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Exposure to Digital Automation and Jobs in Global Value Chains

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Exposure to Digital Automation and Jobs in Global Value Chains*

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Abstract

This paper offers evidence on how exposure to different emerging digital automation technologies – identified on the basis of a uniquely granular classification provided by Prytkova et al. (2025) – is associated with employment changes in Global Value Chains (GVCs). We study in particular how exposure to digital automation technologies is related to the reconfiguration of GVCs across countries, and GVC specific jobs. We match several databases, and decompose employment growth in GVCs in three components: labour productivity, GVC linkages and final demand. We find that (i) Job growth is associated with exposure only to specific digital technology families; (ii) Exposure to digital automation is significantly mediated by three components: final demand, GVC linkages and productivity; (iii) Final demand and productivity most often offset each other, particularly when considering total employment in all countries; (iv) GVC linkages play a role only in specific sectors; (v) Looking at exposure to digital automation in manufacturing and services separately entails different results, with exposure related to productivity increases in manufacturing and to market expansion (both domestic and through GVC linkages) in services.

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1 Introduction and background

1.1 Global Value Chains' reconfiguration within the recent geopolitical context

Within the current geo-economic and geo-political context, both high- and middle-income countries face what has been labeled as a polycrisis. This consists of multiple, exogenous shocks that occur simultaneously and interact in mutually reinforcing ways, such as the increase in geopolitical tensions across trade blocks, global health emergencies such as the COVID-19 pandemics, and climate-induced natural disasters.

Global interconnectedness via Global Value Chains (GVCs) diffuses these shocks across countries, exacerbating the 'slowbalization', i.e. the slowing down of globalization since the financial crisis of 2008 and the mid-2000s (Baldwin, 2022). Polycrises have in fact led several countries to 'turn inward' (Baldwin, 2022), with a resulting reconfiguration of GVCs towards near-shoring and re-shoring of strategic supplies.

This type of reconfiguration of GVCs has been accompanied by an evolution of the industrial policy objectives, especially in advanced countries. This entails a shift towards 'sovereignty' and 'resilience' of GVCs, alongside economic 'security': that is, independence from certain trade partners (Bontadini et al., 2025b), most often emerging countries supplying critical intermediates.

These developments have sparked a debate on the future of globalization, focused on the potential consequences of near-shoring and re-shoring on employment, both for countries that near-shore, re-shore or friend-shore, and those who supply critical and/or basic intermediates to them. These latter are the countries that might be hit by the decrease or loss of foreign demand and the weakening of global trade, with job loss being one of the most disruptive consequences.

Within this context, Europe and middle income countries, for instance the Asia-Pacific area, seem to be on two different trajectories (Bontadini et al., 2025a, 2023). The former exhibits very strong integration on the sourcing side, despite a declining trend that has reversed since 2012, while catering increasingly to final demand from outside Europe. The latter, in contrast, has steadily moved towards regionalisation of value chains, strengthening both upstream and downstream linkages within the Asia-Pacific area Bontadini et al. (2025b). This dual trend is well illustrated in recent work on European trade patterns, emphasizing the co-existence of near-shoring in upstream sourcing and far-sharing in downstream demand, challenging any binary interpretations of global versus regional strategies(see also (Bontadini et al., 2023) and their impact on employment.

1.2 Global Value Chains reconfiguration, digital automation and jobs: The extant literature and our contribution

The geopolitical changes mentioned above have been accompanied by the emergence of digital automation technologies. They have both a direct impact on jobs – via complementing or replacing domestic jobs – and an indirect one – via changes of firm organizations and new opportunities to locate their activities elsewhere.

Over time, Information and Communication Technologies (ICTs) have contributed to facilitating the coordination of activities located far from each other, making GVCs both technically and economically viable. However, digital and non digital automation might displace workers from routine tasks, and/or create new tasks and increase productivity, with ambiguous net effects (Acemoglu and Restrepo, 2019).

Digital automation technologies can replace or complement tasks undertaken by workers, reducing the cost of production. If the cost of adopting and operating digital automation is lower than the labour cost where the firm is located, firms in capital abundant regions may find it more profitable to adapt their productive technologies to their production factor endowment, engaging in either re- or near-shoring as an alternative strategy to the off-shoring of activities that rely on cheaper labour. However, digital automation technologies might also complement workers, for instance by increasing productivity of low skilled workers, rather than replacing them. This would provide incentives for firms to relocate production where technological development is available, with the additional advantage of creating more high-productivity jobs.

Timmer et al. (2014) have shown the importance of GVC participation for job creation, particularly in developing countries (see also World Development Report (2020)). Digital automation technologies may have dual and opposite effects on the process of international fragmentation of production, which in turn might affect the reconfiguration of GVCs: for instance, it enables the relocation of production and thus the 'lengthening' of GVCs, but can it also favour the automation of labour and co-location of activities, shortening GVCs (Giunta et al., 2025).

Digital automation, alongside the geopolitical trends mentioned earlier, could trigger re-shoring or near-shoring of manufacturing (Pahl et al., 2022): Automation makes firms grow, increasing demand for inputs (Stapleton and Webb, 2025), and some of the tasks that are complementary to manual ones, previously imported from abroad, might be 're-shored' (Juhász et al., 2024).

While there is flourishing literature on the impact of adoption of digital automation (among others, see Stapleton and Webb (2025), Juhász et al. (2024)) or intangible assets Bontadini et al. (2024)) on employment, much of this literature is focused either on one technology (often AI or Robotization) (Stapleton and Webb, 2025); (Acemoglu and Restrepo, 2020)) or on the so called AI-enabled technologies (Bank, 2025). Also, very rarely has this literature contributed to the understanding of the mediated effect on employment of GVC reconfigurations linked to automation exposure and adoption (Stapleton and Webb, 2025), with a dearth of contributions focusing on GVC reconfiguration via digitalization in developing countries (Bontadini et al., 2025b). This risks to be a major shortcoming, as digital automation technologies are very heterogeneous, and so are the sectors and jobs exposed to them. Also, in the context of this paper, it is important to understand whether effects on employment hit harder low and middle income countries which are engaged in GVCs.

In sum, heterogeneous digital technologies will not diffuse evenly across countries and industries: the recent wave of emerging digital technologies is likely to affect GVCs' structure across countries and industries depending on their sectoral specialization and trade integration patterns. In summary, the nexus between the exposure to digital automation, the reconfiguration of GVCs and the effects on employment in countries-industries along these GVCs has not been investigated in depth, and all the more so for those emerging countries that rely on GVC participation. The latter is an effect that might underpin a broader concept of polarization linked to both digital technologies and patterns of GVC trade.

This is where the contribution of the present paper is located: we rely on a solid mapping of forty families of digital automation technologies, provided by Prytkova et al. (2025), and take into full account the GVCs linkages. We contribute to the literature on GVCs' reconfiguration, digital automation and their effects on jobs by addressing the following questions:

– How will GVCs' reconfiguration and automation affect employment patterns globally?

– Will digital technology create more jobs in advanced economies, or will it create new job opportunities in emerging economies?

To do so, we look at what effect dominates, conditional on country/industry features, and study how different digital automation technologies are related to the reconfiguration of jobs in GVCs across countries. The novelty of our contribution is in (i) the granularity of the heterogeneous digital technologies considered; (ii) the analysis of the joint effects of digital exposure, adoption and GVC integration.

We find that (i) Job growth is associated with exposure only to specific digital technology families; (ii) Exposure to digital automation matters, but its effect is very differently mediated by the three components: final demand, GVC linkages and productivity; (iii) GVC linkages play a role only in specific sectors; (iv) Final demand and productivity only occasionally reinforce each other, and more often offset each other, particularly when considering total employment in all countries; (v) Looking at exposure to digital automation in manufacturing and services separately entails different results, with exposure driving productivity increases in manufacturing while market expansion (both domestic and through GVC linkages) in services.

2 Empirical framework and descriptive evidence

2.1 Decomposition

We rely mainly on the 2024 release of the inter-country input-output tables (ICIO) and the trade in employment (TiM) companion database, both compiled by the OECD. This data allows us to observe value added flows and domestic employment activated by foreign final demand, which the literature has referred to as "GVC-jobs" (Pahl et al., 2022).

We decompose the growth of employment to study how different technologies may influence job growth through different channels.

First, we decompose the growth of employment into three structural drivers following the framework of Pahl et al. (2022):

1. Productivity driver: changes in the labour intensity of production, the labour required to produce one unit of output (inverse labor productivity).

2. GVC linkage driver: changes in the sourcing structure of intermediate inputs, reflecting a country-industry' integration in GVCs.

3. Final demand driver: changes in the scale of global consumption of final product (both domestic and foreign) affecting employment across country-industries participating in GVCs.

