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Automation, global value chains and functional specialization

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Abstract

We study how technology adoption and changes in global value chain (GVC) integration jointly affect labor shares and business function specialization in a sample of 14 manufacturing industries in 14 European countries in 1999–2011. Increases in upstream, forward GVC integration directly reduce labor shares, mostly through reductions in fabrication, but also via other business functions. We do not find any direct effects of robot adoption; robotization affects labor only *indirectly*, by increasing upstream, forward GVC integration. In this sense robotization is "upstream-biased". Rapid robotization in China shaped robotization in Europe and, therefore, relative demand for labor there.

KEYWORDS

automation, functional specialization, global value chains, labor share, robots, technological change, upstreamness

JEL CLASSIFICATION

E25, F14, F16, 033

1 | INTRODUCTION

Countries and industries that integrate into global value chains (GVCs) gain by specializing in production steps in which they have a comparative advantage, while potentially offshoring other stages of the chain. These changes may manifest in specializing in relatively more downstream activities, that is, closer to final stages of production and assembly—or more upstream activities, that is, production of intermediate inputs. Indeed, GVC integration is considered one of the most important dimensions of globalization in recent decades (e.g., Johnson, 2018).

Beyond their manifestation in trade (and international ownership) patterns, changes in GVC integration also impact payments to domestic primary production factors. Labor and capital intensities vary systematically across stages of production (Antràs et al., 2012). Labor shares, as well as business function (or task) intensities, also vary within value chains (Reshef & Santoni, 2023). Thus, GVC integration affects business function specialization and the overall functional division of income.

Technological change plays an equally important role in determining these evolutions. First, it has a *direct* effect by complementing or substituting labor—both overall and differentially across specific labor tasks. Second, it may have an *indirect* effect on payments to labor and on functional specialization through its impact on changes in the pattern of specialization across stages of production. Characterizing this indirect channel—by which technology adoption affects labor through its impact on the position within GVCs—is one important contribution of this paper. In doing so, we pay special attention to the role of China in inducing the indirect mechanism, since the global integration of China is one of the most important economic events during our period of study. We find evidence for a novel channel through which China has affected GVC integration and, through this, relative demand for labor: by inducing robotization in Europe.

We study the direct and indirect channels in 14 manufacturing sectors across 14 European countries in 1999–2011. Our findings are based on regressions of stacked changes in the presence of country and industry fixed effects, and we bolster the validity of our results by using plausibly excludable instruments. This demanding specification identifies causal effects through "within" variation over time, which, *inter alia*, addresses many of the concerns raised by Grossman and Oberfield (2022) in the context of labor shares.

We assess the specific impacts of distinct categories of technologies, which are allowed to have heterogeneous effects across outcomes. ICT and automation—the latter measured by robot adoption—potentially complement different skills, as well as substitute different types of tasks. In addition, their impact on specialization in production may also vary: for instance, while ICT may support better management of all currently performed tasks, investments in automation may induce specialization in other stages of production. In order to compare the impact of these different groups of technology, we develop a procedure to estimate the value of robot capital stocks (beyond robots counts) separately from other types of capital (in particular, machinery).

When studying direct effects, we find that increases in forward GVC integration, that is, greater specialization in upstream activities, reduces the labor share, which is mainly shouldered by fabrication tasks. This is consistent with previous evidence in Sposi et al. (2021) and Reshef and Santoni (2023). While the impact is greatest for fabrication tasks, we also find significant impacts on other business functions. This is consistent with ideas in Baldwin (2016), whereby offshoring of fabrication tasks necessarily entails offshoring of some of management, marketing and even R&D.

While we observe the expected direct impact of technology adoption on labor (although heterogeneous across different categories of technology), we find no evidence for a direct effect of robots on labor outcomes. The effect of robots on labor shares and on functional specialization works only *indirectly*, through their impact on the position within GVCs. In particular, we find that investment in robots increases the upstreamness of the industry—that is, distance to final step of production—through their disproportional positive impact on upstream, versus downstream, production. These results are consistent with robots being more complementary to tasks that characterize upstream activities more than downstream assembly tasks. Although we cannot identify this at the industry level, aggregate trends clearly indicate that most robot installations are not in assembly, but in handling and welding applications, which appear to be more characteristic of upstream production tasks. We call this phenomenon "upstream-biased" robotization. This finding is an important contribution of our paper.

When studying variations in labor shares in the time period of our study, the role of China in the reshaping of GVC must indeed be addressed (Reshef & Santoni, 2023). China's accession to the World Trade Organization in 2001 is different, because of the size of the country, it is relatively low wages, and its capabilities in the industrial sector. Often depicted as the "world factory", China is both a source of intermediary inputs, a destination market and a competitor. This unique combination has led to labor outcomes extensively documented in the literature (Autor et al., 2013; Autor et al., 2016). But what is not documented in the literature is the impact of *automation in China*. Thus, another contribution of this paper is to investigate how automation in China—not only as a vast labor market with low wages, but as a country which has rapidly embraced robotization—has ultimately impacted GVC patterns by inducing automation elsewhere, in the rest of the world.

We find that robotization in China induces robotization in Europe through three channels: inputs supply, market demand in China, and competition from China. The first channel captures the effects of robotization in China via greater efficiency and standardization of Chinese inputs that are used in European industries. The second channel captures the effect of robotization in China on competition in Chinese markets. The third channel captures the so-called "China syndrome" effect of greater productivity of Chinese exporters to Europe, and, thus, supply of Chinese goods. All three induce greater robotization in Europe.

Our paper contributes to different strands of literature. First, we contribute to the study of the relationship between GVC integration and labor. Sposi et al. (2021) extend a model of sequential GVC production proposed by Antràs and De Gortari (2020) to include Heckscher-Ohlin mechanics, and argue that declines in trade barriers cause relocation of relatively capital-intensive upstream stages to relatively capital abundant countries. Reshef and Santoni (2023) study empirically how the evolution of labor shares is affected by GVC integration; they find that declines in labor shares were driven by upstream, forward GVC integration, that is, exporting of intermediate goods, coinciding with China's rapid integration into international production networks (as as purchaser of these intermediate inputs). Timmer et al. (2019) show that revealed comparative advantage indices across business functions—measured in payments to labor—based on gross trade statistics deviate significantly from those based on trade in value added, which are more sensible. Since these functions have heterogeneous incidences at different stages of value chains, we show that this is another way how GVC integration affects functional specialization.

We also relate to the literature that studies the relationship between technology adoption and labor outcomes. Several studies have focused on the polarizing role of ICT technologies according to the skills' level (Autor et al., 2008; Goos & Manning, 2007; Harrigan et al., 2021; Michaels et al., 2014). 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 (Acemoglu & Restrepo, 2018; Acemoglu & Restrepo, 2019; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). A different strand of the literature has focused on the role of technology sophistication for resilience to shocks: Comin et al. (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. We contribute to this literature through our study of direct impacts on labor outcomes.

Finally, and no less importantly, our paper contributes to the literature that studies the impact of automation on international trade. In so doing, we are among the first to study the impact of robotization on labor market outcomes that are channeled via GVC integration. Artuc et al. (2020) provide evidence that robotization increases North-South trade. We add to this the salience of the impact of robotization on upstream, intermediate inputs exports, not on downstream final good production. Thus, robot adoption can be said to be "upstream-biased". As discussed above, this is due to the nature of applications that robots are assigned to. The upstream-biased nature of robotization affects relative demand for labor due to changes in GVC integration.

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 and Section 5 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 hypothesize that both the position of a country-sector in the value chain and the adoption of new technologies that automate repetitive tasks have an impact on labor outcomes. This relationship is represented in Figure 1. First, since different stages of the production process are characterized by different combinations of tasks, a change in GVC position will induce a change in the tasks performed in an industry-country. The footprint of this specialization is ultimately observed in variation of payments to primary factors. We refer to it in the following as the *direct* impact of GVC position on labor, denoted by α in Figure 1. The effect of investment in technology also has a direct impact on labor, denoted by β, due to substitution or complementarity with labor. Second, we also consider an *indirect* impact of technology on GVC positioning, denoted by γ in Figure 1, which propagates its effect on 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 effect of technology via GVC positioning.

The vertex "labor" is taken here in a broad sense, since we are interested in the direct and indirect impacts on different functions within industries, beyond the labor share itself. We will consider four broad groups of functions: Fabrication, R&D, Management and Marketing.

