 occupations associated to each business functions.

(29), Electrical & Optical equipment (30-33), Transport equipment (34-35), Other Manufacturing (36-37).

Table 2 provides the list of countries and industries with the highest values for the main variables in our study. As concern the labor share top 5 countries have more than the 70% of value added that is absorbed by labor, with UK reaching the 80%. Looking at industries, it is not surprising the first place for textile. The same holds when looking at the most upstream sectors, with Basic Metals, Rubber and Wood. Focusing on technology, we find that Germany has the largest stocks for ICT, and especially, machinery and robots. Among industries, the same role is detained by the Transport equipment industry.

Table 2: Top 5 countries and industries for main variables

Top 5	**LS** (%)	**Ups** (# stages)	**Mach** (bil $)	**Technology ICT** (bil $)	**Robots** (bil $)
Countries	UK (80)	FIN (2.65)	DEU (78)	DEU (4.5)	DEU (0.9)
	DNK (74)	CZE (2.50)	ITA (30)	FRA (4.1)	ITA (0.2)
	DEU (72)	ESP (2.38)	FRA (27)	ITA (1.6)	FRA (0.2)
	ITA (72)	BEL (2.37)	UK (25)	UK (1.4)	ESP (0.1)
	FRA (70)	SVK (2.36)	NLD (15)	ESP (1.2)	UK (0.1)
Industries	Text (78)	B. Met (2.99)	Tr Eq (93)	Tr Eq (6.0)	Tr Eq (2.2)
	O. man (77)	Rubb (2.70)	E&O Eq (50)	E&O Eq (5.1)	B Met (0.3)
	Tr Eq (77)	Wood (2.70)	Chem (50)	Mach (2.6)	E&O Eq (0.2)
	E&O Eq (76)	N Met (2.63)	B. Met (39)	Chem (2.4)	Rubb (0.1)
	Mach (76)	Paper (2.60)	Mach (35)	B. Met (1.8)	Mach (0.1)

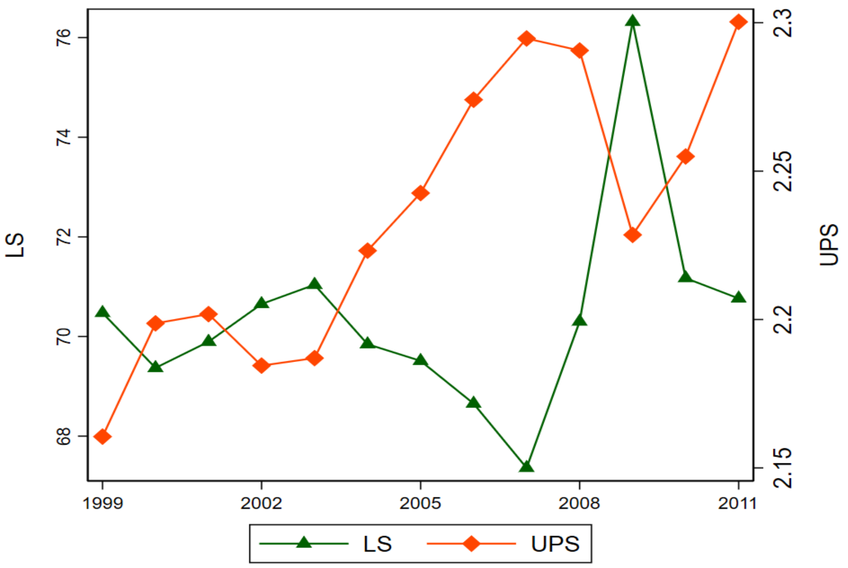
Notes: The table reports country and industries averages across the period 1999-2011. Country-industry value added is used as weight.

Being interested in changes, we focus our attention in the next figures to variation over time.

Figure 2 depicts the variation of *Ups* and of the labor share, *LS*, throughout our period. We show a clear negative correlation between the two variables, suggesting an association of more upstream stages with less labor intensive productions.