Second, we carry out this decomposition both for total employment and the jobs generated through foreign linkages (GVC jobs).

We then project these components onto the exposure to nine distinct families of digital automation technologies (Prytkova et al., 2025) to assess their conditional correlations, with total and GVC employment and their three channels.

To carry out our decomposition we start from a standard input-output framework:

$$Employment = E'(I-A)^{-1}F' = E'VBF' \tag{1}$$

Where E' is a diagonalised vector of employment per unit of value added across all available ICIO countries, i.e. the inverse of nominal labour productivity. VB is the Leontieff inverse capturing all inter-country and inter-industry relationships, pre-multiplied by a vector of value added per unit of output[1] F' is a diagonalised vector of final demand. Each element of this square matrix represents the number of jobs in each country-industry on the row that is activated by the final demand of each GVC on the columns.[2] Pahl et al. (2022) identify "GVC jobs" as those activated by foreign final demand for manufacturing products. We take here a slightly different approach and look at employment in exports for all industries:

$$GVCjobs = E'V\hat{B}F' \tag{2}$$

where $\hat{B}$ is the Leontieff inverse, with all domestic linkages set equal to zero. This matrix therefore identifies all jobs activated by foreign final demand. This is a rather broad definition of GVCs since direct export of final products would also be included, but it does offer a complete view of employment activated by country-industries integration with global markets.

Based on this empirical set up, we interpret the different drivers of GVC jobs following Pahl et al. (2022) :

1. Productivity driver: Reflects changes in the labor requirement vector E'. This is the inverse of employment per unit of value added. If a technology requires employers to hire new workers, for instance to perform new tasks, the number of workers needed to produce a unit of value added increases, all things equal. If the technology automates workers, then the number of workers needed to produce a unit of value added decreases, all things equal.

2. GVC linkages: Captures changes in the Leontief inverse VB. This reflects the "fragmentation" effect: if a country-industry increases its participation in a value chain as a supplier, the multiplier effect increases, activating more jobs, ceteris paribus. For example, this could be a technology that facilitate transactions.

3. Global demand: Captures the scale effect F'. If final demand (either domestic of foreign) increases, this will have a scale effect and increase the number of jobs required to produce the new level of demanded output, ceteris paribus. For instance, because a technology reduces the cost or increases the quality of a product or service produced.

More formally, the variation in employment between period $t1$ and $t0$ (ΔEBF) in each country-industry can be decomposed, following the polar average approach detailed in Dietzenbacher and Los (1998) and Miller and Blair (2022) as:

[1] The VB matrix sums up to one along the columns and captures the share of final output of each GVC (on the columns of VB) that each country-industry accounts for (on the rows of VB), revealing country-industries' importance across GVCs.

[2] It is worth pointing out that pre-multiplying VB by E' yields a diagonalised vector of employment per unit of gross output, $\hat{E}$, which would then be post-multiplied by BF' in a more traditional approach (Miller and Blair, 2022). However, the approach we take, in line with Pahl et al. (2022), allows us to interpret the three elements, E', VB, and F' in an economically meaningful way, i.e. as the productivity, GVC linakges and final demand components, respectively. In contrast, employment per nominal gross output or the sole Leontieff inverse are not as readily interpretable in terms of productivity or shares of GVC linkages.

$$
\begin{aligned}
\Delta EBF = E'BF'_{t1} - E'BF'_{t0} = \Delta E' + \Delta VB + \Delta F' = \\
\underbrace{\frac{\left(E'_{t1} - E'_{t0}\right) VB_{t0} F'_{t0} + \left(E'_{t1} - E'_{t0}\right) VB_{t1} F'_{t1}}{2}}_{\text{Producitivity}} \\
+ \underbrace{\frac{E'_{t0} \left(VB_{t1} - VB_{t0}\right) F_{t1} + E'_{t1} \left(VB_{t1} - VB_{t0}\right) F_{t0}}{2}}_{\text{GVC linkages}} \\
+ \underbrace{\frac{E'_{t0} VB_{t0} \left(F'_{t1} - F'_{t0}\right) + E'_{t1} VB_{t1} \left(F'_{t1} - F'_{t0}\right)}{2}}_{\text{Global demand}}
\end{aligned}
\tag{3}
$$

Notice that these mechanisms do not change when we decompose growth in GVC jobs. In that case we are simply shutting out changes in domestic linkages captured in B but not in $\hat{B}$.

2.2 Contributions of different components to GVC jobs

Based on the decomposition exercise illustrated above, we look at the three contributing components of total employment and GVC jobs, and offer some descriptive evidence across countries and sectors.

As we discussed in the previous section, our methodology distinguishes between changes in total employment and in the portion of employment activated by GVC linkages, which we refer to as "GVC jobs", in line with the literature (Pahl et al., 2022).

Figure **??** displays the share of GVC jobs across all countries for 2012 and 2019. These shares are significant, especially in smaller, highly open economies, such as Belgium, Austria, Bulgaria, Estonia, Ireland, Luxembourg and the 'Factory Asia' economies (Vietnam, Taiwan, and Malaysia). In these countries, almost one in four jobs is activated through GVCs.

Large economies, such as the US and China, exhibit smaller shares of GVC jobs, consistent with the notion that domestic demand dominates in large countries, although we also find mid size emerging economies such as Pakistan and Bangladesh with fairly small shares of GVC jobs. This evidence suggests that, if total employment is a much broader dimension than GVC jobs, they still represent a significant share of it and deserve specific attention when assessing their relationship with digital technologies.

In what follows we discuss our decomposition of both total employment and GVC jobs, highlighting divergences in patterns.

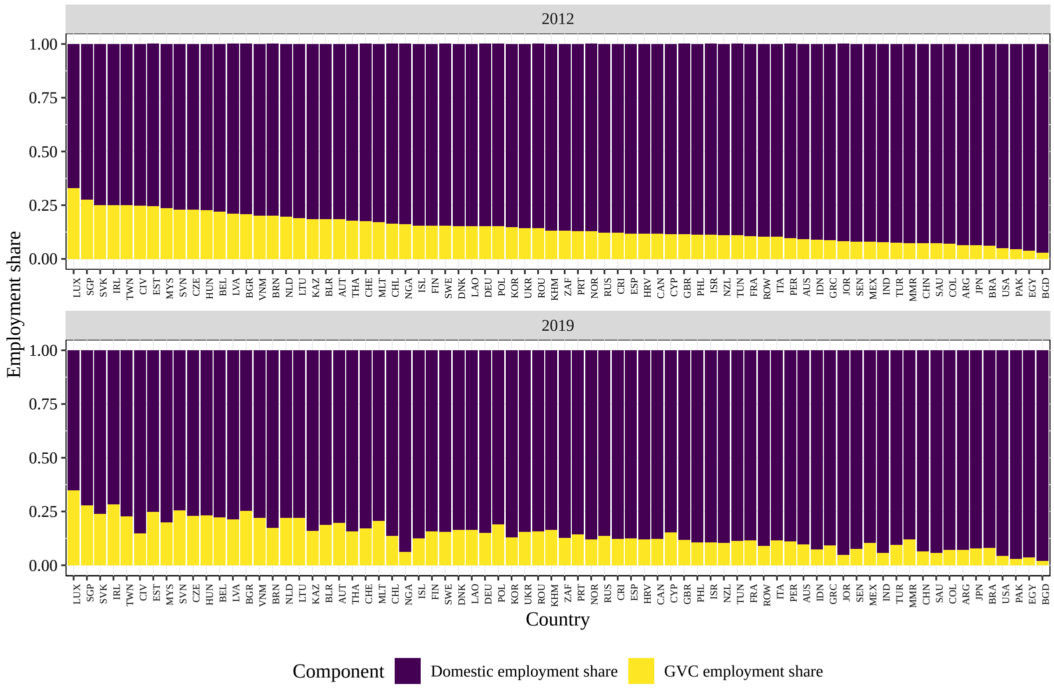


Figure 1: Share of GVC jobs in total employment in 2012 and 2019

Figure 2 ranks industries by drivers of employment growth. We find the final demand driver to be consistently positive, reflecting the fact that, over time, demand for final products has grown and this has contributed to generating additional employment. Conversely, the productivity driver is almost always negative, consistent with Baumol's cost disease mechanisms and labor-saving efficiency gains. There are exceptions for real estate (L), accommodation (I) and mining related services (B09), for which accurate measurement of value added and employment is notoriously challenging.

Overall, this suggests that over time (nominal) productivity growth is associated to a lower number of workers required to produce one unit of value added, providing a negative contribution to employment growth. The two main components, final demand and productivity growth, as expected, systematically contribute in opposite direction to employment growth.