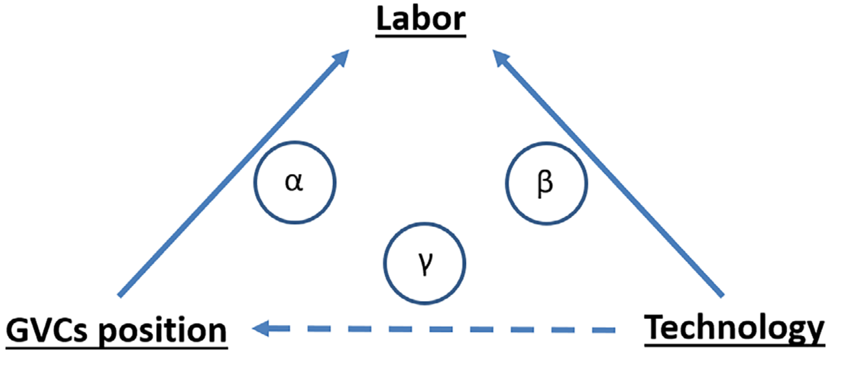

FIGURE 1 The impact of GVC position and technological change on labor (We discuss how we estimate α, β, and γ in the dedicated subsections below. The econometric specifications are reported in Equation (1) and (4)). [Colour figure can be viewed at wileyonlinelibrary.com]

This conceptual framework refines the estimation of the impact of GVC integration and technology on labor with respect to standard representations in the literature. The introduction of the indirect impact of technology on GVC integration allows us 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 potentially biased estimates for the impact of technological change when investigating the role of specific types of technologies.

Despite its virtues, estimation of this framework raises econometric challenges. Taking into account such a complex interaction of different effects raises endogeneity concerns. To address these issues we perform our estimation procedure in two steps. In the first step we estimate the direct impact of GVC position and technology on labor, respectively α and β, adopting a theory-consistent estimator to perform causal inference. We address endogeneity by using an instrumental variable approach: we instrument for both changes in GVC position and robot adoption, the latter being the category of technology of our interest. In the second step, we study the impact of technology on GVC integration, γ, providing estimates for a set of instrumental variables for robot adoption, which address potential reverse causality.

In the following subsections we discuss the estimation procedure and provide details on econometric specifications.

2.1 | The direct impact of GVC integration and technology adoption on labor

We wish to identify the direct impact of technology and GVC integration. Our measure of GVC integration is upstreamness, that is, "distance" from final good production. In particular, we ask how changes in the relative demand for labor—overall, or of a given type—in a country-sector-year, as reflected in its share in total costs, is impacted by the changes in GVC integration of the same triplet, controlling for changes in capital intensity, and for unobserved time-invariant country and industry trends and characteristics. We split capital into different types, with a focus on robots. In addition to the difficult measurement of robot acquisition (beyond counts of installed robots), the challenge is the endogeneity of the labor share with technology adoption and with positioning in the value chain.

We first derive a specification for the direct impact of GVC integration and technology on labor from the theoretical expression of the translog 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 GVC, we can write in changes as follows:[1]

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

In Equation (1) α and β are the two direct impacts of, respectively, GVC position and technology adoption on labor outcomes, which are depicted in Figure 1. We estimate these coefficients in a panel of stacked differences with Δ denoting changes in 2011–2007, 2007–2003, 2003–1999. In Equation (1) $\ln(K/VA)$ is the log of the ratio of capital to value added; we further split to account for the stock value of machinery, $\ln(Mach/VA)$, ICT, $\ln(ICT/VA)$, and robots, $\ln(Robots/VA)$.[2] To measure GVC integration we use the distance from final good production, *Ups* (Antràs et al., 2012; Miller & Temurshoev, 2017). FE_c and FE_k are respectively country and industry fixed effects to absorb trends in relative wages and other factors.

In order to address endogeneity we build on Antràs and De Gortari (2020) and instrument for GVC integration with a measure of market access. We instrument *Ups* with market access for intermediate goods, MA^{int}_{ckt}. We construct the instrument at the country-industry-year level as the weighted sum of the expenditure E by each foreign country d in intermediate goods, *int*, produced by a given industry k, with weights being the exogenous variation of geographical distance between the two countries, $dist_{ck}$:

$$MA^{int}_{ckt} = \sum_{d=1}^{D} \frac{E^{int,d}_{k} t}{dist_{cd}}. \tag{2}$$

The instrument for changes in *Ups*, that is, the distance from the final stage of production, of industry k in country c is given by taking changes of Equation (2) over the appropriate years.

In order to address the endogeneity between the labor share and robot adoption we construct an instrument building on Artuc et al. (2020). In Equation (3) we use the triple interaction between (i) the share of wage in a given industry replaceable by robots, (ii) the country GDP per capita, and (iii) robots installation in the world (out of our sample):

$$IV^{Artuc\ et\ al.}_{ckt} = shW^{repl}_{k(US),1990} * \ln(GDPc)_{ct} * \ln\left(\sum_{j\notin C} Inst^{Robots}_{jt}\right). \tag{3}$$

The first component in Equation (3), $shW^{repl}_{k(US),1990}$, captures industry level variation in the scope of automatable tasks. We calculate the share of wages replaceable by robots in each industry using IPUMS Census Data for US for year 1990. In order to identify labor occupations replaceable by robots we follow the procedure in Graetz and Michaels (2018): an occupation is replaceable if its description contains at least a word included in the description of robots applications.[3] The description of robots applications is sourced from International Federation of Robotics (IFR). Capturing industry characteristics in the United States in 1990, this component is plausibly exogenous to specific country-industry dynamics in our sample. The second component, $ln(GDPc)_{ct}$, captures country variation in the average cost of production. This, combined with the scope for automation, gives country-industry variation in the incentive to robotize. We use GDP per capita series from World Bank. The third component, $\ln\left(\sum_{j\notin C} Inst^{Robots}_{jt}\right)$, accounts for robots installations elsewhere in the world (out of our sample) as a proxy for the price of robots, thus capturing time-level variation. Country-industry cells with high incentive to robotize will do so more intensively when the cost is lower. Installations of robots are sourced from the IFR.

As for the instrument for changes in *Ups*, the instrument for robot adoption of industry k in country c is given by taking changes of Equation (3).

2.2 | The indirect impact of technology through GVC

We study the impact of technology adoption on GVC integration by investigating whether robot adoption is associated with variation in the distance from the final stage of production, or with variation in intermediate input production (and exporting) *versus* final goods assembly and production. The estimated equation is:

$$\Delta GVC_{ckt} = \kappa + \gamma_1 \Delta \ln(Robots)_{ckt} + \gamma_2 \Delta \ln(Mach)_{ckt} + \gamma_3 \Delta \ln(ICT)_{ckt} + \mathrm{FE}_c + \mathrm{FE}_k + \varepsilon_{ckt}. \tag{4}$$

In Equation (4), γ_1 captures the channel from robot adoption to GVC position (as depicted in Figure 1), which in turn impacts *indirectly* labor outcomes. This position is measured in multiple ways: by the distance from final good production of industry k in country c, by intermediate goods sales relative to final goods sales for this industry-country pair, or separately by intermediate goods sales versus final goods sales. Concretely, we measure ΔGVC_{ckt} with the variation in upstreamness ΔUps, already defined above, and with the log variation in the ratio of sales of intermediate inputs (m) over final goods (f) sales, $\Delta lnSales^{mf}$. We also consider the separate impacts on the numerator and the denominator, respectively $\Delta lnSales^{m}$ and $\Delta lnSales^{f}$. $\Delta \ln(Mach)_{ckt}$ and $\Delta \ln(ICT)_{ckt}$ controls for the variation in the stock of machinery and ICT. Also in this case, we estimate Equation (4) in a panel of stacked differences with periods equal to 2011–2007, 2007–2003, 2003–1999.

In order to estimate γ we again need to address endogeneity. For example, a foreign demand shock may affect both output and the propensity to invest in technology, thus leading to estimate a biased relationship between the two. More generally, investments, increases in market size and deepening of international sourcing may be complementary (e.g., Lileeva and Trefler (2010) and Bøler et al. (2015)). While these are distinct from changes in GVC position—which may occur in relative terms or in absolute levels—we acknowledge that there may be complex relationships between GVC integration and investments in technology. Recognizing this, we took care to address potential endogeneity by using instruments that plausibly address the reverse impact of GVCs on technology adoption.

In this second step, we focus our attention on the role of robots: we instrument for this variable while controlling for the role of machinery and ICT.

To instrument for robots, we first use IV_{ckt}^{Artuc} as defined in Equation (3). Importantly, we provide three additional instruments that focus on the role of China in global markets, which has drastically reshaped patterns of GVC and affected labor outcomes in advanced economies. In contrast to the usual approach, we do not consider here China as a vast labor market with low wages, but as a country which has rapidly embraced robotization. We investigate here the role of automation in China in impacting GVC integration through inducing automation elsewhere, in this case, in Europe. We consider three channels for the impact of Chinese automation based on different types of GVC linkages.[4]

The first channel considers the role of China as an *input producer*. As depicted in Equation (5), to account for industry variation we use the share of Chinese intermediate inputs used in a given US industry k in 1999, $shINPUTS_{k(US),1999}^{fromCHN}$. We then use total installation of robots in China to account for technology upgrading and automation of the Chinese economy, $\ln\left(Inst_{CHN,t}^{Robots}\right)$. The instrument captures the cost reduction due to Chinese automation that induces robotization in Europe through greater supply of intermediate inputs at lower prices and greater standardization of inputs. Country variation is captured by the log of GDP per capita:

$$IV_{ckt}^{CHN,inp} = shINPUTS_{k(US),1999}^{fromCHN} * ln(GDPc)_{ct} * \ln\left(Inst_{CHN,t}^{Robots}\right). \tag{5}$$

In the second channel we consider the role of China as a *destination market*. We modify Equation (5), by using the share of a given US industry k exports to China in 1999, $shEXPORT_{k(US),1999}^{toCHN}$. The instrument captures robot adoption induced by competition in China: due to automation in the Chinese economy, higher market shares in China may induce automation in Europe as a way to protect the Chinese market from domestic Chinese competition.

$$IV_{ckt}^{CHN,mkt} = shEXPORT_{k(US),1999}^{toCHN} * ln(GDPc)_{ct} * \ln\left(Inst_{CHN,t}^{Robots}\right). \tag{6}$$

In the third channel we consider the role of China as a *competitor* in European markets. In Equation (7), we use as industry variation the share of imports from China by US in 1999 of goods produced by a given industry k, $shIMPORT^{fromCHN,k}_{US,1999}$. It is important to take note of the difference with the first channel: in this case we consider the output market for industry k whereas Equation (5) considers the input reliance for industry k. The instrument captures robot adoption as *escape competition* (Aghion et al., 2005).

$$IV^{CHN,comp}_{ckt} = shIMPORT^{fromCHN,k}_{US,1999} * ln(GDPc)_{ct} * \ln\left(Inst^{Robots}_{CHN,t}\right). \tag{7}$$

As for our baseline instrument in Equation (3), the instruments for robot adoption of industry k in country c are given by taking changes of Equation (5)–(7).