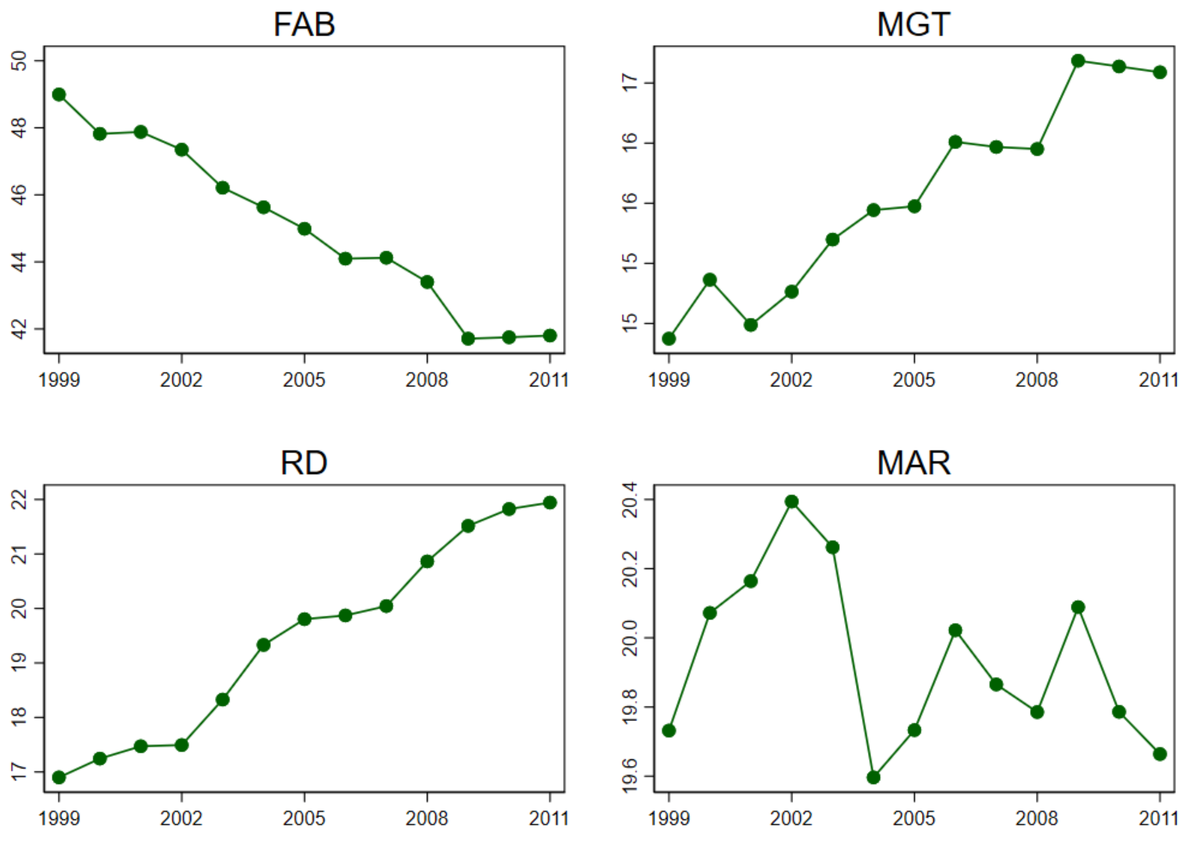
Given that the impact of GVCs on labor may manifest through a change in activities performed which in turn affects labor requirements, it is important to look at the variation through time of different business functions. The average pattern of the labor share may be indeed the result of a composition effect across different functions. Figure 3 provide such evidence by showing the within-labor variation of different functions. In our period, we have a clear reduction of payments to the fabrication function that reduces its share by about 7pp. Management and especially R&D take this stake by increasing their share of 2 and 5pp, respectively. The share of Marketing is instead constant around the 20%.

Figure 2: GVCs position and the labor share



Notes: The figure reports yearly weighted averages. Country-industry value added is used as weight.

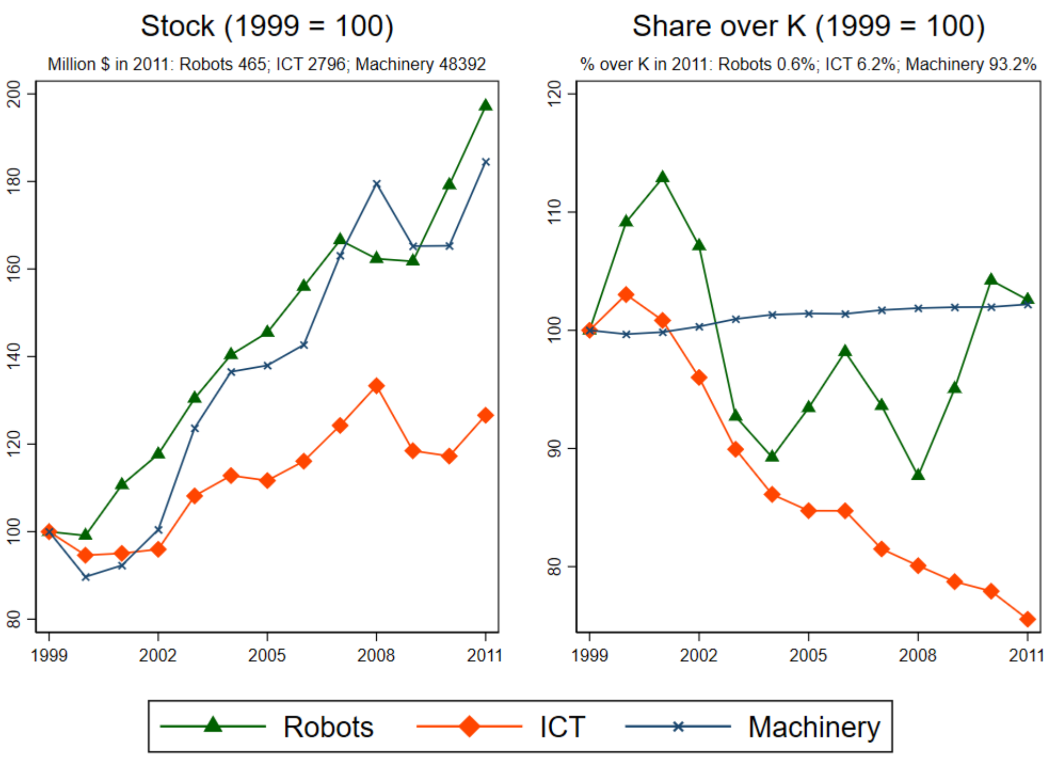
Figure 3: Labor functions



Notes: The figure reports yearly weighted averages. Country-industry value added is used as weight. Business shares are calculated within the labors shares: VA(funct)/VA(LS)