Conversely, the GVC linkages driver displays significant heterogeneity across *sectors*. It acts as a strong driver of employment growth in the transport sector (H) internet services (J62_63), as well as administrative and business services (N and M, respectively), reflecting the "servicification" of manufacturing value chains (Baldwin, 2022). In contrast, only three manufacturing industries show large contributions from GVC linkages: manufacture of computer, electronic and optical equipment (C26) and of electrical equipment (C27) and the textile industry (C13_15). However, total employment growth in these industries has been modest or negative, due to large productivity increases that have more than offset the growth in final demand and in GVC linkages.

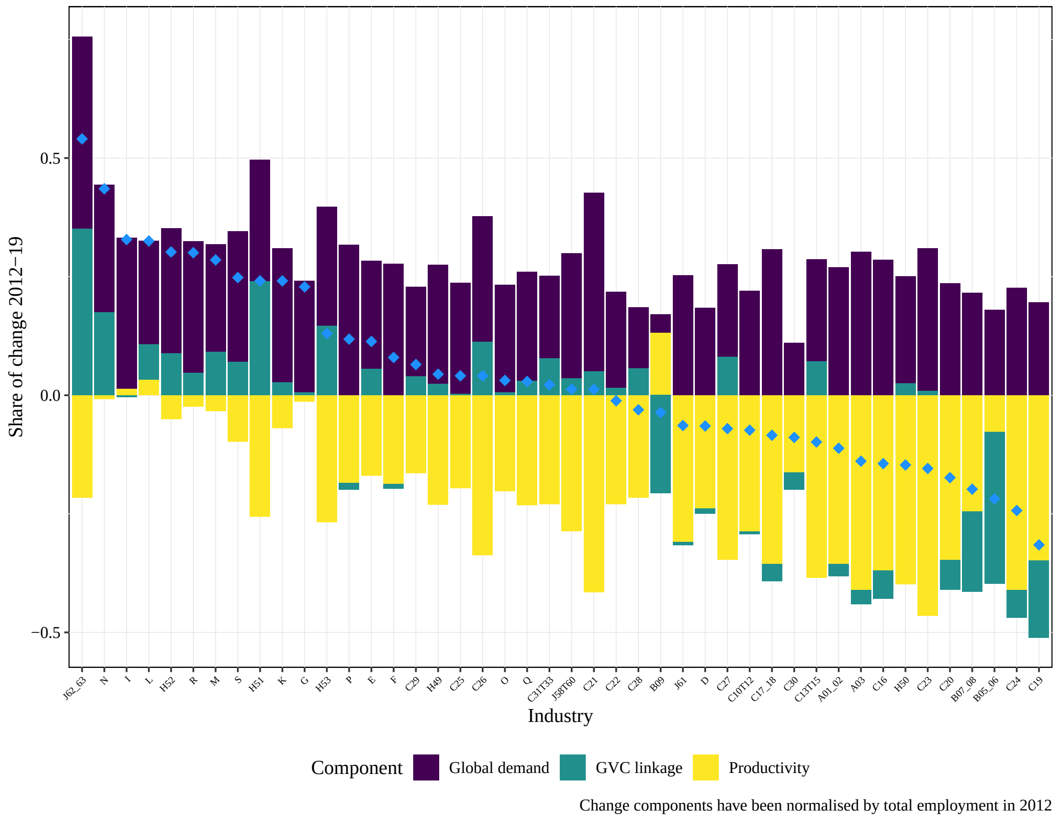


Figure 2: Employment growth and its components

Figure 3 reports the decomposition of GVC jobs, as defined in equation 2. GVC linkages are now a much larger contributor of the activation of total employment: the share that each country accounts for as a supplier becomes a much larger driver of employment growth. Noticeably, GVC linkages now often have a negative contribution, especially in sectors such as refining of coke (C19), non-market services (O,P, and Q) and telecommunications (J61). They remain fairly large in very much the same sectors that we identified when looking at total employment in Figure 2. Interestingly, internet services is the sector in which they are by far the largest contributor to the very large growth in GVC jobs.

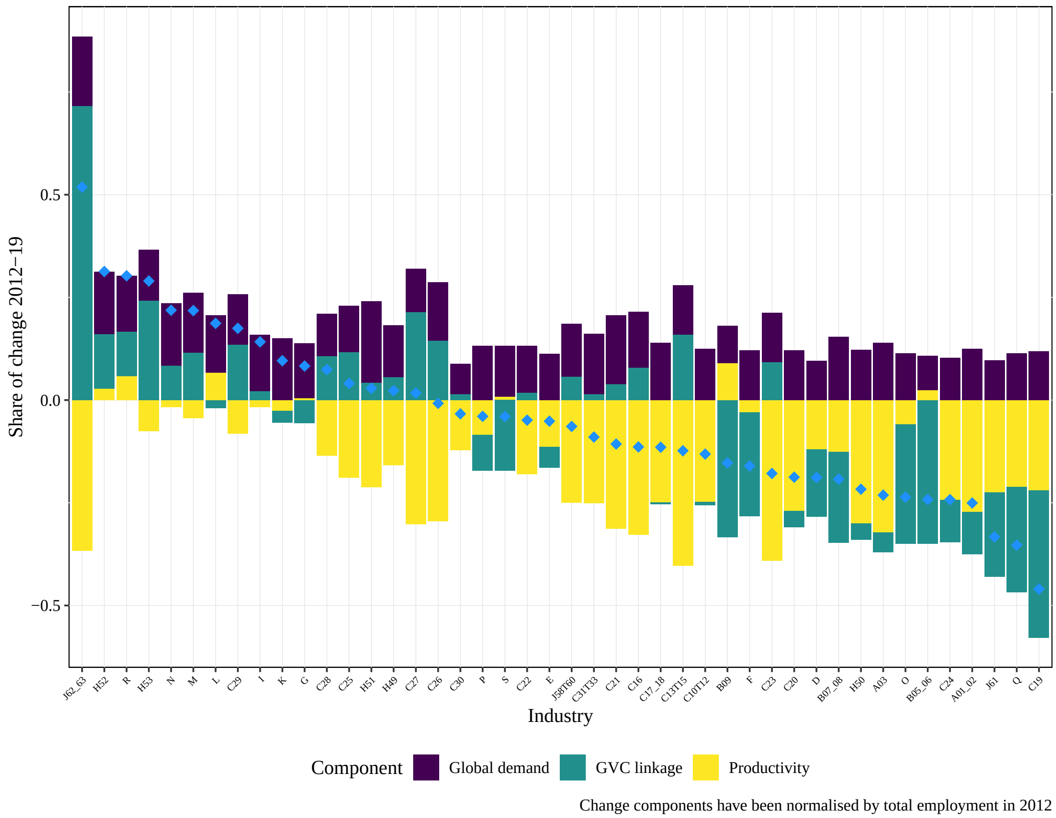


Figure 3: GVC jobs growth and its components

Finally, we briefly compare differences in the components' contribution to employment growth across the countries belonging to income groups as identified by the World Bank. We find here too quite heterogeneous patterns, which we summarise below.

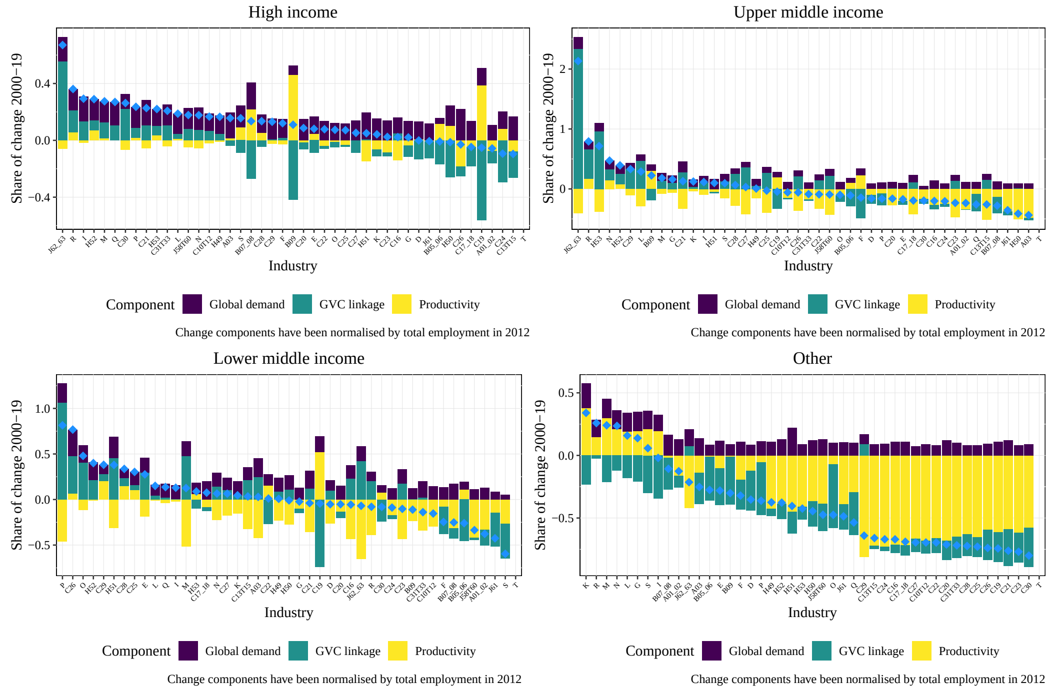


Figure 4: Employment growth and its components by income groups

- High Income Countries (HIC): Total employment growth is mainly attributable to demand-led GVC; GVC linkages is the component that is mostly responsible for employment gains in services (ICT, business services, transport);
- Upper Middle Income Countries (UMIC): Deepening GVC participation expands labour-intensive stages of the GVCs; job gains in mid/high-tech manufacturing and textiles/garments are attributable to final demand; GVC linkages are responsible for the large increase in IT services;
- Lower Middle Income Countries (LMIC): interestingly, we find that GVC linkages are the dominant contributor to job gains, which are higher than in HIC; labour intensive sectors such as food, textiles, and low-tech manufacturing are supported by the final demand component.