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).[5]

GVC position is measured using international input-output tables from the WIOD 2013 release. We follow the methodologies and definitions proposed by Antràs et al. (2012) and Miller and Temurshoev (2017) to calculate upstreamness, *Ups*, as distance from final good production. To construct the instrument we source gravity variables from the CEPII gravity dataset.

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 and non-ICT capital. ICT capital comprises computers and hardware (IT), communication technologies (CT) and Software and Databases. Non-ICT capital comprises the rest of the capital stock, notably machinery. Since we are interested in the distinct role of robots, it is important to estimate their value and remove it from the total of non-ICT capital. To do this, we source information on stock and investments of units of robots from the IFR. Matching the IFR with the WIOD nomenclature and exploiting the standardization of robots capabilities and prices (Acemoglu & Restrepo, 2020), we convert stocks of units to stocks of values using unit prices series from IFR. This procedure gives the stock of robots in the same terms in which ICT and non-ICT capital are measured in EU-KLEMS. We exploit this to remove the stock of robots from non-ICT capital stocks, thus avoiding double counting. To our knowledge, we are the first to do this. Therefore, combining these different sources we end up with three categories of technology: *ICT*, *Robots*, and the rest of technology, which we refer to as *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

TABLE 1 Top 5 countries and industries for main variables.

			Technology		
	LS	Ups	Mach	ICT	Robots
Top 5	**(%)**	**(# stages)**	**(bil $)**	**(bil $)**	**(bil $)**
Countries	UK (81)	FIN (2.65)	DEU (82)	DEU (4.5)	DEU (0.9)
	DNK (74)	CZE (2.50)	ITA (31)	FRA (4.1)	ITA (0.2)
	DEU (72)	ESP (2.38)	FRA (29)	ITA (1.8)	FRA (0.2)
	ITA (72)	BEL (2.37)	UK (28)	UK (1.3)	ESP (0.1)
	FRA (70)	SVK (2.36)	NLD (17)	ESP (1.1)	UK (0.1)
Industries	Text (78)	B. Met (2.99)	Tr Eq (98)	Tr Eq (6.0)	Tr Eq (2.1)
	O. man (77)	Rubb (2.70)	E&O Eq (53)	E&O Eq (5.1)	B Met (0.3)
	Tr Eq (77)	Wood (2.70)	Chem (53)	Mach (2.7)	E&O Eq (0.2)
	E&O Eq (76)	N Met (2.63)	B. Met (41)	Chem (2.4)	Rubb (0.1)
	Mach (76)	Paper (2.60)	Mach (37)	B. Met (1.8)	Mach (0.1)

Note: The table reports country and industries averages across the period 1999–2011. Country-industry value added is used as weight. Technology is expressed in volume (ref. price 2010).

metals and Fabricated metals (27–28), Machinery (29), Electrical & Optical equipment (30–33), Transport equipment (34–35), Other Manufacturing (36–37).

Table 1 provides the list of countries and industries with the highest values for the main variables in our study. Looking first at labor shares, 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 that the first place is taken by Textiles. The most upstream industries are 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. Since we are interested in changes, we focus our attention in the next figures to variation over time.

Figure 2 depicts the variation of the distance from final good production, *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. It is important to note that in the same period the change in upstreamness is driven by an increase in its foreign component, that is, the change in the international linkages of the production network. Thus, changes in upstreamness are driven by changes in forward GVC integration.[6]

Given that the impact of GVC integration 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 overall pattern of the labor share may be indeed the result of a composition effect across different functions. Figure 3 provides such evidence by showing the within-labor variation of different functions. In our period, we observe a clear attrition of payments to the fabrication function that reduces its share by about 7% points. Management and especially R&D take this stake by increasing their share of 2% and 5% points, respectively. The share of Marketing is instead constant around the 20%.

Figure 4 provides the evolution of technology adoption. We consider volumes with 2010 reference prices. On the left panel, we show that all categories of technology grew between 1999 and

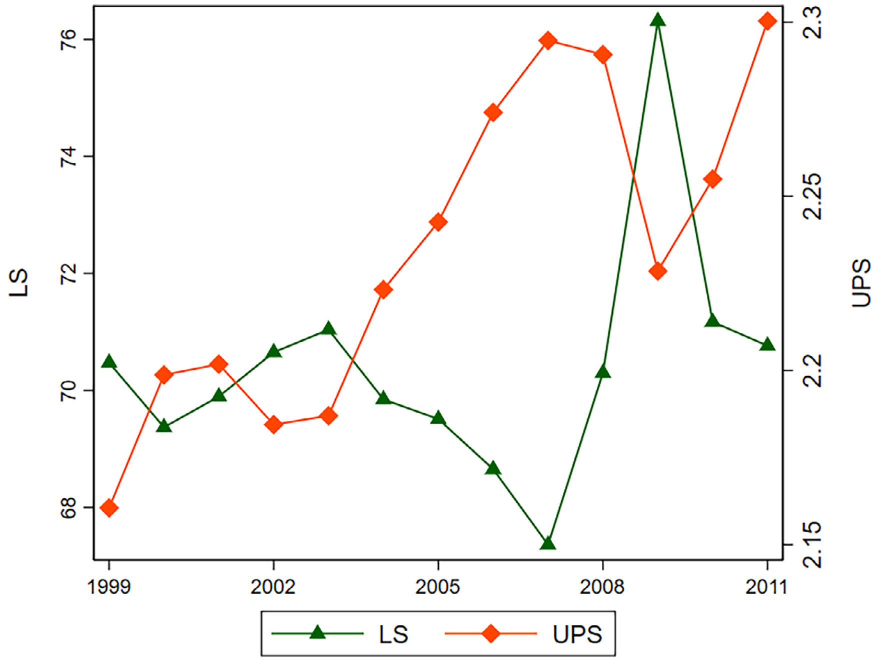

FIGURE 2 GVC position and the labor share (The figure reports yearly weighted averages. Country-industry value added is used as weight). [Colour figure can be viewed at wileyonlinelibrary.com]

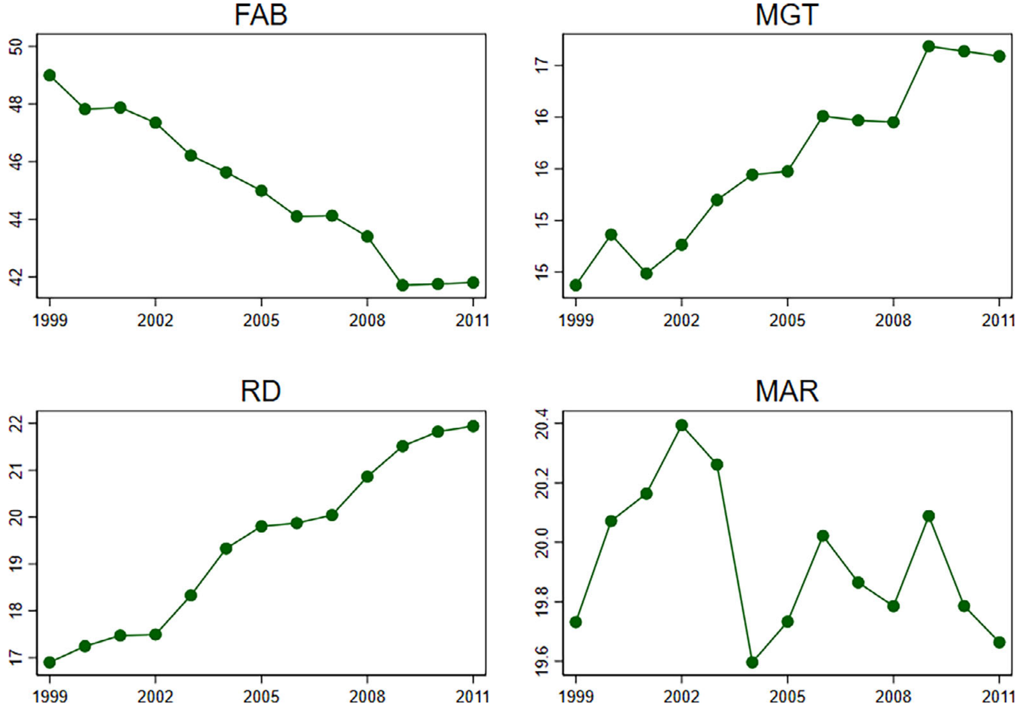

FIGURE 3 Labor functions (The figure reports yearly weighted averages. Country-industry value added is used as weight. Business shares are calculated within the labors share: VA(funct)/VA(LS)). [Colour figure can be viewed at wileyonlinelibrary.com]