Figure 4 provides the evolution of technology adoption. On the left panel, we show that all categories of technology grew between 1999-2011, even if ICT at a much smaller pace. Machinery and especially robots, doubled they stock value in the period. On the right panel, we depicts the variation of the share of each category over total capital: ICT reduced their share while robots and machinery remained constant. It is worth stressing that, in 2011, machinery still accounts for the large majority of capital (93%); on the contrary, despite having doubled their stock value, robots account on average for the 0.6%.

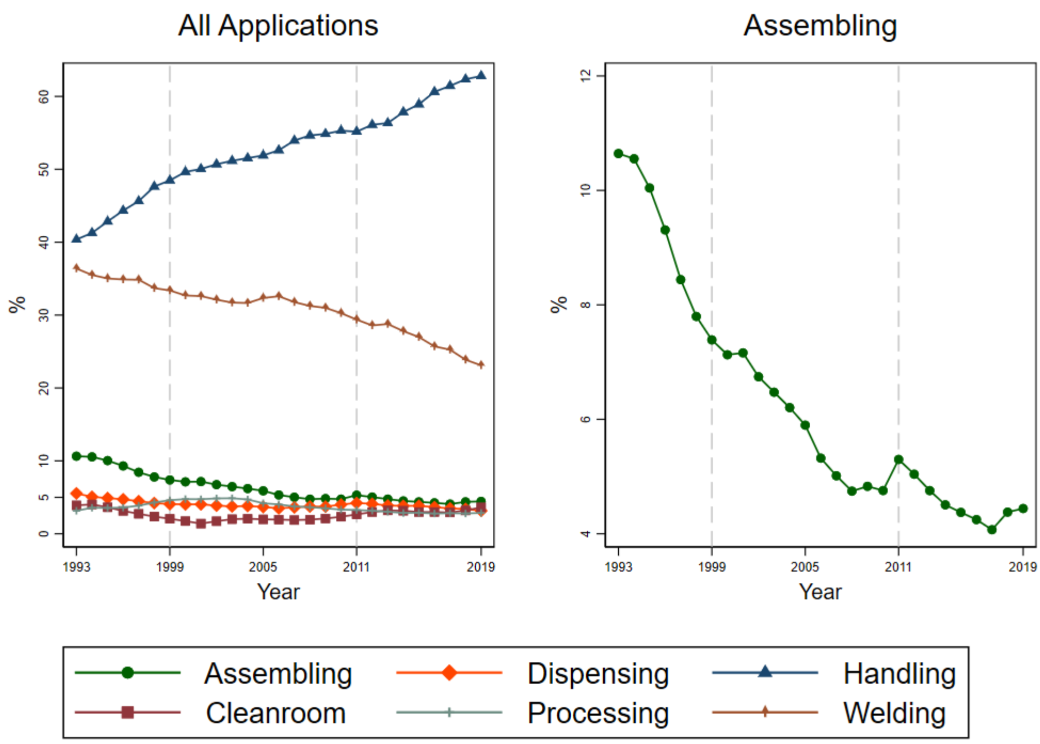
Figure 4: Technology adoption



Notes: The figure reports yearly weighted averages. Country-industry value added is used as weight.

Finally in Figure 5 we provide additional information on robots adoption. Given that we envisage an impact of robots on GVCs through their capacity of changing the activity of specialization, here we focus on the tasks that robots can actually perform within the production process. IFR reports indeed also information for the application of installed robots; unfortunately the latter is available only at the country level, without further disaggregation at the industry level. On the left panel, we show that the majority of robots provide handling and welding tasks, with the former that increased their share by 30pp between 1993 and 2019. Other applications, such as dispensing, processing and assembling do not reach the 10%. On the right panel, we further focus on assembling robots. The small share for this category is surprising to us, as robots have been often thought as a break to GVCs integration because of their potential to substitute low-value added off-shored activities such as assembling. We show, that the share of assembling robots not only was already low in 1993, but it also halved in the following 25 years. Robots have never been just assemblers, and in fact are less and less so. On the contrary they can provide highly specialized tasks along with the highest level of precision and reprogrammability: for all these reasons we argue that they are likely to affect the specialization of the production process creating narrower niches and affecting the position along GVCs.

Figure 5: Robots applications over time



Notes: The figure reports yearly averages on country level data. Shares are calculated over the total of robots with "Specified" application: the share of unspecified robots has decreased sharply from 1993 to 2019, falling from 33 to 9pp. In Figure A.1 in Appendix we report the same figure with shares calculated over total robots.