2.3 Digitalisation and GVC jobs

Digital automation technologies affect the three drivers of employment in equation 3 through distinct theoretical channels.

First, demand creation. Product innovation (e.g., digital Services) can expand final demand. For instance, quality improvements in or even the emergence of new digital-related products and services may trigger final demand for these products and services.

Second, trade costs and offshoring. Technologies that lower monitoring costs (e.g., tracking, logistics, transports, quality control) may increase GVC participation, reducing the "spatial friction" of trade. For instance, improvements in logistics or e–payment systems may improve the relative position of country-industries participating in value chains.

Third, labor substitution or creation. On the one hand, automation technologies (e.g., embedded systems, computer vision, additive manufacturing) directly reduce labor requirements per unit of output. These technologies are likely to increase labour productivity replacing jobs. On the other hand, technologies may also create new tasks, or require more workers to include additional services. In this case technologies increase productivity by creating activities that require more jobs.

While the existing literature focuses on aggregate measures of AI or robotics (Acemoglu and Restrepo, 2020; De Vries et al., 2020; Domini et al., 2022; Michaels et al., 2014), it is reasonable to expect that different granular technologies contribute to either of the three drivers differently. We exploit heterogeneity across technologies to disentangle these opposing forces.

To disentangle which technology creates or reduces job opportunities through GVCs (and their different drivers of employment growth), we combine standard measures of ICT exposure with a novel measure of exposure of industries to several digital automation technologies. To measure the former, we use gross fix capital formation in ICT, while to measure the latter we rely on data from the TechXposure Database (Prytkova et al., 2025), containing information on exposure to nine families of digital automation technologies at the industry level, which we report in Tables of Annex 5.

Prytkova et al. (2025) compute this measure relying on global patenting activity over the period 2012-19. They then deploy sentence transformers to compute the similarity between patents and industries at the 3-digits NACE classification. [3].

After clustering all digital automation technologies' patents in 40 technologies and nine technology families, they compute the exposure of each 3-digit industry to each technology and family by summing the exposure to each of the relevant patents. The exposure measure of an industry to a technology/family can therefore be understood as capturing the relevance of the technology in performing activities in the industry. Figure 5 plots the exposure of each of our ISIC industries to four technology families: 3D Printing, Embedded Systems, Digital Services, and Computer Vision. For a description of each family please refer to Tables 1 in Annex 5.

[3] We revert the reader to a detailed correspondence between ISIC and NACE classification in NACE background

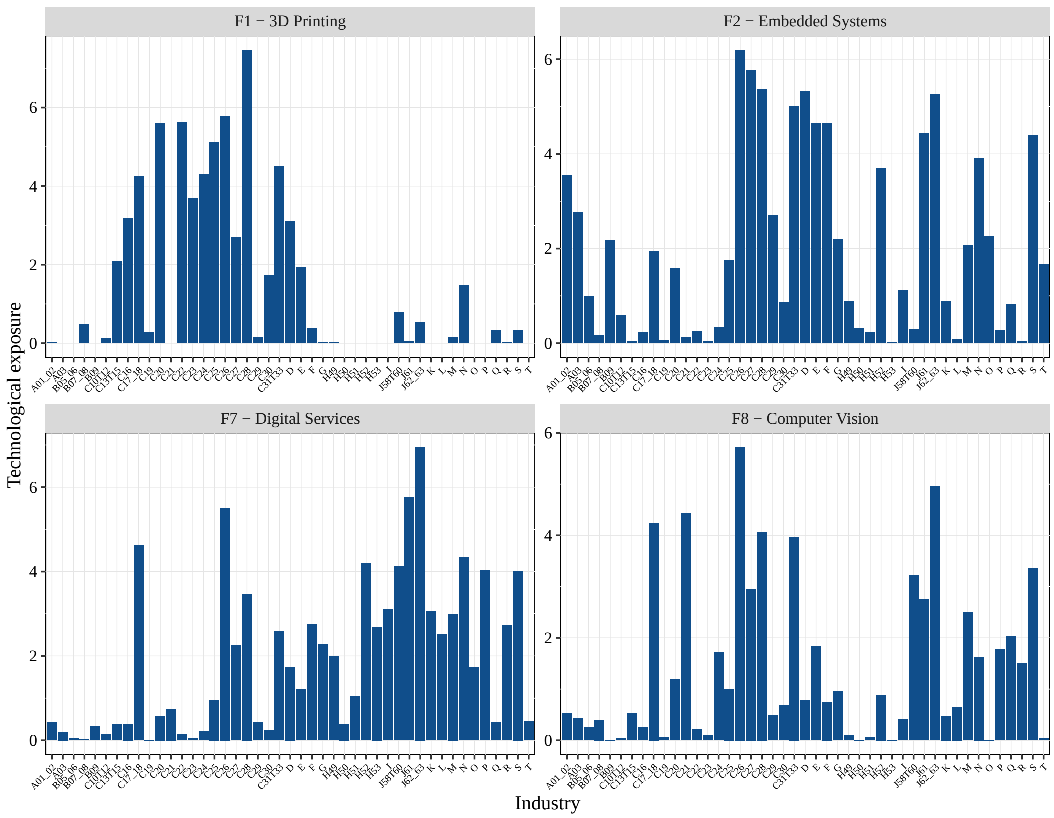


Figure 5: Technological exposure for selected emerging digital technologies

Similarly to how ICT investments affect employment in different ways, depending on the information/automation technology used, digital automation technologies will not affect employment equally across countries. Exposure to a digital automation technology will depend also on the extent to which country level infrastructures allows their adoption. This is likely to vary substantially across countries with different income and technology levels.

For instance, global technological change in AI is likely to affect software services more than the textile sector, which are differently exposed to it, and within each industry it is likely to affect China differently than Bangladesh, which are different adopters of AI.

We thus construct a country-industry-specific measure of digital automation technology *adoption potential*. Since data on the direct stock of specific digital technologies is unavailable globally, we assume that the adoption of a technology depends on (i) the global relevance of that technology to the industry (measured by patent texts) and (ii) the local capacity to implement digital tools (proxied by ICT hardware investment). In practice, we combine the TechXposure measure with investment in digital capital.

Because investment in digital capital is not readily available for all the countries in the ICIO industries, we proxy it with the gross fixed capital formation (GFCF) in capital goods, produced by the computer, electronic, and optical equipment industry (C26).

Formally, our measure of digital technology adoption potential in the period $y = 2012 - 19$ for each of the nine families of digital automation technologies is constructed as follows:

$$\text{Digit}_{ijy}^{\text{tech}} = \text{TechXposure}_{j}^{\text{tech}} \times \overline{cpte}_{i,07-11} \tag{4}$$

where $\overline{cpte}_{i,07-11}$ is country i average investment supplied by industry C26 per worker over the pre-sample period 2007-11;[4] $\text{TechXposure}_{j}^{\text{tech}}$ is the exposure of industry j to technology $tech$. While this measure cannot account for depreciation of ICT assets, it does capture the effort that countries have made to increase their stock by purchasing capital goods produced by the manufacture of computer, electronic and optical equipment, which provide the core infrastructure underpinning the deployment of digital technologies.