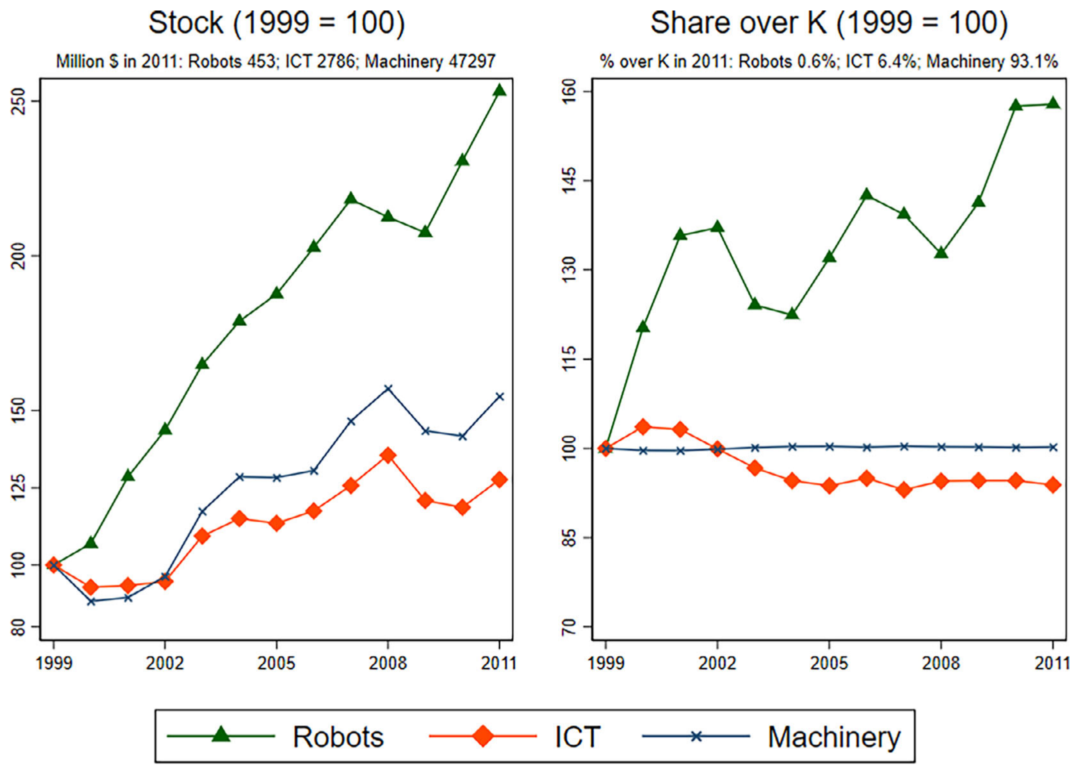

FIGURE 4 Technology adoption (The figure reports yearly weighted averages. Country-industry value added is used as weight. Technology is expressed in volume (ref. price 2010)). [Colour figure can be viewed at wileyonlinelibrary.com]

2011, even if robots at a much faster pace. On the right panel, we depict the variation of the share of each category over total capital: ICT slightly reduced its share, machinery remained constant, while robots grew substantially.

Despite the rapid growth of robots, in both absolute and relative terms, it is worth stressing that, in 2011, machinery still accounts for the large majority of capital in manufacturing industries (91.2%); robots account on average for only 0.6%.

In Figure 5 we provide additional information on robot adoption. Given that we envisage an impact of robots on GVC through their capacity of changing the activity of specialization, here we focus on the tasks that robots can actually perform within the production process. The IFR reports information for the application of installed robots; unfortunately this information is available only at the country level, without disaggregation at the industry level. On the left panel, we show that the majority of robots provide handling and welding tasks; handling tasks increased their share by 30% points between 1993 and 2019. Other applications, such as dispensing, processing and assembling account for less than 10% of robot installations.[7] On the right panel, we further focus on assembling robots. The small share for this category was surprising to us, as robots have been often thought of as a force that halts or even reverses GVC integration due to their potential to substitute labor-intensive offshored activities, such as assembly.[8] We show that the share of assembly 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:

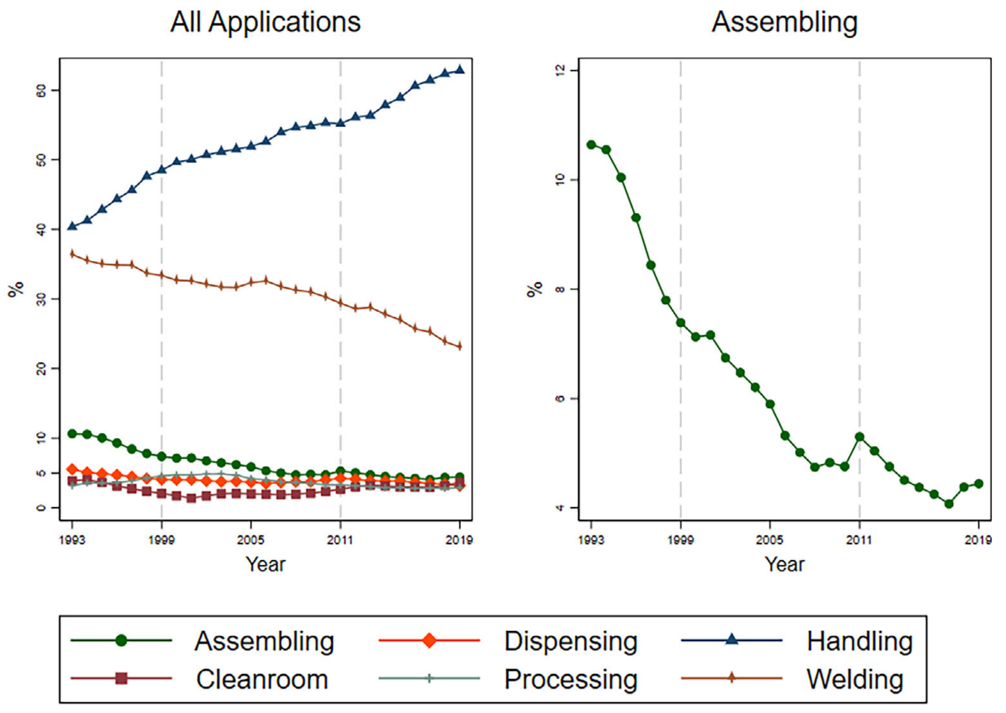

FIGURE 5 Robots applications over time (The figure reports yearly averages on country level data. Shares are calculated over the total of robots with "Specified" application: the share of unspecified robots has decreased sharply from 1993 to 2019, falling from 33 to 9pp. In Figure A2 in Appendix, we report the same figure with shares calculated over total robots). [Colour figure can be viewed at wileyonlinelibrary.com]

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 GVC.

4 | RESULTS

This section presents the results estimated following the econometric approach discussed in Section 2. All regressions are estimated in a panel of stacked changes in 3 periods: 2011–2007, 2007–2003 and 2003–1999. In all specifications observations are weighted using country-industry value added in 1999. We include country and industry fixed effects to absorb trends within these units. This renders our specification quite demanding.

It is useful to keep in mind the framework that is represented in Figure 1, which embodies the hypotheses about both the direct and indirect impact of robotization on labor outcomes. Thus, the questions addressed in the different specifications estimated below are: what is the impact of technology adoption and GVC integration on the relative demand for labor (see β and α in Figure 1)? Is there an indirect effect of technology adoption on labor due to the impact on the type of GVC integration, here captured by distance to final good production (γ)? These questions pertain not only to the labor share, but also to the four functions involved in the different stages of production, and we therefore distinguish between the impact on manufacturing tasks and the impact on management tasks, for example.

We show that specialization in upstream activities reduces the share of value added accruing to labor, in particular in fabrication tasks. In contrast, robots have no direct effects on labor

TABLE 2 The direct impact of GVC and technology on the labor share.