4 Results

This section presents the results estimated following the econometric approach discussed in Section 2. All regressions are in changes with 3 delta periods equal to 2011-2007, 2007-2003 and 2003-1999; observations are weighted using country-industry value added in 1999; we also include country and industry fixed effects to absorb trends.

In Table 3 and 4 we report the direct impact of a variation in GVCs position and in technology adoption on the labor share.

In Table 3 we focus on the impact of different measures of GVCs position and control for the variation in the log ratio of total capital over value added, $\Delta \ln(K/VA)$. Explicitly, we consider the variation in upstreamness, ΔUps, in downstreamness, ΔDwn, and in total length of the chain, $\Delta Length$. For each measure, we run an OLS (Col. 1, 3 and 5) and an IV estimation (Col. 2, 4 and 6); as instruments we use the above described measures of market access from Antràs & De Gortari (2020). All right-hand side (RHS) variables are standardized. Among the different measures of GVCs position, only an increase in upstreamness (Col. 1 and 2) has a significant impact on the labor share. We find that a standard deviation increase in upstreamness reduces the labor share by 8pp. The remarkable magnitude of the coefficient is due to the fact that the distribution of ΔUps has very thick tails: a variation of one standard deviation corresponds indeed to moving from the lowest to the highest decile of the distribution. On the contrary, the coefficient for downstreamness is not significant (Col. 3 and 4). The effect of upstreamness seems to prevail on that of downstreamness: we find indeed a significant coefficient for also $\Delta Length$ (Col. 6). All in all, these results suggest that integration in GVCs through exporting of intermediate inputs increases the capital intensity of the production and leads to a geographical relocation of the payments to primary inputs. Table A.3 in Appendix provides further evidence by showing that the average effect of upstreamness is due to increased distance with respect to *foreign* final production. Finally, as concerns the direct impact of technology we find significant capital-labor complementarity across all regressions: a standard deviation increase in $\Delta \ln(K/VA)$ leads to an increase of the labor share between 3 and 4pp.

Given the results just discussed, we keep our attention on upstreamness and investigate how different measures of technology adoption directly affect the labor share, Table 4. We disentangle capital in three categories: ICT, robots and the rest of capital (Machinery). Col. (2) and (4) provide evidence of the differential impact of these categories, while Col. (1) and (3) are reported from Table 3 as a comparison.

Table 3: The direct impact of GVCs and technology on the labor share

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:			ΔLS			
$\Delta \ln(K/VA)$	3.780^a	2.860^a	4.098^a	3.871^a	3.927^a	3.349^a
	(0.931)	(1.019)	(0.914)	(0.983)	(0.948)	(1.017)
ΔUps	-2.042^a	-7.996^a				
	(0.767)	(1.736)				
ΔDwn			0.044	-3.753		
			(0.942)	(2.472)		
$\Delta Length$					-1.291	-5.728^a
					(0.903)	(1.593)
Obs.	587	587	587	587	587	587
Model	OLS	IV	OLS	IV	OLS	IV
IV	-	MA^{int}	-	MA^{fin}	-	$\mathrm{MA}^{int+fin}$
F-test	-	50.57	-	44.06	-	77.57
FE	c k	c k	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" $p < 0.01$, "b" $p < 0.05$, "c" $p < 0.1$. Weighted regressions using country-industry VA in 1999 as weights. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. All RHS variables are standardized.

We find that machinery and ICT are complementary to labor, with a standard deviation increase that leads to about 2pp higher labor share. Surprisingly, we do not find any effect for robots adoption: the coefficient is indeed not different from 0.

In Table 5 we investigate whether the documented effects are heterogeneous across different labor functions. For this purpose, we regress the variation in the share of each business function over value added against upstreamness and the different categories of technology. In Col. (1) we report the average effect on the labor share as in Table 4 (Col. 4): by construction of the dependent variables, coefficients in Col. (1) are the sum of those in Col. (2)-(5). We find that the impact of upstreamness is mainly absorbed by occupations related to fabrication (Col. 2). A standard deviation increase in *Ups* has about a 2.5 higher impact on this business function than on the other. Nonetheless, also *RD*, *MGT*, and *MAR* are negatively impacted. As one could expect, the impact of technology is even more heterogeneous: investments in machinery affect (positively) only *RD*, while it has no impact on the other business functions; on the contrary, adoption of ICT positively increases the share of *FAB* and *MAR*. Also in this case, the coefficient for robots is not significant.

Table 4: The impact of different categories of technology

	(1)	(2)	(3)	(4)
Dep Var:		ΔLS		
ΔUps	-2.042^a	-1.981^a	-7.996^a	-7.861^a
	(0.767)	(0.741)	(1.736)	(1.667)
$\Delta \ln(K/VA)$	3.780^a		2.860^a	
	(0.931)		(1.019)	
$\Delta \ln(Mach/VA)$		2.629^a		2.034^b
		(1.014)		(0.967)
$\Delta \ln(ICT/VA)$		2.049^a		1.719^b
		(0.761)		(0.842)
$\Delta \ln(Robots/VA)$		0.267		-0.144
		(0.386)		(0.364)
Obs.	587	587	587	587
Model	OLS	OLS	IV	IV
IV	-	-	MA^{int}	MA^{int}
F-test	-	-	50.57	49.79
FE	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" p < 0.01, "b" p < 0.05, "c" p < 0.1. Weighted regressions using country-industry VA in 1999 as weights. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. All RHS variables are standardized. Robots are expressed in values. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.