2.4 Econometric strategy

We test the relationship among the technological variables in equation 4 and growth in employment ($\Delta E_{ij,y}$) in country i and industry j in a simple OLS framework, for $y = 2012 - 19$:

$$\Delta E_{ij,y} = \alpha + \beta_{tech} \sum_{tech} Digit_{ij,y}^{tech} + \kappa_i + \delta_J + \varepsilon_{ij,y} \tag{5}$$

Where $\Delta E_{ij,y}$ is in turn the change in total employment ($E'VBF'$) over the period 2012-19, or any of its three components from equation 3: final demand, GVC linkages, or productivity – all divided by the initial level of employment (i.e. in 2012). We replicate this analysis for changes in GVC jobs ($E'V\,\hat{B}\,F'$) and its components, resulting in eight outcome variables $\Delta E_{ij,y}$. $Digit_{ij,y}^{tech}$ is explained in Equation 4, κ_i are country fix effects (absorbing country-wide trends like exchange rates or other macro-shocks) and δ_J are industry fixed effects (absorbing global sectoral trends). We cluster standard errors at the industry-country level i, j.

The interaction term $Digit_{ij,y}^{tech}$ follows a logic similar to a Bartik instrument: it projects global technological advances (the "shift") onto local investment capacities (the "share"). However, we interpret estimates as conditional correlations rather than causal parameters, as we do not control for unobservable country-level shocks that may be correlated with ICT investment. By including all nine families, we estimate the role of each technology controlling for the role of complementary digital technologies.

We exclude from the sample all non-market service sectors where output measurement is non-standard: Public administration, defense and social security (O), Education (P), Human health and social work activities (Q), and Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T). We also exclude Real estate activities (L). We also exclude the primary sector, because as suggested by Figure 5, all industries have minimal variation in technological exposure, which would attenuate estimates. We also winsorize the data to mitigate the influence of outliers driven by small denominators in the growth rate calculation. We exclude observations that are 1.5 times the inter-quartile range above (below) the third (first) quartile, if the employment share in 2012 of that industry-country is in the bottom ten percent. That is, we remove all outliers that are so because they have small employment shares in the first year.

[4]Using pre-sample investment mitigates simultaneity concerns regarding contemporaneous demand shocks.

3 Results

Figure 6 presents the baseline OLS estimates of equation (5) for nine technology families estimated jointly. The four panels from left to right display the conditional correlation between exposure to digital automation technologies and (i) total *employment* growth, and its decomposition into (ii) the *Final Demand* driver (changes in domestic and foreign expenditure), (iii) the *GVC linkages* driver (changes in inter-industry demand), and (iv) the *Productivity* driver (variation in labour per unit of value added). The top panels report total employment, and the bottom panels report employment activated by GVC, i.e. GVC jobs.

When pooling manufacturing and services, the aggregate relationship between digital exposure and total employment, is largely statistically indistinguishable from zero. However, this null result masks significant heterogeneity across the structural drivers with opposite signs. Consistent with canonical task-based models, we observe that productivity gains (displacement effects) are frequently offset by demand expansion (reinstatement or scale effects). GVC linkages are, in this first set of results, less relevant.

For *3D printing*, while the aggregate employment effect is null, the decomposition highlights a classic automation story. A one unit increase in exposure is associated with a ∼0.0016 percent point (pp) reduction in employment through the productivity channel (labour-saving), which is fully offset by a ∼0.01pp increase through final demand. The GVC linkage coefficient is negligible, suggesting that 3D printing may not significantly alter cross-border intermediate trade in the aggregate sample – by enabling local production.

Exposure to *smart mobility* technologies (including logistics, telematics, and transportation systems) is associated with a ∼0.01pp reduction in employment through final demand. However, this is not large enough to show in a statistically significant relation with total employment growth.

In the case of *food services* technologies (platform-based delivery and logistics), a one-unit increase in exposure is associated with a ∼0.01pp increase in employment through GVC linkages. This suggests that these digital platforms reduce transaction costs, thereby deepening the integration of these activities into domestic and international supply chains. Again, the relation is not large enough to show a statistically significant relationship with total employment growth.

Exposure to *e-commerce* technologies shows a robust labour-saving profile. A unit increase in exposure is associated with a ∼0.02pp reduction in employment through productivity gains. While there is a weakly positive relation via GVC linkages ($p<0.10$), possibly due to increased logistics requirements, the productivity effect dominates in magnitude. The net effect on total employment remains statistically insignificant.

Computer vision technologies are associated with a ∼0.04pp contraction in employment attributed to the final demand driver. This negative demand coefficient is puzzling but it may reflect a shift in consumption away from sectors heavily exposed to early-stage automation, or that these technologies may dampen demand for labour-intensive activities, without affecting productivity or GVC-linkages.

Conversely, exposure to *health technologies* is positively associated with employment growth (∼0.03pp) through final demand (significant at the 10% level). This is consistent with the "Baumol's cost disease" narrative in healthcare, where technological intensity coincides with rising demand and labor shares.

No statistically significant associations are detected for embedded systems, payment systems, or digital services with respect to total employment drivers.

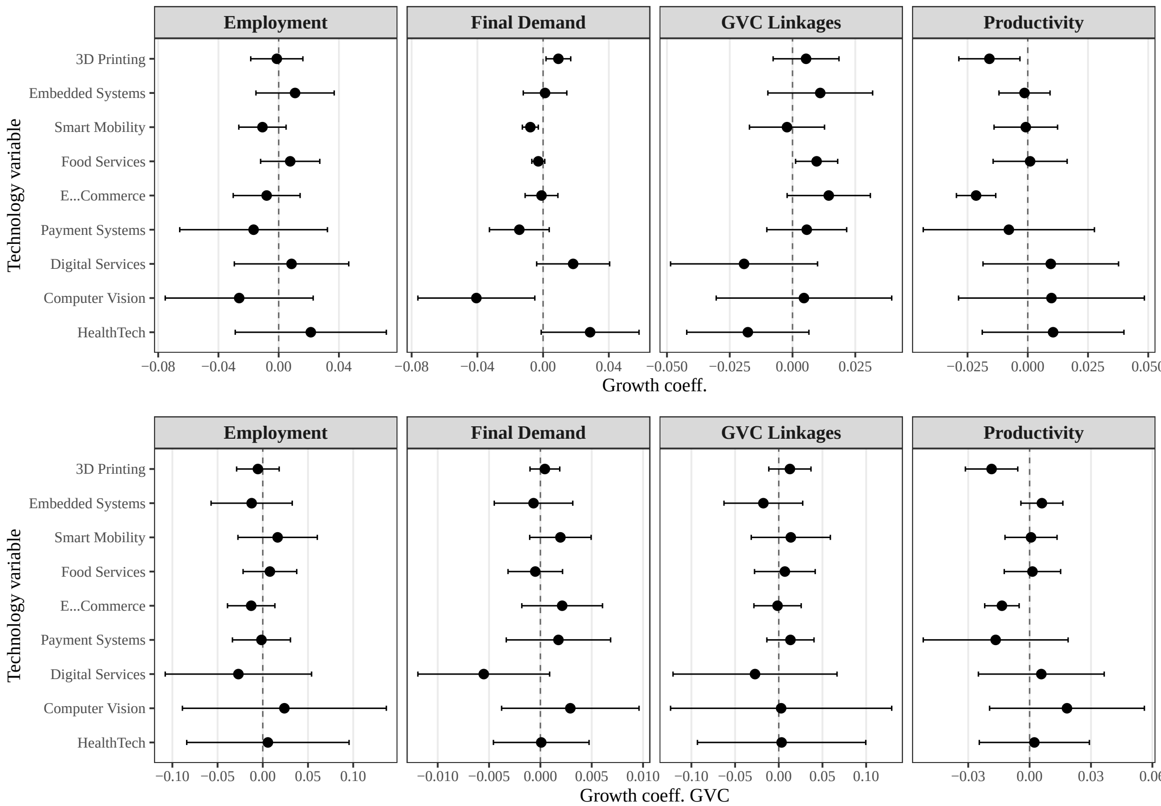


Figure 6: Marginal effects for each technology family – Baseline (Manufacturing and Services)

Notes: Each panel plots OLS coefficients from (5) for nine exposure variables (technology families) estimated jointly. From left to right, the dependent variable ΔE_{ij} include: (i) the average change in *employment*, and its decomposition into changes attributable to (ii) the *Final Demand* driver (changes in domestic and foreign expenditure), (iii) the *GVC linkages* driver (changes in inter-industry demand), and (iv) the *Productivity* driver (variation in labour per unit of value added). From top to bottom the dependent variable ΔE_{ij} include total employment (top) and employment activated by GVC (bottom). Drivers are decomposed using an average-polar structural decomposition over the period 2012-2019. All specifications include country fixed effects (κ_i) and industry fixed effects (δ_j). Markers show point estimates $\hat{\beta}_f$; whiskers denote 95% confidence intervals based on robust standard errors. A rightward (leftward) estimate indicates a positive (negative) association between exposure and the employment outcome, conditional on the other technology families and fixed effects. In the *Productivity* panel, negative coefficients indicate employment-reducing (labour-saving) changes in labour intensity; positive coefficients indicate employment-increasing (labour-using) changes. Industry coverage excludes Public administration, defence and social security (O), Education (P), Human health and social work activities (Q), Real estate activities (L) Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T), and the Primary industries.