	(1)	(2)	(3)	(4)	(5)
Dep Var	**ΔLS**				
ΔUps	−2.108***	−2.014***	−8.205*	−1.915***	−9.664*
	(1.128)	(1.146)	(1.324)	(1.112)	(1.820)
$\Delta \ln(K/VA)$	3.206*				
	(1.237)				
$\Delta \ln(Mach/VA)$		2.307***	1.899***	1.723	2.764**
		(1.216)	(1.113)	(1.269)	(1.273)
$\Delta \ln(ICT/VA)$		1.836***	0.860	1.561	1.103
		(0.994)	(1.178)	(1.060)	(1.265)
$\Delta \ln(Robots/VA)$		0.034	−0.090	2.228	−3.690
		(0.367)	(0.341)	(1.773)	(2.997)
Obs.	587	587	587	587	587
IV Ups	–	–	✓	–	✓
IV Robots	–	–	–	✓	✓
F−test	–	–	32.2	29.4	7.2
FE	c k	c k	c k	c k	c k

Note: Clustered standard errors (country-period) in parentheses. 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. Technology variables are expressed in volume, ref. prices 2010.
***$p < .01$, **$p < .05$, *$p < .1$.

outcomes. Instead, we show that the adoption of robots leads to a specialization away from the final step of production and assembly, on upstream activities. Combining these two results indicates that robot adoption indirectly reduces the labor share due to the "upstream-biased" nature of robotization.

We show that the "upstream-biased" robotization mechanism is partially triggered by robotization in China, due to three distinctive roles: as an input producer, a market for intermediate inputs, and as a competitor on domestic markets. While all three channels are at play, the largest impact comes from China as an input producer. This highlights an understudied role of China's integration into the global economy. With this roadmap in mind, we can now examine the results of the various estimates.[9]

In Table 2, we report the direct impact of variations in GVC position and in technology adoption on the labor share, measured in percent of value added. All right-hand side (RHS) variables are standardized, to ease comparisons.

We start with weighted least squares (WLS) results. In Column 1 we focus on the impact of the change in the distance to the final good production ΔUps and of capital-output ratio (total capital stock divided by value added), $\Delta \ln(K/VA)$. We find that an increase by one standard deviation in upstreamness reduces the labor share by 2.1% points. Capital intensity is found to be complementary to labor: a one standard deviation increase in $\Delta \ln(K/VA)$ leads to an increase of the labor share by 3.2% points. This result is consistent with capital-labor complementarity.

In Columns 2–5 we split total capital stock in different categories: Machinery, ICT and Robots. In Column (2) we continue to use the WLS estimator, where we find that only Machinery and

TABLE 3 First-stage regressions for Table 2.

VARIABLES	(1) ΔUps	(2) $\Delta \ln(Robots/VA)$	(3) ΔUps	(4) $\Delta \ln(Robots/VA)$
ΔMA^{int}	0.290*		0.245*	0.048
	(0.051)		(0.063)	(0.048)
$\Delta IV^{Artuc\ et\ al.}$		−0.308*	0.083	−0.316*
		(0.057)	(0.064)	(0.062)
$\Delta \ln(Robots/VA)$	0.011			
	(0.027)			
ΔUps		0.085		
		(0.072)		
$\Delta \ln(Mach/VA)$	−0.043	0.231*	−0.033	0.229*
	(0.055)	(0.075)	(0.054)	(0.075)
$\Delta \ln(ICT/VA)$	−0.067	0.083	−0.063	0.084
	(0.073)	(0.101)	(0.072)	(0.101)
Observations	587	587	587	587
FE	c k	c k	c k	c k
Col. in Table 2	(3)	(4)	(5)	
$F-$test	32.2	29.4	7.2	

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

ICT are complementary to labor, while we do not estimate any impact for robot adoption. Notice that this is not only a statistical result: the coefficient to robots in column (2) is tiny.

In Column (3) we instrument for *Ups* using the measure of market access describe in Equation (2) (changes thereof), based on Antràs and De Gortari (2020). We find that a standard deviation increase in upstreamness reduces the labor share by 8.2% points—four times larger than the WLS point estimate. The remarkable magnitude of this coefficient need not be overemphasized, due to the fact that the distribution of ΔUps has very thick tails: a variation of one standard deviation corresponds to moving from the lowest to the highest decile of the distribution. The instrument is strong, with a Kleinbergen-Paap $F-$stat of over 30.

In Column (4), we instrument for robot adoption using the instrument based on Artuc et al. (2020). As when using the WLS estimator, here too we do not find a significant impact for robots, while the instrument itself is strong.

In Column (5) we report estimates using instruments for both upstreamness and robots. Results are in line those reported in columns (3) and (4). The first stage regressions reported in Table 3 justify why we are not concerned with the relatively low test statistic of 7.2 for weak instruments.

In Table 3, we report first stage regressions for IV regressions in Table 2 in (Columns 3–5). In column 1 of Table 3 we report the first stage regression for ΔUps as endogenous variable, controlling for the variation in capital stock, that is, $\Delta ln(Robots/VA)$, $\Delta ln(Mach/VA)$ and

$\Delta ln(ICT/VA)$. The instrument for the variation of *Ups* is the variation in market access for intermediate inputs, ΔMA^{int}. We find a positive and significant coefficient, with an $F-$test ensuring the strength of the instrument. The positive coefficient indicates that country-industries becoming relatively closer to larger buyers of intermediate goods specialize in more upstream production.

In column 2 of Table 3, we report the first stage regression for $\Delta ln(Robots/VA)$ as the endogenous variable and controlling for the variation in the distance to final production, ΔUps, and for the other two categories of capital stock, $\Delta ln(Mach/VA)$ and $\Delta ln(ICT/VA)$. We find a negative and significant coefficient indicating that robotization elsewhere in the world reduces the robots-to-value added ratio in a given country-industry. We interpret this coefficient as a relatively higher increase in value added due to robot adoption with respect to the increase in robot stock itself. This is consistent with a strong productivity-enhancing effect of robots, consistent with findings in Graetz and Michaels (2018). We will come back to this point below, when studying the indirect effects of robotization. We obtain an $F-$test statistic well above conventional thresholds.

In columns 3 and 4 of Table 3, we report the two first stage regressions for both ΔUps and $\Delta ln(Robots/VA)$ as endogenous variables. The two regressions provide reassuring results for our identification strategy. First, the coefficients to the instrument are unaffected, both in terms of magnitude and significance, compared to when each appears on its own in columns 1 and 2. Second, each endogenous variable is explained only by its own designated instrument, while the instrument for the other endogenous variable is not statistically significant. This ensures that the second stage regressions reported in Table 2 exploit predicted values for the endogenous variable that rely on the variability induced by the appropriate instrument. Thus, given the sign and the magnitude of the first stage coefficients, the strength of the instruments separately, as well as the difficulty in interpreting the first stage statistic in the case of multiple endogenous variables, we remain confident about the reliability of the IV estimation, despite a somewhat lower $F-$stat in column 5 of Table 2.

In Table 4 we investigate whether the impact of robotization and GVC integration differ across business 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. We instrument for both upstreamness and for robotization. In column (1) we report the effect on the labor share as in column (5) of Table 2. By construction of the business functions, the coefficients in column (1) are the sum of the corresponding ones in columns (2)–(5). We find that the impact of upstreamness is mainly shouldered by occupations related to fabrication (column 3). A standard deviation increase in *Ups* has about a 2.5 higher impact on this business function than on the others. However, ΔRD, ΔMGT and ΔMAR are also negatively impacted. In line with Baldwin (2016), offshoring of production not only concerns fabrication tasks, but also necessarily entails offshoring of some of management, marketing and R&D. As one could expect, the impact of technology is even more heterogeneous: investment in machinery are positively associated with ΔRD, while this has no impact on the other business functions; in contrast, adoption of ICT is positively associated with an increase in management functions. In all specifications in Table 4 robots have no significant effect.

To summarize, we find heterogeneous *direct* effects of the impact of GVC position and technology adoption on different business functions. In line with previous literature, we find a negative impact of increases in upstreamness. For technology adoption, we find that machinery and ICT are on average (weakly) complements to labor, while this varies across different business functions.

What is surprising is the null effect of robots adoption across all business functions. This is surprising, since the literature on robotization highlights its strong labor-replacing effect. Recent

TABLE 4 The direct impact of GVC and technology on labor functions.

Dep Var	(1) ΔLS	(2) ΔRD	(3) ΔFAB	(4) ΔMGT	(5) ΔMAR
ΔUps	−9.664*	−1.829**	−4.465*	−1.840*	−1.531**
	(1.820)	(0.744)	(0.941)	(0.628)	(0.655)
$\Delta \ln(Mach/VA)$	2.764**	1.151**	1.003	0.290	0.320
	(1.273)	(0.438)	(0.812)	(0.304)	(0.302)
$\Delta \ln(ICT/VA)$	1.103	0.079	0.294	0.525***	0.205
	(1.265)	(0.382)	(0.670)	(0.301)	(0.337)
$\Delta \ln(Robots/VA)$	−3.690	−1.021	−1.640	−1.042	0.013
	(2.997)	(1.033)	(1.225)	(1.137)	(0.892)
Obs.	587	585	585	585	585
IV Ups	✓	✓	✓	✓	✓
IV Robots	✓	✓	✓	✓	✓
FE	c k	c k	c k	c k	c k

Note: Clustered standard errors (country-period) in parentheses. 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. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010.
***$p < .01$, **$p < .05$, *$p < .1$.

papers have indeed estimated a meaningful impact of robots adoption on various employment outcomes (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). Therefore, our study of the indirect effect on labor, through changes in intra-industry composition that is associated with GVC integration is particularly interesting.