Table 5: The direct impact on business functions

	(1)	(2)	(3)	(4)	(5)
Dep Var:	ΔLS	ΔRD	ΔFAB	ΔMGT	ΔMAR
ΔUps	-7.861^a	-1.350^b	-3.645^a	-1.412^a	-1.454^a
	(1.667)	(0.544)	(0.948)	(0.530)	(0.444)
$\Delta \ln(Mach/VA)$	2.034^b	1.101^a	0.513	0.295	0.125
	(0.967)	(0.364)	(0.496)	(0.266)	(0.229)
$\Delta \ln(ICT/VA)$	1.719^b	0.026	0.800^c	0.167	0.725^b
	(0.842)	(0.345)	(0.469)	(0.323)	(0.286)
$\Delta \ln(Robots/VA)$	-0.144	-0.144	-0.055	0.048	0.006
	(0.364)	(0.244)	(0.243)	(0.120)	(0.144)
Obs.	587	585	585	585	585
Model	IV	IV	IV	IV	IV
IV	MA^{int}	MA^{int}	MA^{int}	MA^{int}	MA^{int}
F-test	49.79	49.78	49.78	49.78	49.78
FE	c k	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" p < 0.01, "b" p < 0.05, "c" p < 0.1. Weighted regressions using country-industry VA in 1999 as weights. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. All RHS variables are standardized. Business functions are expressed as shares over value added. Robots are expressed in values. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.

Summing up, studying the direct impact of GVCs position and technology adoption on labor outcome, we find heterogeneous effects across different measures. As concerns GVCs position, in line with previous literature, we find a negative impact for upstream movements, while a variation in downstreamness has no effect. As concerns technology adoption, machinery and ICT on average complement labor, even if different business functions are concerned. What is surprising is the null effect of robots adoption. A fast growing literature has indeed estimated a meaningful impact of robots adoption on various employment outcomes (Graetz & Michaels 2018, Acemoglu & Restrepo 2020). We argue that our results are driven by the fact that we contemporaneously investigate the impact of variation in GVCs position. We consider indeed that the effect of robots mainly channel as a specialization effect, thus affecting activities performed: if that is the case, when controlling for GVCs position, which precisely measures the variation in production content, we are not able to find a direct effect for robots. On the contrary we should find that robots adoption are a salient determinant for the variation in GVCs position.

To test our predictions we move on in our empirical analysis to show the indirect impact of technology through GVCs. Table 6 provides the estimation of Equation 10. The dependent variable is the variation in GVCs position, measured either as upstreamness (Col. 1) or as gravity-based productivity in intermediate vs final goods production (Col. 2-4). Technology adoption is measured as the variation in the log stock value of the different categories of capital. We find that one standard deviation increase in robots adoption increases upstreamness by 0.08 standard deviations. This effect is due to the increase in the relative productivity in intermediates goods production (Col. 2). Col. (3) and (4) split the latter effect to show the specific impact on the two components: robots increases only productivity for intermediate goods while their impact is equal to 0 for final good production. These results seem to support our hypothesis concerning the impact of robots through GVCs, as well as the lack of a direct impact on labor. In addition, we also find interesting results for the other categories of technology. Adoption of ICT does not impact GVCs position (Col. 1). However, adopting the same line of reasoning than that for robots, this is not surprising. ICT mainly act as a support for the core activities of production, therefore their impact manifests in an increase in productivity for both intermediate and final goods production (Col. 3 and 4). On the contrary, adoption of machinery increases upstreamness while at the same time increasing productivity in final goods production. At this stage of the work, this remains a puzzling result.[3]

[3] Various hypotheses to better understand possible underlying explanations are currently under scrutiny and this constitutes one of the several improvements we plan for the paper. The latter are briefly presented in the next section.

Table 6: The indirect impact of technology on GVCs position

Dep Var:	(1) ΔUps	(2) $\Delta\varphi^{ay}_{ck}$	(3) $\Delta\varphi^{a}_{ck}$	(4) $\Delta\varphi^{y}_{ck}$
$\Delta\ln(Mach)$	0.282^a	-0.063^b	-0.015	0.048^b
	(0.059)	(0.026)	(0.022)	(0.019)
$\Delta\ln(ICT)$	0.094	-0.013	0.041^c	0.054^b
	(0.070)	(0.030)	(0.025)	(0.025)
$\Delta\ln(Robots)$	0.083^a	0.032^a	0.035^a	0.003
	(0.028)	(0.009)	(0.006)	(0.008)
Obs.	587	587	587	587
Model	OLS	OLS	OLS	OLS
FEs	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" p < 0.01, "b" p < 0.05, "c" p < 0.1. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. Both the dependent and the RHS variables are standardized. Robots are expressed in values. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.