We turn to "GVC jobs" – employment activated by foreign final demand (bottom panels of Figure 6). The results here largely mirror the total employment findings but are more concentrated in the productivity driver.

For *3D printing* and *e-commerce*, the labor-saving productivity coefficients are statistically significant and larger in magnitude for GVC jobs than for total employment (a one unit increase in exposure is associated, respectively, with a ∼0.02pp and ∼0.014pp reduction in GVC employment). This suggests that firms integrated into Global Value Chains are faster to adopt labor-saving automation than firms serving purely domestic markets. They also suggest that efficiency gains from digitalisation reduce labour-intensive requirements along global value chains.

Across all other technology families – including smart mobility, food services, payment systems, computer vision, and health technologies – no statistically significant effects on GVC employment are detected at conventional levels.

Overall, these results indicate that, when manufacturing and service industries are estimated jointly, statistically significant employment effects of the exposure to digital automation technologies are modest, and observable only through specific drivers. Productivity-enhancing technologies such as 3D-printing and e-commerce are consistently associated with labour savings, both for total employment and for GVC jobs. The demand-side driver is also small and technology-specific, with food services and health technologies showing positive associations with total job growth (though not in GVC jobs specifically) through GVC linkages or final demand.

These components compensate each other, resulting in no statistically significant relation between exposure to any of the technologies and employment. These findings thus underscore the importance of decomposing employment effects into demand, productivity, and GVC-linkage drivers, as aggregate employment growth often masks off-setting mechanisms operating simultaneously. In order to ascertain this, we proceed by estimating the effects on the different sub-samples of manufacturing and service industries separately.

Figure 7 reports OLS estimates from equation (5) for manufacturing industries only. Again, the top panel refers to total employment, while the bottom panel reports employment activated by global value chains (GVC jobs). We focus on statistically significant associations and quantify the corresponding effects.

For total employment, we find statistically significant relations for a limited number of technologies, although again this is because different drivers compensate each other.

Exposure to *food services* is positively associated with employment growth in manufacturing. A one-unit increase in exposure is associated with a $\sim$0.03pp increase in total employment, driven entirely by a $\sim$0.03pp increase through GVC linkages. No significant relation is detected through productivity or final demand, suggesting that stronger inter-industry demand within value chains is the main driver of job creation in manufacturing.

Exposure to *digital services* technologies shows a combination of channels that offset each other. A one-unit increase in exposure is associated with a $\sim$0.1pp increase in employment through productivity, indicating creation of labour-intensive/non-routine jobs within these industries. But it is also associated with a $\sim$0.07pp reduction through GVC linkages and a $\sim$0.03pp reduction through final demand. These opposing drivers largely offset each other, resulting in no statistically significant net coefficient on total manufacturing employment.

Exposure to *computer vision* technologies is associated with labour-saving. A unit increase in exposure corresponds to a $\sim$0.09pp reduction in employment through productivity, partially offset by a $\sim$0.06pp increase through GVC linkages. The net relation with total employment remains not statistically significant.

Finally, exposure to *health technologies* is associated with a $\sim$0.07pp increase in employment through productivity (creation of non-routine jobs), accompanied by a $\sim$0.04pp reduction through GVC linkages.

We also confirm for manufacturing the labor-saving role of e-commerce and the positive relation with 3D printing technologies through final demand (although significant only at 10%).

The remaining technology families (embedded systems, smart mobility, and payment systems) do not display statistically significant associations with total manufacturing employment nor with its drivers.

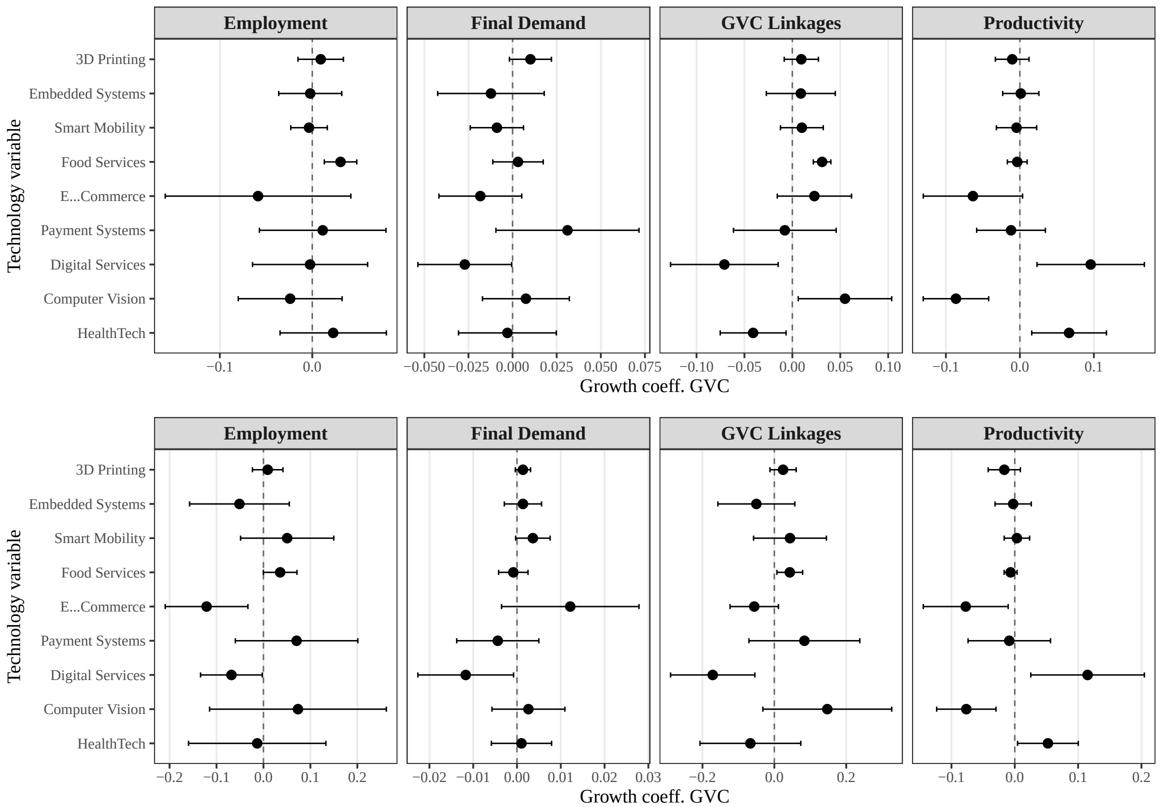


Figure 7: Marginal effects for each technology family – Only Manufacturing industries

Notes: Each panel plots OLS coefficients from (5) for nine exposure variables (technology families) estimated jointly. From left to right, the dependent variable ΔE_{ij} include: (i) the average change in *employment*, and its decomposition into changes attributable to (ii) the *Final Demand* driver (changes in domestic and foreign expenditure), (iii) the *GVC linkages* driver (changes in inter-industry demand), and (iv) the *Productivity* driver (variation in labour per unit of value added). From top to bottom the dependent variable ΔE_{ij} include total employment (top) and employment activated by GVC (bottom). Drivers are decomposed using an average-polar structural decomposition over the period 2012-2019. All specifications include country fixed effects (κ_i) and industry fixed effects (δ_j). Markers show point estimates $\hat{\beta}_f$; whiskers denote 95% confidence intervals based on robust standard errors. A rightward (leftward) estimate indicates a positive (negative) association between exposure and the employment outcome, conditional on the other technology families and fixed effects. In the *Productivity* panel, negative coefficients indicate employment-reducing (labour-saving) changes in labour intensity; positive coefficients indicate employment-increasing (labour-using) changes. Industry coverage excludes Public administration, defence and social security (O), Education (P), Human health and social work activities (Q), Real estate activities (L) Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T), and the Primary industries.

When we consider GVC jobs, results for manufacturing are similar to those for total employment, showing a slightly more systematic role of the productivity driver – alongside fewer demand-side offsets.

First, a one-unit increase in exposure to *food service* technologies is associated with a 0.043pp increase in GVC jobs through GVC linkages, compared to a 0.031pp increase in total employment. This suggests that the employment gains associated with food service technologies are more concentrated along internationally fragmented production processes.

Second, labour savings are more pronounced for GVC jobs than for total employment. In particular, exposure to *e-commerce* technologies is associated with a $\sim$0.08pp reduction in GVC employment through productivity, compared to a smaller and less precisely estimated coefficient for total employment. Similarly, exposure to *computer vision* technologies is associated with a $\sim$0.08pp decline in GVC jobs through productivity, whereas the corresponding coefficient for total employment is partially offset by positive GVC-linkage effects.