Beyond the differences in the empirical specifications, we argue that our results differ, *inter alia*, by the fact that we control for the contemporaneous impact of variation in GVC position. As explained above, we allow for robot adoption to induce specialization of the production process, thus affecting GVC positioning. If that is the only salient channel, then when controlling for GVC position, which captures the variation in production content, we should not be able to find a direct effect for robots. In contrast, we should find that robot adoption is a salient determinant for the variation in GVC position.

To test our predictions we move on in our empirical analysis to the indirect impact of technology on labor outcomes through GVC integration. Table 5 provides the estimation of Equation (4). The dependent variable is the variation in GVC position, measured either as upstreamness (column 1) or as sales in intermediate versus final goods production (columns 2–4).

We focus our attention on the impact of robot adoption. Therefore, we report in Table 5 the coefficient for this variable across specifications, which differ in the estimation procedure.[10] Each column pertains to a different outcome variable. In the first panel we report coefficients estimated by WLS. We find that a one standard deviation increase in robots adoption increases upstreamness by 0.086 standard deviations. This effect is due to the increase in intermediate goods sales relative to final goods sales (column 2). In columns (3) and (4) we split the latter effect to show the specific impact on the numerator and denominator of $\Delta lnSales^{mf}$: robots increase both good types' sales, but the effect is almost twice as large for intermediate goods sales. These results are consistent

TABLE 5 The impact of technology on GVC position.

Δ ln(*Robots*)	**(1)** **Δ*Ups***	**(2)** **Δ*lnSales*^{mf}**	**(3)** **Δ*lnSales*^{m}**	**(4)** **Δ*lnSales*^{f}**
WLS	0.086*	0.014***	0.031*	0.017*
	(0.030)	(0.007)	(0.006)	(0.007)
$\Delta IV^{Artuc\ et\ al.}$	0.612*	0.119**	0.295*	0.176*
(F 1st: 22.7)	(0.200)	(0.050)	(0.071)	(0.047)
$\Delta IV^{CHN,inp}$	0.428**	0.060	0.163**	0.102**
(F 1st: 39.7)	(0.192)	(0.042)	(0.062)	(0.040)
$\Delta IV^{CHN,mkt}$	0.442**	0.072**	0.142*	0.070*
(F 1st: 32.1)	(0.170)	(0.035)	(0.043)	(0.025)
$\Delta IV^{CHN,comp}$	0.351	0.034	0.198***	0.164**
(*F* 1st: 14.7)	(0.253)	(0.060)	(0.101)	(0.077)
Obs.	587	587	587	587
Ctrl for Mach & ICT	✓	✓	✓	✓
FEs	c k	c k	c k	c k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both Δ*Ups* and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. We proxy ΔGVC_{ckt} sequentially with the variation in Upstreamness Δ*Ups* in column (1), with the log variation in the ratio of intermediate, m, over final goods, f, sales, $\Delta lnSales^{mf}$ in column (2), with the log variation in the sales of intermediate goods $\Delta lnSales^{m}$ in column (3) and of final goods respectively $\Delta lnSales^{f}$ in column (4). ***$p < .01$, **$p < .05$, *$p < .1$.

with our hypothesis that the impact of robots on labor operates through the composition of activities performed by labor, and therefore through variation in GVC position.

In the other panels Table 5, we report estimates of the coefficient to robots using different instrumental variables. Results across different specifications are in line with those reported in the WLS panel. Importantly, the last three panels support our hypothesis for the role of China in inducing robot adoption. These results provide evidence for an additional channel through which China has affected GVC patterns.

The instrumented coefficients of $\Delta ln(Robots)$ are much larger than the WLS estimates. This is consistent with mismeasurement of effective robot capital services, but we consider this a "straw-man" explanation. A better argumented explanation is that the instrumented regressions identify a local country-industry effect. This is easiest to see by examining the instrument based on Artuc et al. (2020). Given the price reduction in robots, industries that have more replaceable tasks in countries with higher production costs are more likely to install robots. If there are fixed costs for robot installation that are not captured by the price of robots themselves (for example, so-called "peripheral" costs), then the same variation in the instrument (a reduction in price-range of tasks-production costs) will have a larger impact on take-up of treatment when the benefits are larger. The result is larger coefficients for IV compared to WLS. Concerning their magnitude, consider the coefficient for the impact of robots on $\Delta lnSales^{m}$ using $IV^{Artuc\,et\,al.}$ as instrument: an increase by one standard deviation increases sales of intermediate goods by 0.29. Looking at the distribution of $\Delta lnSales^{m}$ this implies a shift from the 50th percentile of the distribution ($\Delta lnSales^{m} = 0.18$) to around the 80th percentile of the distribution ($\Delta lnSales^{m} = 0.46$).[11]

TABLE 6 First-stage regressions for "The impact of technology on GVC position–Table 5".

Variables	(1) Δ ln(*Robots*)	(2)	(3)	(4)
$\Delta IV^{Artuc\ et\ al.}$	0.261*			
	(0.055)			
$\Delta IV^{CHN,inp}$		1.038*		
		(0.165)		
$\Delta IV^{CHN,mkt}$			0.615*	
			(0.109)	
$\Delta IV^{CHN,comp}$				0.700*
				(0.182)
Δ ln(*Mach*)	0.022	0.072	0.035	0.116
	(0.083)	(0.079)	(0.082)	(0.081)
Δ ln(*ICT*)	0.135	0.115	0.087	0.145
	(0.096)	(0.089)	(0.080)	(0.101)
Observations	587	587	587	587
FE	c k	c k	c k	c k
F−test	22.7	39.7	32.1	14.7

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

In Table 6, we provide estimates of the first stages for IV regressions in Table 5. In all regressions we control for the variation in the stock of capital in machinery and ICT. The F−test statistics across different specifications in Table 6 imply that all instruments are strong. In column 1 we use as instrument $\Delta IV^{Artuc\ et\ al.}$. We find a positive and significant coefficient, which suggests that the global drop in robot prices spurred robotization in industries that had larger scope for replacing repetitive tasks by robots, in countries where production costs are large. This also supports our interpretation for the coefficient found in Table 3, column 2.

In columns 2–4, we investigate the impact of robotization in China through different channels: China as an input supplier, as a destination market, and as a competitor. All of the channels are at work, with a remarkable impact for China as a supplier of intermediate inputs (column 2). Robotization in China strongly induces robotization in European manufacturing industries that tend to rely more on China as a supplier of intermediate inputs, as a market for their outputs, and as a competitor in their domestic markets. These results provide a new mechanism through which China has shaped GVC patterns, that is, inducing robotization elsewhere in the world (here, in Europe), which impacted GVC integration.

With the estimates 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, $\alpha\gamma$. Using coefficient estimates from Table 2 (column 5) and Table 5 (column 1), we find that a standard deviation increase in robots adoption reduces the labor share by 4% to 6% points.[12]

These results show that neglecting the indirect impact of robotization through GVC leads to misleading inference on the effect of technological change. Indeed, the indirect impact is economically large, and it acts as an important channel for the impact on the labor share, and similarly, business functions.

5 | CONCLUSIONS

Technological change and the rise of GVC integration are two of the main forces that have shaped economic growth and development in the last couple of decades. In this paper we study their joint effect on relative demand for labor. A large literature has studied this topic focusing on the single effect of GVC or of technology adoption. Here we propose a framework that encompasses both of these mechanisms, as well as a combined impact. We argue that beyond the direct channel, technology affects labor through GVC integration, by affecting the specialization of production and, therefore, inducing movements in the position within GVC.

We estimate separately each of these effects, while taking into account 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 tasks. We estimate that Machinery and ICT are complementary with labor overall, with heterogeneous impacts on different business functions. We estimate a nil direct effect of robotization on these outcomes. In contrast, robotization significantly affects intra-industry position within GVCs, by shifting the composition of production tasks to be more upstream. We also show new channels through which China induced robot adoption, due to its own rapid robotization. This provides an alternative channel for the role of China in reshaping GVC patterns and, through this, affecting relative demand for labor in European manufacturing industries.

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DATA AVAILABILITY STATEMENT

Data on robot installations that support the findings of this study are available from the International Federation of Robotics. Restrictions apply to the availability of these data, which were used under license for this study. All other data that support the findings of this study are openly available in the supporting websites of the WIOD https://www.rug.nl/ggdc/valuechain/wiod/ and from the Supplementary Materials to the paper Timmer et al. (2019).

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ENDNOTES

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

[2] All technology accounts are in volume, using reference prices in 2010.