Armed with the estimation of the indirect effect of technology, we can provide a quantification of the total impact on labor. As discussed in Section 2, the total impact of technology on labor can be written as the sum of the direct, β, and indirect component, $\alpha\gamma$. Retrieving coefficients from Table 4 (Col. 4) and 6 (Col. 1) we find that a standard deviation increase in robots adoption reduces the labor share by 0.8pp: $\beta^{Robots} + \alpha\gamma^{Robots} = -0.144 + (-7.861 \times 0.083) \approxeq -0.8pp$. Considering machinery, the indirect impact through GVCs offsets the complementarity detected in Table 4, leading to a total negative impact on the labour share: $\beta^{Mach} + \alpha\gamma^{Mach} = 2.034 + (-7.861 \times 0.282) \approxeq -0.2pp$. These results show that neglecting the indirect impact of technology through GVCs leads to unbiased estimates of the effect on technological change. Indeed, the indirect impact is significant and it acts as an important channel for the impact on the labor share.

5 Next steps

The following refinements and enlargements to the paper are on the agenda.

First we intend to further investigate the relationship between technology adoption and GVCs position. To do so, we aim at developing a theoretical characterization that could more formally describe how technological change may affect activities performed and specialization patterns. This could benefit the empirical specification by offering testable theoretical predictions as well as more suitable tools for interpreting the results. Along this line, we also plan to find an instrument for technology adoption, at least for robots. This could allow to address endogeneity that still affects our estimation despite the gravity-based alternative for GVCs position.

Moreover, we purpose to enlarge baseline results on the direct impact on labor along two main directions. First, by focusing also on employment outcomes. This could allow to study the implications in number of jobs instead of in value added terms, therefore providing additional policy insights as well as a more direct comparison with other studies in the literature. Secondly, we intend to decompose GVCs position from also a geographical point of view. In other words, we intend to split upstreamness in the sum of different components measuring distance to final production taking place in *different* group of countries (or in principle also in single countries). This would show whether the average impact is driven by exposure towards specific areas thus offering further evidence on the underlying mechanisms.

6 Conclusions

Technological change and the rise of GVCs are two of the main forces that have shaped economic growth and development in the last decades. A crucial issue is to understand what is their impact on labor outcomes. Extensive literature has studied this topic focusing on the single effect of GVCs and of technology adoption. In this article we propose a framework encompassing both of these impacts as well as a combined impact. We argue indeed that, beyond the direct channel, technology affects labor in combination with GVCs, by affecting the specialization of production and therefore inducing movements in the position within GVCs.

We estimate separately all of these single effects taking into consideration the differences among groups of technologies as well as the impact on different groups of occupations. We find that an increase in upstreamness reduces the labor share with a pronounced impact on occupations related to fabrication. The effect of different groups technology is heterogeneous: ICT impact the labor share only directly, robots only indirectly, while for machinery the indirect effect offsets the direct one. All in all, this shows the importance of accounting for the combined impact of GVCs and technology and calls for further research on the issue to provide new empirical evidence as well as appropriate theoretical frameworks.

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A Appendix

A.1 Additional descriptive statistics

Table A.1: Labor Functions and Occupations

Labor Function	**ISCO-88 Classification**	
	Major title	Sub-Major title
Management	(1) Legislators	All
R&D	(2) Professionals	(21) Phys., Math. & Eng. Prof. (22) Life Sc. and H Prof. (23) Teaching Prof.
	(3) Technicians & Ass. Prof.	(31) Ph., Math. & Eng. Ass. Prof. (32) Life Sc. and H Ass. Prof. (33) Teaching Ass. Prof.
Marketing	(2) Professionals	(24) Other Prof.
	(3) Tech. & (34) Ass. Prof.	(34) Other Ass. Prof.
	(4) Clerks	All
	(5) Service & Sales wks	All
	(9) Elementary occ.	(91) Service & Sales Elem. Occ.
Fabrication	(6) Skilled Agr. and Fish. wks	All
	(7) Craft wks	All
	(8) Plant & Machine oper. & ass.	All
	(9) Elementary occ.	(92) Agr., Fish. and rel. wkr (93) Min., Cons., Manuf & Tr. wkr