Third, for *digital services*, while total manufacturing employment exhibits offsetting productivity and demand drivers, GVC employment shows a consistently negative relation across all drivers. A one-unit increase in exposure is associated with a $\sim$0.12pp increase in GVC jobs through productivity that is more than compensated by the $\sim$0.17pp reduction through GVC linkages, and $\sim$0.012pp reduction through final demand.

Overall, the manufacturing sector results indicate that also for these industries statistically significant employment relation between digital automation technologies and employment are driver-specific, although not always off-setting each other. Demand-expanding technologies such as food services tend to increase employment through stronger GVC linkages, while productivity-enhancing technologies such as e-commerce and computer vision are associated with labour-saving effects, especially for employment activated by global value chains. We also observe a number of technologies that are associated with an increase in the number of non-automated jobs, hinting at the presence of complementarity effects.

Figure 8 reports OLS estimates from Equation (5) for service industries only, controlling for country and industry fixed effects. The top panel refers to total employment, while the bottom panel reports employment activated by global value chains (GVC jobs).

Unlike for manufacturing, we observe substantial differences in the relation between exposure to digital automation technologies and total jobs on the one hand, and GVC jobs on the other.

For total employment, statistically significant relations are limited and mainly operate through the GVC demand driver.

Exposure to *embedded systems* is associated with an increase in employment through final demand. A one-unit increase in exposure is linked to a $\sim$0.01pp increase in employment through final demand, with no statistically significant effects through productivity or GVC linkages. This suggests that embedded and IoT-related technologies stimulate downstream demand for services without directly affecting labour efficiency.

As for manufacturing, exposure to *e-commerce* technologies is associated with labour saving. A one-unit increase in exposure is associated with a $\sim$0.03pp reduction in employment through productivity gains, partially offset by a $\sim$0.021pp increase through GVC linkages (significant at the 10% level). The net effect on total employment is not statistically significant.

A unit increase in the exposure to digital services technologies is associated with a $\sim$0.03pp increase in employment through GVC linkages (10% significance), suggesting that these technologies strengthen inter-industry and inter-firm service demand, without significantly relating to productivity or final demand.

For *computer vision*, a one-unit increase in exposure is instead associated with a $\sim$0.03pp reduction in employment through GVC linkages, indicating a contraction in inter-industry demand for service tasks related to AI.

Finally, exposure to *health technologies* also shows a weakly significant $\sim$0.01pp reduction in employment through GVC linkages.

No statistically significant associations are detected for 3D printing, smart mobility, food services, or payment systems with respect to total service employment.

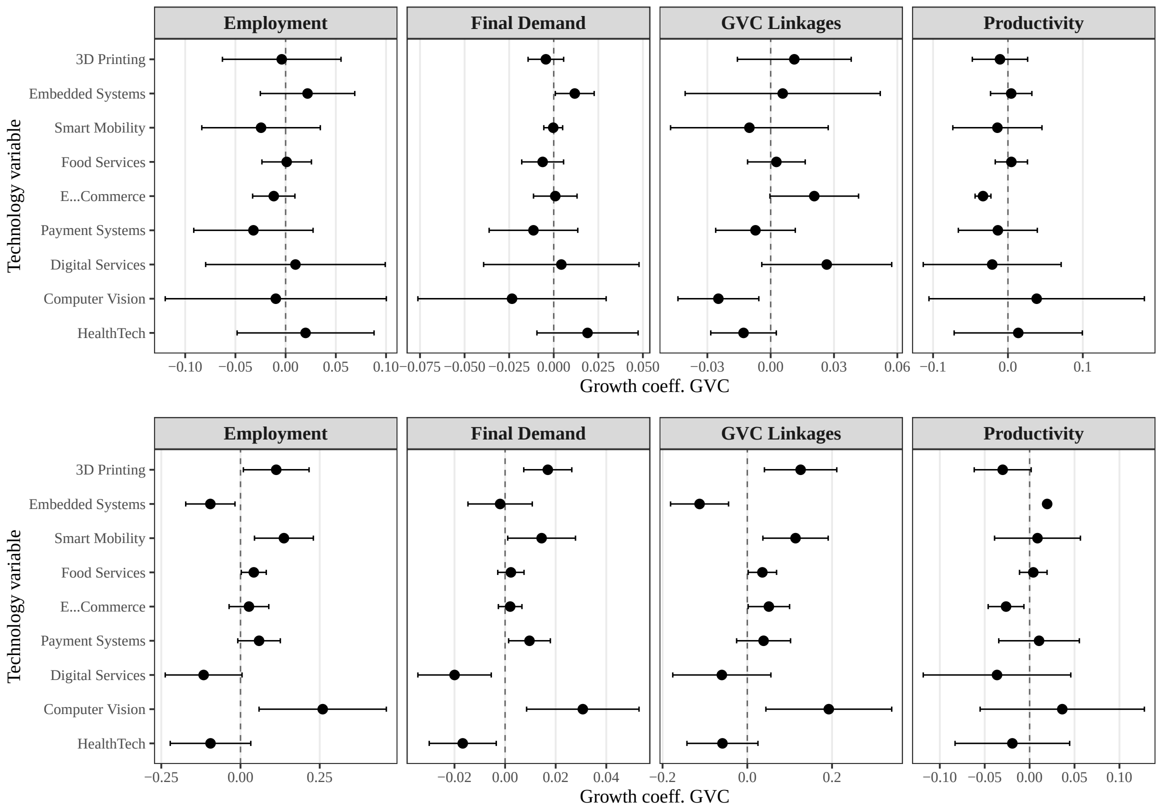


Figure 8: Marginal effects for each technology family – Only Service industries

Notes: Each panel plots OLS coefficients from (5) for nine exposure variables (technology families) estimated jointly. From left to right, the dependent variable ΔE_{ij} include: (i) the average change in *employment*, and its decomposition into changes attributable to (ii) the *Final Demand* driver (changes in domestic and foreign expenditure), (iii) the *GVC linkages* driver (changes in inter-industry demand), and (iv) the *Productivity* driver (variation in labour per unit of value added). From top to bottom the dependent variable ΔE_{ij} include total employment (top) and employment activated by GVC (bottom). Drivers are decomposed using an average-polar structural decomposition over the period 2012-2019. All specifications include country fixed effects (κ_i) and industry fixed effects (δ_j). Markers show point estimates $\hat{\beta}_f$; whiskers denote 95% confidence intervals based on robust standard errors. A rightward (leftward) estimate indicates a positive (negative) association between exposure and the employment outcome, conditional on the other technology families and fixed effects. In the *Productivity* panel, negative coefficients indicate employment-reducing (labour-saving) changes in labour intensity; positive coefficients indicate employment-increasing (labour-using) changes. Industry coverage excludes Public administration, defence and social security (O), Education (P), Human health and social work activities (Q), Real estate activities (L) Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T), and the Primary industries.

Turning to GVC employment, service industries display stronger and more systematic demand- and GVC linkage-driven correlations than those observed for total employment. These are not always compensated by changes in productivity, extending these correlation to GVC jobs.

Exposure to *3D printing* is associated with a sizable increase in GVC jobs. A one-unit increase in exposure is linked to a ∼0.11pp increase in GVC employment, due to the combination of a ∼0.13pp increase through GVC linkages and a $\sim$0.02pp increase through final demand, partially offset by a $\sim$0.03pp reduction through productivity (10% significance). This pattern suggests that, in services, 3D printing primarily allows for the increase in related services through intermediate and final demand.

A one-unit exposure to *embedded systems* is associated with a $\sim$0.1pp reduction in GVC employment, mainly reflecting a $\sim$0.1pp decline through GVC linkages, not compensated by a $\sim$0.02pp increase through labour intensive activities. This suggests that these tangible automation technologies may reduce cross-border service linkages by increasing national production.

Exposure to smart mobility technologies shows a significant positive association with GVC jobs. A one-unit increase in exposure corresponds to a $\sim$0.14pp increase in GVC employment, driven by both GVC linkages ($\sim$0.11pp) and final demand ($\sim$0.01pp). This points to the importance of logistics, transport coordination, and platform-based mobility services in activating employment along global value chains.

Similarly, *food service* technologies are associated with a $\sim$0.04pp increase in GVC employment, all due to a $\sim$0.04pp increase through GVC linkages.

For *e-commerce*, GVC employment differs from total employment (in both services and manufacturing). While total employment shows only productivity-driven labour saving, GVC employment exhibits a $\sim$0.05pp increase through GVC linkages, offset by a $\sim$0.03pp reduction through productivity. This suggests that e-commerce reallocates service GVC employment toward internationally linked activities, while also increasing productivity, as noted before.