[3] The description of robots applications is reported in Table A2

[4] Two factors concerning robotization in China merit further discussion. First, Cheng et al. (2019) document a sharp increase in automation in China from 2010 onwards, while our period of analysis ends in 2011. Nonetheless, we show that the stock of robots in China increased even more, in relative terms, in the period of our analysis than in the after it ends (starting from a much lower base). Figure A1 (right panel) in Appendix A.2 demonstrates this: the operational stock of robots in China increased by a factor of 135 from 1999 to 2011, while it increased “only” tenfold from 2011 to 2019. Second, one may be concerned that robotization in China might have been at least in part driven by the same economic forces driving robotization in Europe: if that were the case, then the exclusion restriction for our instrument would be violated. The left panel of Figure A1 depicts the trends in operational stocks of robots in both China and in our estimation sample in 1999–2011. The trends are clearly different: compared to the aforementioned increase by 135 times for China, the robot stock in Europe it only doubled in the period 1999–2011. These facts give credence to the validity and strength of our instruments: Chinese robots increased sharply during our sample (instrument strength) and in a way that is quite different from robotization in Europe (exclusion restriction).

[5] Table A1 provide the ISCO-88 occupations associated to each business functions.

[6] As shown in Reshef and Santoni (2023), it is straightforward to split the upstreamness measure into a domestic and an international component. Overall, changes in upstreamness are driven by international transactions. For the average country-industry, in the 1999–2011 period, the foreign component of upstreamness increased by 39.7% while the domestic component decreased slightly by −5.9%.

[7] The list of all robots applications is reported in Table A2.

[8] A caveat is the aforementioned limitation of the data. As we do not have sectoral detail, part of the evolution at stake might be driven by the generalization of handling robots in the distribution sector.

[9] Our results are robust to several sensitivity checks. First, we drop the last period of analysis (2007–2011) to check whether the results are sensitive to possible impacts of the global financial crisis; this hardly affects the results. We also drop separately other periods (1999–2003 and 2003–2007); our results are mainly driven by the 2003–2007 period, which exhibits the strongest wave of GVC integration, and is consistent with findings in Reshef and Santoni (2023). As an additional sensitivity check we drop separately, as well as jointly, Germany and the automotive sector; despite their size and relative importance in robotization, dropping these observations does not change our results materially. Deatiled results are available upon request.

[10] Full regression tables including machinery and ICT as controls are reported in Appendix A.4 (Tables A3–A7).

[11] In Appendix A.5 we study the effect of robotization on structural gravity-based measures of productivity in intermediate input production and in final goods production. The results are in line with those presented in the main text: robotization is associated with higher productivity in production of intermediate inputs versus final goods.

[12] $\beta^{Rbt} + \alpha\gamma^{Rbt}$. Here we take $\beta^{Rbt} = 0$ as not statistically different from 0, $\alpha = -9.664$ and γ^{Rbt} between 0.428 and 0.612.

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APPENDIX

A.1 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, for example, 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:

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

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

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

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

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

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

$$S_i = \alpha_i + \sum_{j>1} \beta_{ij}\left(w_j - w_1\right) + \sum_j \gamma_{ij}\left(k_j - y\right), \tag{A1}$$

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

We can augment (A1) with the position in GVC. 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 (1):

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

Note that $\sum_{j>1} \beta_{ij}(w_j - w_1)$ in A1 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.2 Robotization in China

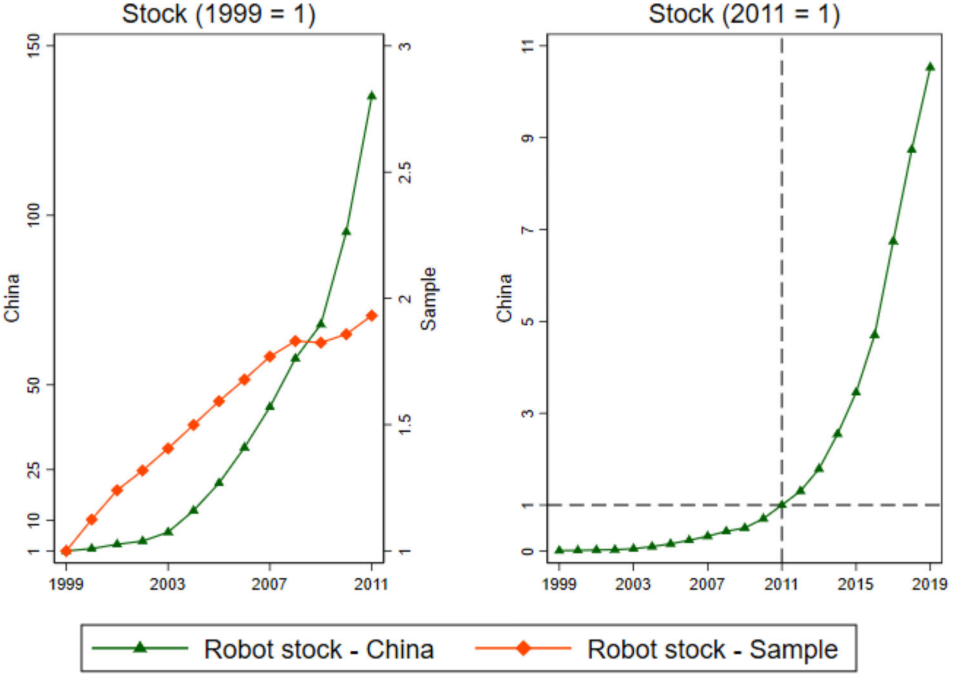

FIGURE A1 Robots operational stock over time–China and sample (On the left panel we report the operational stock of robots for the period of our analysis (1999–2011) in China (left y-axis) and in our sample (right y-axis) normalized with respect to 1999 operational stock. On the right panel we report the operational stock of robots for the period 1999–2019 in China normalized with respect to 2011 operational stock. The operational stock of robots in China increased by a factor of 135 from 1999 to 2011 (right and left panels), while it increased "only" tenfold from 2011 to 2019 (right panel). In the period 1999–2011 the robot stock in Europe doubled (left panel)). [Colour figure can be viewed at wileyonlinelibrary.com]

A.3 Additional descriptive statistics

TABLE A1 Labor functions and occupations.

	ISCO-88 classification	
Labor function	**Major title**	**Sub-major title**
Management	(1) Legislators, senior officials and managers	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

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

TABLE A2 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	

Note: IFR classification. Codes in parentheses.

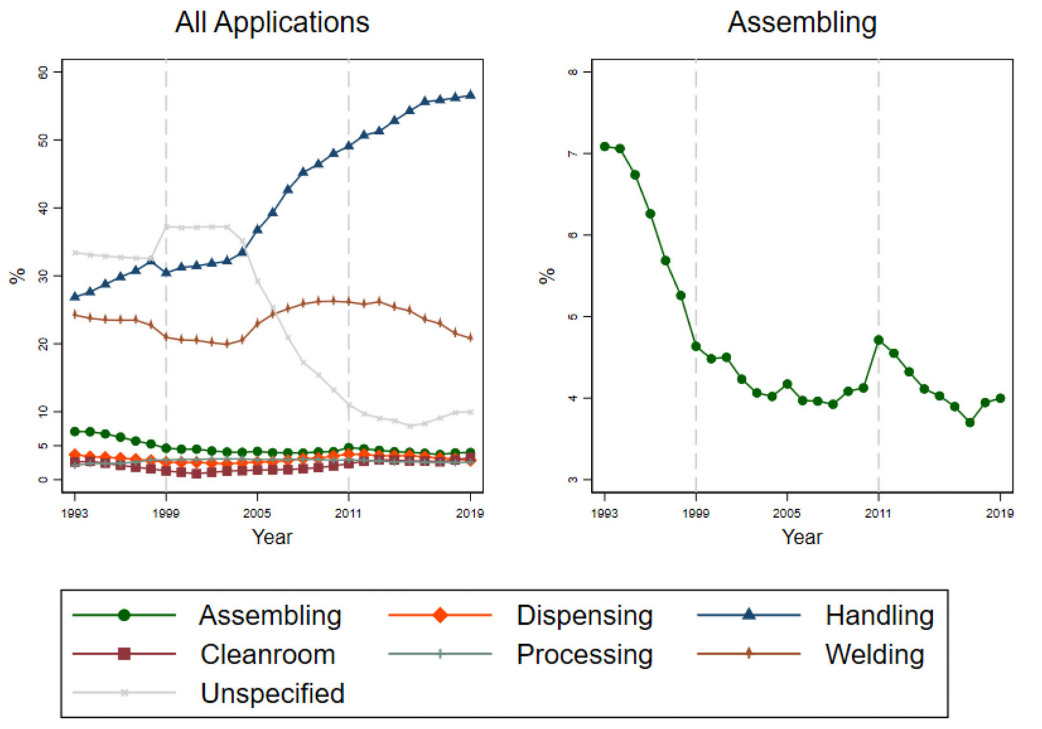

FIGURE A2 Robots applications over time (The figure reports yearly averages on country level data. Shares are calculated over the total of robots). [Colour figure can be viewed at wileyonlinelibrary.com]

A.4 Additional tables

TABLE A3 Table 2 full version—OLS.