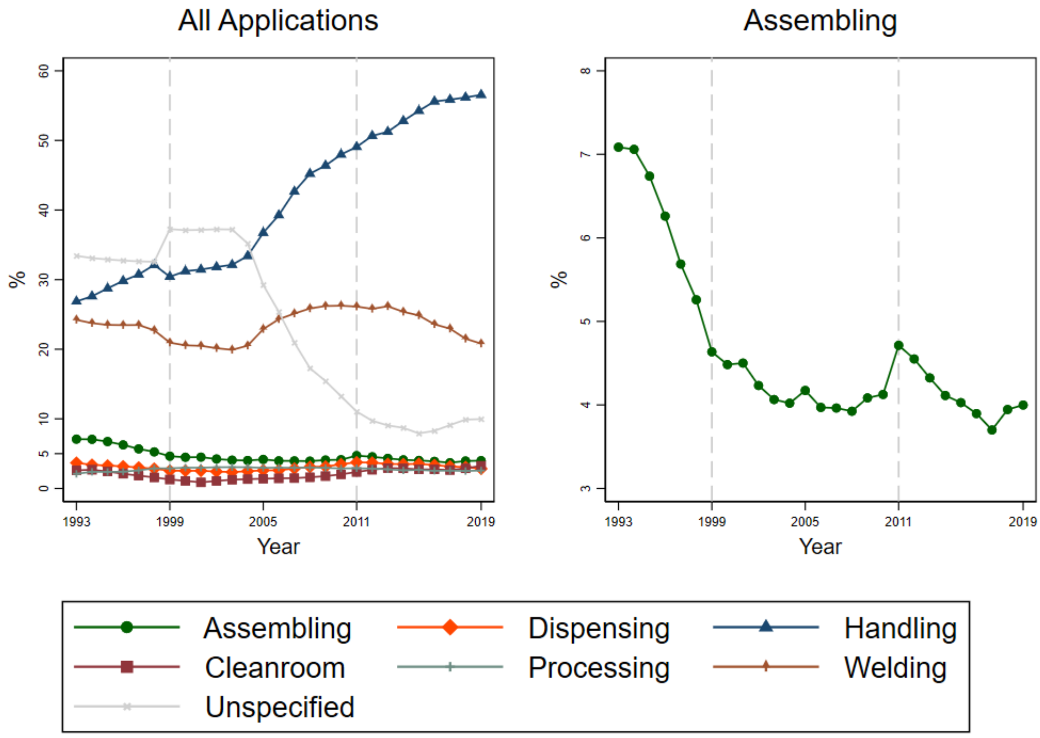
Notes: Classification by Timmer et al. (2019). ISCO-88 codes in parentheses.

Table A.2: Robots applications - IFR classification

Category	**Application**
(11) Handling Operations & mach. tending	(111) Metal casting (112) Plastic moulding (113) Stamping, forging, bending (114) Handling operations at machine tools (115) Machine tending for other processes (116) Measurement, inspection, testing (117) Palletizing (118) Packaging, picking, placing (119) Material handling (120) Handling operations unspecified
(16) Welding & soldering	(161) Arc welding (162) Spot welding (163) Laser welding (164) Other welding (165) Soldering (166) Welding unspecified
(17) Dispensing	(171) Painting & enamelling (172) Application of adhesive, sealing material (179) Other dispensing/spraying (180) Dispensing unspecified
(19) Processing	(191) Laser cutting (192) Water jet cutting (193) Mechanical cutting/grinding/deburring (198) Other processing (199) Processing unspecified
(20) Assembling & disassembling	(201) Assembling (203) Disassembling (209) Assembling unspecified
(90) Others	(901) Cleanroom for FPD (902) Cleanroom for semiconductors (903) Cleanroom for others (905) Others
(99) Unspecified	

Notes: IFR classification. Codes in parentheses.

Figure A.1: Robots applications over time



Notes: The figure reports yearly averages on country level data. Shares are calculated over the total of robots.

A.2 Cost share function

Let L be a vector of variable inputs with per-unit of input costs W; here L includes labor and, in principle, materials. Let K denote a vector of quasi-fixed types of capital, e.g., ICT, machinery and robots. Denote output as Y. Variable costs are given by $C = L'W = \sum_i L_i W_i$. If the L_i's are the argmin of costs, then C is the variable cost function. The logarithm of C can be approximated by a translog cost function:

$$\begin{aligned}
\ln(C) = & \sum_i \alpha_i \ln(W_i) + \sum_i \epsilon_i \ln(K_i) + \epsilon_y \ln(Y) + \\
& + \frac{1}{2}\left[\sum_i \sum_j \beta_{ij} \ln(W_i) \ln(W_j) + \sum_i \sum_j \epsilon_{ij} \ln(K_i) \ln(K_j) + \epsilon_{yy} \ln(Y)^2\right] \\
& + \sum_i \sum_j \gamma_{ij} \ln(W_i) \ln(K_j) + \sum_i \gamma_{iy} \ln(W_i) \ln(Y) + \sum_i \epsilon_{iy} \ln(K_i) \ln(Y) \ .
\end{aligned}$$

Symmetry implies $\alpha_{ij} = \alpha_{ij}$ and $\beta_{ij} = \beta_{ij}$. By Shephard's lemma, $\partial C/\partial W_i = L_i$, so that the cost share of L_i is

$$S_i \equiv \frac{W_i L_i}{C} = \frac{W_i}{C}\frac{\partial C}{\partial W_i} = \frac{\partial \ln(C)}{\partial \ln(W_i)} \ .$$

The cost share is the elasticity of cost w.r.t. the input price. Then, for a particular input i we have

$$S_i = \alpha_i + \sum_j \beta_{ij} \ln(W_j) + \sum_j \gamma_{ij} \ln(K_j) + \gamma_{iy} \ln(Y) \ .$$

Using lower case for log values we can write

$$S_i = \alpha_i + \sum_j \beta_{ij} w_j + \sum_j \gamma_{ij} k_j + \gamma_{iy} y \ .$$

By linear homogeneity of cost with respect to prices, cost shares are homogeneous of degree zero in input prices; therefore $\sum_j \beta_{ij} = 0$. This allows writing

$$S_i = \alpha_i + \sum_{j>1} \beta_{ij}(w_j - w_1) + \sum_j \gamma_{ij} k_j + \gamma_{iy} y$$

for some input indexed by 1, where $w_j - w_1$ is the log relative wage w.r.t. input 1. This is useful for not worrying about differences in costs that affect all inputs proportionately. The interpretation of the γ_{ij}'s is a shift in relative demand for factor i, controlling for input prices. This is the equation that underlies much of the empirical capital-skill complementarity literature.

By linear homogeneity of the production function we have $\sum_j \gamma_{ij} + \gamma_{iy} = 0$ (increasing all inputs by the same factor increases output by same factor, but this should not affect the cost share; effects on optimal quantities of L are captured in the γs). This allows writing

$$S_i = \alpha_i + \sum_{j>1} \beta_{ij} \left(w_j - w_1\right) + \sum_{j} \gamma_{ij} \left(k_j - y\right) \ , \tag{A.1}$$

where $k_j - y$ is the log capital output ratio (expressed in value added) for capital type j.

We can augment (A.1) with the position in GVCs. Expressing the relationship in changes and adapting the notation of coefficient to the conceptual framework provided in Figure 1, we derive the empirical specification in **??**.

$$\Delta LS_{ckt} = \kappa + \alpha \Delta GVC_{ckt} + \beta \Delta \ln(K/VA)_{ckt} + \mathrm{FE}_c + \mathrm{FE}_k + \varepsilon_{ckt}$$

Note that $\sum_{j>1} \beta_{ij} \left(w_j - w_1\right)$ in A.1 are absorbed by FE_c and FE_k. If we assume that wages (in levels) combine a time-invariant ck component and time varying ct and kt components,

$$W_{ckt} = W_{ck} \cdot W_{ct} \cdot W_{kt} \ ,$$

then in logs

$$w_{ckt} = w_{ck} + w_{ct} + w_{kt} \ ,$$

and

$$\Delta w_{ck} = \Delta w_c + \Delta w_k \ .$$

A.3 Additional results

Table A.3: Ups from *foreign* vs *domestic* final production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ΔLS		ΔRD		ΔFAB		ΔMGT		ΔMAR	
$\Delta \ln(K/VA)$	4.000***	4.230***	1.277***	1.303***	1.357***	1.518***	0.649***	0.646***	0.717***	0.763***
	(0.838)	(0.840)	(0.354)	(0.331)	(0.388)	(0.410)	(0.185)	(0.183)	(0.201)	(0.213)
ΔUps^{for}	-3.156***		-0.390		-1.549***		-0.561***		-0.655***	
	(0.675)		(0.284)		(0.381)		(0.161)		(0.161)	
ΔUps^{dom}	-0.291		-0.011		-0.483		0.264		-0.060	
	(0.556)		(0.280)		(0.306)		(0.177)		(0.178)	
ΔFwd		-2.488***		-0.349		-1.027***		-0.627***		-0.485***
		(0.661)		(0.221)		(0.382)		(0.144)		(0.147)
β (ΔUps)	-2.042***	-	-0.237	-	-1.214***	-	-0.166	-	-0.424**	
	(0.767)	-	(0.320)	-	(0.376)	-	(0.197)	-	(0.202)	-
Obs.	587	587	585	585	585	585	585	585	585	585
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
FE	c k	c k	c k	c k	c k	c k	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" p $<$ 0.01, "b" p $<$ 0.05, "c" p $<$ 0.1. Weighted regressions using country-industry VA in 1999 as weights. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. All RHS variables are standardized. β (ΔUps) reports the coefficient of ΔUps for a comparison with the disaggregation in its two components, Ups^{for} and Ups^{dom}.

Table A.4: The indirect impact of technology on GVCs position - Units of robots

Dep Var:	(1) ΔUps	(2) φ^{ay}_{ck}	(3) φ^{a}_{ck}	(4) φ^{y}_{ck}
$\Delta\ln(Mach)$	0.279***	-0.063**	-0.015	0.048**
	(0.058)	(0.026)	(0.022)	(0.019)
$\Delta\ln(ICT)$	0.094	-0.012	0.042*	0.054**
	(0.070)	(0.030)	(0.025)	(0.025)
$\Delta\ln(Robots)$	0.083***	0.025***	0.028***	0.003
	(0.029)	(0.009)	(0.006)	(0.008)
Obs.	587	587	587	587
Model	OLS	OLS	OLS	OLS
FEs	c k	c k	c k	c k

Notes: Robust standard errors in parentheses. "a" $p < 0.01$, "b" $p < 0.05$, "c" $p < 0.1$. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011-2007, 2007-2003, 2003-1999. Both the dependent and the RHS variables are standardized. Robots are expressed in units. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.