Variables	(1) ΔUps	(2) $\Delta lnSales^{mf}$	(3) $\Delta lnSales^{m}$	(4) $\Delta lnSales^{f}$
Δ ln(*Robots*)	0.086*	0.014***	0.031*	0.017*
	(0.030)	(0.007)	(0.006)	(0.007)
Δ ln(*Mach*)	0.285*	0.062*	0.166*	0.105*
	(0.065)	(0.020)	(0.025)	(0.021)
Δ ln(*ICT*)	0.016	0.017	0.068**	0.052*
	(0.079)	(0.021)	(0.029)	(0.017)
Observations	587	587	587	587
FEs	cty k	cty k	cty k	cty k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both ΔUps and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. For the definition of the proxies for ΔGVC_{ckt} see note of Table 5.

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

TABLE A4 Table 2 full version—IV Artuc et al.

Variables	(1) ΔUps	(2) $\Delta lnSales^{mf}$	(3) $\Delta lnSales^{m}$	(4) $\Delta lnSales^{f}$
Δ ln(*Robots*)	0.612*	0.119*	0.295*	0.176*
	(0.200)	(0.050)	(0.071)	(0.047)
Δ ln(*Mach*)	0.217*	0.048*	0.132*	0.084*
	(0.075)	(0.018)	(0.026)	(0.024)
Δ ln(*ICT*)	−0.066	−0.000	0.027	0.027
	(0.100)	(0.024)	(0.044)	(0.028)
Observations	587	587	587	587
FEs	cty k	cty k	cty k	cty k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both ΔUps and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. FOr the definition of the proxies for ΔGVC_{ckt} see note of Table 5.
***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A5 Table 2 full version—$IV^{CHN,inp}$.

Variables	(1) ΔUps	(2) $\Delta lnSales^{mf}$	(3) $\Delta lnSales^{m}$	(4) $\Delta lnSales^{f}$
Δ ln(*Robots*)	0.428**	0.060	0.163**	0.102**
	(0.192)	(0.042)	(0.062)	(0.040)
Δ ln(*Mach*)	0.241*	0.056*	0.149*	0.094*
	(0.072)	(0.020)	(0.025)	(0.023)
Δ ln(*ICT*)	−0.037	0.009	0.048	0.038***
	(0.091)	(0.021)	(0.034)	(0.022)
Observations	587	587	587	587
FEs	cty k	cty k	cty k	cty k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both ΔUps and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. For the definition of the proxies for ΔGVC_{ckt} see note of Table 5.
***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A6 Table 2 full version—$IV^{CHN,mkt}$.

Variables	(1) ΔUps	(2) $\Delta lnSales^{mf}$	(3) $\Delta lnSales^{m}$	(4) $\Delta lnSales^{f}$
Δ ln(*Robots*)	0.442**	0.072**	0.142*	0.070*
	(0.170)	(0.035)	(0.043)	(0.025)
Δ ln(*Mach*)	0.239*	0.054*	0.152*	0.098*
	(0.072)	(0.020)	(0.025)	(0.022)
Δ ln(*ICT*)	−0.039	0.007	0.051	0.043**
	(0.089)	(0.021)	(0.031)	(0.019)
Observations	587	587	587	587
FEs	cty k	cty k	cty k	cty k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both ΔUps and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. For the definition of the proxies for ΔGVC_{ckt} see note of Table 5.
***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A7 Table 2 full version—$IV^{CHN,comp}$.

Variables	(1) ΔUps	(2) $\Delta lnSales^{mf}$	(3) $\Delta lnSales^{m}$	(4) $\Delta lnSales^{f}$
Δ ln(*Robots*)	0.351	0.034	0.198***	0.164**
	(0.253)	(0.060)	(0.101)	(0.077)
Δ ln(*Mach*)	0.251*	0.059*	0.145*	0.086*
	(0.075)	(0.020)	(0.027)	(0.026)
Δ ln(*ICT*)	−0.025	0.013	0.042	0.029
	(0.095)	(0.024)	(0.039)	(0.028)
Observations	587	587	587	587
FEs	cty k	cty k	cty k	cty k

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight. Δ periods equal to 2011–2007, 2007–2003, 2003–1999. Both ΔUps and the RHS variables are standardized. For the logarithmic transformation of robots we use Inverse Hyperbolic Sine (IHS) transformation. Technology variables are expressed in volume, ref. prices 2010. For the definition of the proxies for ΔGVC_{ckt} see note of Table 5.
***$p < .01$, **$p < .05$, *$p < .1$.

A.5 Upstreamness and productivity in intermediate versus final goods production

In the text we show how robots contribute to increase upstreamness of production by improving the relative performances in the production of intermediate goods vs final goods. In this Appendix, we want to push further this hypothesis by looking at the impact of robot on productivity. To do so we estimate a measure of productivity in intermediate goods production and productivity in final goods production exploiting the virtues of the gravity framework. 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 $Z = [z_{cd}^{kj}]$, 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 $z_{cd}^{k} = \sum_j z_{cd}^{kj}$. Import shares are given by $\pi_{cd}^{k} = z_{cd}^{k} / \sum_c z_{cd}^{k}$. We model these along the lines of Eaton and Kortum (2002),

$$\begin{aligned}
\pi_{cd}^{k} &= \frac{T_c^k (C_c^k)^{-\theta_k} \left(\tau_{cd}^{k}\right)^{-\theta_k}}{\sum_{c',k} \left(T_{c'}^k / C_{c'}^k\right)^{\theta_k} \left(\tau_{c'd}^{k}\right)^{-\theta_k}} \\
&= \exp\left\{ \ln \frac{T_c^k (C_c^k)^{-\theta_k} \left(\tau_{cd}^{k}\right)^{-\theta_k}}{\sum_{c',k} \left(T_{c'}^k / C_{c'}^k\right)^{\theta_k} \left(\tau_{c'd}^{k}\right)^{-\theta_k}} \right\} \\
&= \exp\left\{ \underbrace{\ln T_c^k (C_c^k)^{-\theta_k}}_{\alpha_c^k} + \underbrace{\left[-\ln \sum_{c',k} \left(T_{c'}^k / C_{c'}^k\right)^{\theta_k} \left(\tau_{c'd}^{k}\right)^{-\theta_k} \right]}_{\beta_d^k} + \underbrace{\ln \left(\tau_{cd}^{k}\right)^{-\theta_k}}_{\epsilon_{cd}^k} \right\},
\end{aligned} \tag{A2}$$

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 and 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 and Parro (2015).

We estimate (A2) by PPML in panels 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 $\tau_{c'd}^{k}$:

$$\pi_{cdt}^{(k)} = e^{dist_{cdt} + International_{cdt} + \alpha_{ct}^{(k)} + \beta_{dt}^{(k)} + \varepsilon_{cdt}^{(k)}}. \tag{A3}$$

Using the estimates we can construct

$$\text{Source}: \widehat{T}_{ct}^{(k)} \left(\widehat{C}_{ct}^{(k)}\right)^{-\theta_k} = e^{\widehat{\alpha}_{ct}^{(k)}}, \tag{A4}$$

$$\text{Destination}: \sum_{c'k} \widehat{T}_{c't}^{(k)} (\widehat{C}_{ct}^{(k)})^{-\theta_k} \left[\widehat{\tau}_{cdt}^{(k)}\right]^{-\theta_k} = \widehat{\Phi}_{cdt}^{(k)} = e^{-\widehat{\beta}_{dt}^{(k)}}, \tag{A5}$$

$$\text{Bilateral}: \left[\widehat{\tau}_{cd}^{(kt)}\right]^{-\theta_k} = e^{\widehat{\varepsilon}_{cdt}^{(k)}}. \tag{A6}$$

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

Table A8 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. On the contrary, we find a negative coefficient for productivity in final goods production. The estimation includes year and

TABLE A8 Correlation between *Ups* and φ.

Var.	(1) Ups	(2) Ups
$\ln(\varphi^a)$	0.264*	0.315*
	(0.010)	(0.009)
$\ln(\varphi^y)$	−0.212*	−0.241*
	(0.010)	(0.010)
Obs	2545	783
R^2	0.988	0.984
FEs	y ck	y ck
Year	all	99-03-07-11

Note: Clustered standard errors (country-period) in parentheses. Weighted regressions using country-industry VA in 1999 as weight.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

TABLE A9 Robots adoption and productivity.

Var.	(1) $\ln(\varphi^a)$	(2) $\ln(\varphi^y)$
ln(*Robots*)	0.099**	0.080
	(0.040)	(0.063)
Obs	2531	2531
FEs	y ck	y ck
Cluster	ck	ck
Model	IV	IV
IV	$IV^{CHN,inp}$	$IV^{CHN,inp}$
$F-$test	9.935	9.935
1st β	−0.997	−0.997
Ctrl for Mach & ICT	✓	✓

Note: Weighted regressions using country-industry VA in 1999 as weight. IV estimation using $IV^{CHN,inp}$ as instrument. $F-$test coefficient: 9.935 (Col. 1 and 2) and 9.939 (Col. 3 and 4).
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

country-industry fixed effects, thus estimating the effect of a variation in productivity within a given country-industry. Col. (2) provide the same estimation on the subsample of years on which we compute stacked differences in the main estimation in the text.

Table A9 provides results for the impact of robots on productivity. Columns (1 and 2) are panel regressions with country-industry and year fixed effects. In line with results reported in Table 5, we find a positive and significant impact on intermediate goods productivity, while lower and not significant for final goods productivity.