Payment systems, instead, act through the total final demand, not just GVC demand. A one unit increase in exposure to *payment systems* is associated with an increase in GVC jobs through final demand by 0.01pp.

Instead, a one-unit increase in exposure to *digital services* technologies is associated with a $\sim$0.02pp reduction in GVC employment through final demand, indicating that digital coordination and platform services may reduce labour requirements.

Computer vision shows the largest positive association with GVC jobs in services (contrary to manufacturing). A one-unit increase in exposure is linked to a $\sim$0.26pp increase in GVC employment, driven by both GVC linkages ($\sim$0.2pp) and final demand ($\sim$0.03pp), suggesting that AI applications may substantially expand internationally fragmented service activities and employment related to them.

Finally, exposure to health technologies is associated with a reduction in GVC employment through final demand. This pattern is consistent with a localisation of service provision enabled by digital health technologies, which reduce reliance on foreign service inputs.

In sum, in service industries, digital technologies are substantially more related to GVC jobs than to total employment. While total service employment shows only limited and offsetting responses, several technologies – including smart mobility, 3d printing, food services, e-commerce, and computer vision – are strongly associated with increases in employment activated by global value chains. This pattern indicates that digitalisation in services primarily reshapes the international organisation of service production rather than generating broad-based changes in domestic employment levels.

3.1 Summary of main findings

Our analysis reveals several important patterns of how exposure to nine heterogeneous families of digital automation technologies is associated with employment growth across countries and industries, and macro sectors.

First, the limited significant relationship between industry-country exposure to digital automation technologies and employment often reflects significant but opposing – and hence offsetting – effects occurring through the underlying drivers of employment change, i.e. final demand, global value chain (GVC) linkages, and productivity. This supports our methodological choice of looking into these three different components, which represent very different channels through which digitalisation affects both total and GVC-activated employment.

Second, the association between exposure to digital automation and employment growth – via its drivers – varies substantially according to macro sector. Digital technologies seem to act more as labour-saving automation in manufacturing, and as market-expanding digital infrastructures in services.

In manufacturing, several digital technologies – such as e-commerce, computer vision, and digital services – are associated with (negative) employment effects, particularly linked to productivity gains. Demand and GVC-linkage effects are weaker and less systematic. This pattern, which is consistent with automaton-driven technological change in manufacturing, is largely similar for total and GVC jobs. In many cases, however, the productivity driver is not large enough to drive the employment figures, and is offset by demand compensation.

In services, exposure to the same technologies shows different patterns. Digital technologies – particularly smart mobility, E-commerce, computer vision, food services, 3d printing and payment systems – are associated with positive GVC-linkage and final-demand drivers. They primarily reshape organisation, fragmentation, and market access rather than replacing labour. This helps explain why we observe more significant relations with the growth of GVC-activated jobs rather than total employment.

Third, within manufacturing – mainly experiencing labour saving automation – and services – mainly showing GVC and final demand-driven labour creation – there are important differences across technologies. For instance, two typical service-related technologies such as digital services and health technologies are associated with labour creation, increasing labour per unit of value added. In manufacturing, these technologies add activities such as coordination, monitoring, and compliance, which create new employment. Healthcare seems a classical Baumol's cost disease case, where health-tech increases the quality of service, but also the number of tasks and employees – e.g. diagnostic, administrative, and coordination tasks. In other words, digital services introduce organisational and informational layers that require novel human input through task creation and servification.

Finally, changes in GVC employment are driven primarily by the relationship between technology exposure and GVC linkages in service industries.

4 Conclusions and Policy Implications

This paper contributes to the intersection of international trade and labor economics by explicitly linking granular digital automation technologies to the reconfiguration of GVCs and their constituent employment outcomes. By matching patent-based technology exposure (Prytkova et al., 2025) with Input-Output employment decompositions, we move beyond the aggregate "robot vs. labor" dichotomy to uncover heterogeneous effects across technology families.

While recent literature has extensively documented the local labor market effects of robots and AI, and few contributions have specifically focused on the nexus between reconfiguration of GVC and employment, the nexus between these technologies and the spatial reorganization of production remains under-explored.

This analysis is particularly timely given the current context of geo-political fragmentation and the resurgence of industrial policy. Economies need to govern and address the side effects of massive digitalization, while at the same time having to face an increasing tendency toward 'turning inwards' from international trade in the attempt to address renewed issues of economic (and military) security. We have argued that facing a situation of poly-crises is difficult in general and particularly for emerging countries, where policy priorities must take into account the trade-offs between 'turning inwards', failing to rely on international trade, having to catch up with the frontier of digitalization, while at the same time making sure that people remain employed in quality jobs.

Historically, firms in advanced countries faced a binary choice: automate domestic production or offshore to low-wage destinations to cut domestic jobs. Our results suggest that new digital technologies fundamentally alter this trade-off. Certain technologies (e.g., 3D printing) facilitate reshoring by substituting labor with capital (increasing productivity but reducing GVC linkages), while others reduce trade costs, thereby deepening GVC integration and expanding demand.

Now the global context has changed and what seemed an obvious, productivity driven, offshore option has turned into a less obvious, more complex, geopolitically driven, near-, re-, or friend-shoring strategy. This might not offset the employment losses or reconfiguration due to digital automation in the (mostly advanced) countries 'turning inwards' and might be a net loss for emerging countries, which, although not yet losing jobs to robots or digital automation, might significantly be hit by the contraction in foreign intermediate (and henceforth labour) demand.

At any rate, it is crucial to ground policy decisions in evidence. Given the considerations above, we have adapted a framework (Pahl et al., 2022) and used a range of matched data that are able to capture not only the total employment changes but also those job gains or losses resulting from foreign activated (or dis-activated) intermediate demand. We have covered several combinations of effects: total employment affected by digital automation enhanced productivity gains, by final domestic demand and by foreign intermediate demand (countries' participation in GVCs). We also dive into the same components, this time activating the 'GVC jobs', which are those jobs activated by foreign final demand, as in (Pahl et al., 2022).

Our empirical decomposition yields four main results with direct implications for this new landscape.

First, the aggregate association with "employment effects" of digitization is often null, but this masks a structural compensation. Productivity gains (labor-saving) are frequently offset by demand expansion (scale effects) and deepening GVC linkages. When we observe employment growth, this is associated with exposure to specific families of digital technologies, mainly those related to market and platform transactions and involving services.

Second, technology heterogeneity is paramount. We have seen that "market-expanding" technologies (food services platforms, smart mobility) tend to generate employment via final demand and GVC linkages, whereas "efficiency-enhancing" technologies (3D, e-commerce, or computer vision in manufacturing) tend to reduce employment via the productivity channel. When GVC linkages dominate, we observe a significant, often positive, employment outcome.

Third, the role of GVC linkages is both sector- and region-specific. The employment drivers diverge between manufacturing and services. In manufacturing, digital exposure is mainly labor-saving, consistent with standard automation. In contrast, in services, digital exposure facilitates the cross-border provision of tasks.

Fourth, productivity and final demand effects do not systematically reinforce each other; rather, they often operate in opposite directions, particularly when total employment across all countries is considered, suggesting that productivity gains may be accompanied by demand reallocation or displacement effects.

Taken together, these findings underscore that the employment effects of digital automation are highly contingent on technological characteristics, sectoral structures, and countries' positions within GVCs. They caution against overly aggregate assessments of the labour-market implications of digitalisation. Hence, these results call for granularity in analysis and a joint consideration of GVC activated jobs, which respond differently to such a variety of exposure.

Policies aimed at harnessing the employment potential of digital technologies need to be tailored to specific technology families, sectors, and stages of GVC participation. In manufacturing, where productivity-enhancing effects dominate, specific support for functional upgrading within GVCs is crucial to translate productivity gains into sustained employment growth. In services, where digital automation appears to drive market expansion, policies that facilitate access to international markets, promote interoperability standards, and reduce barriers to cross-border digital services trade may be particularly effective.

More broadly, the differentiated role of GVC linkages highlights the importance of trade and industrial policies that strengthen countries' positions within value chains, especially in middle–income regions such as Asia–Pacific where GVC integration amplifies the employment effects of digital technologies. Finally, the frequent offsetting between productivity and final demand effects suggests that digital and innovation policies should be coordinated with macroeconomic and demand-side policies to mitigate displacement risks and ensure that productivity gains translate into inclusive employment outcomes.

Overall, this paper argues for a more cautious positioning when it comes to 'turning inwards' for matters of economic security or geopolitical narratives. This might entail missing opportunities for GVC-activated jobs, for developing digital capabilities increases and for benefiting from upgrading opportunities linked to integration in GVCs.

5 Appendix: Results without outliers and excluding primary sector

Total employment without outliers using IQR threshold and below 1st decile of the distribution of evb0.

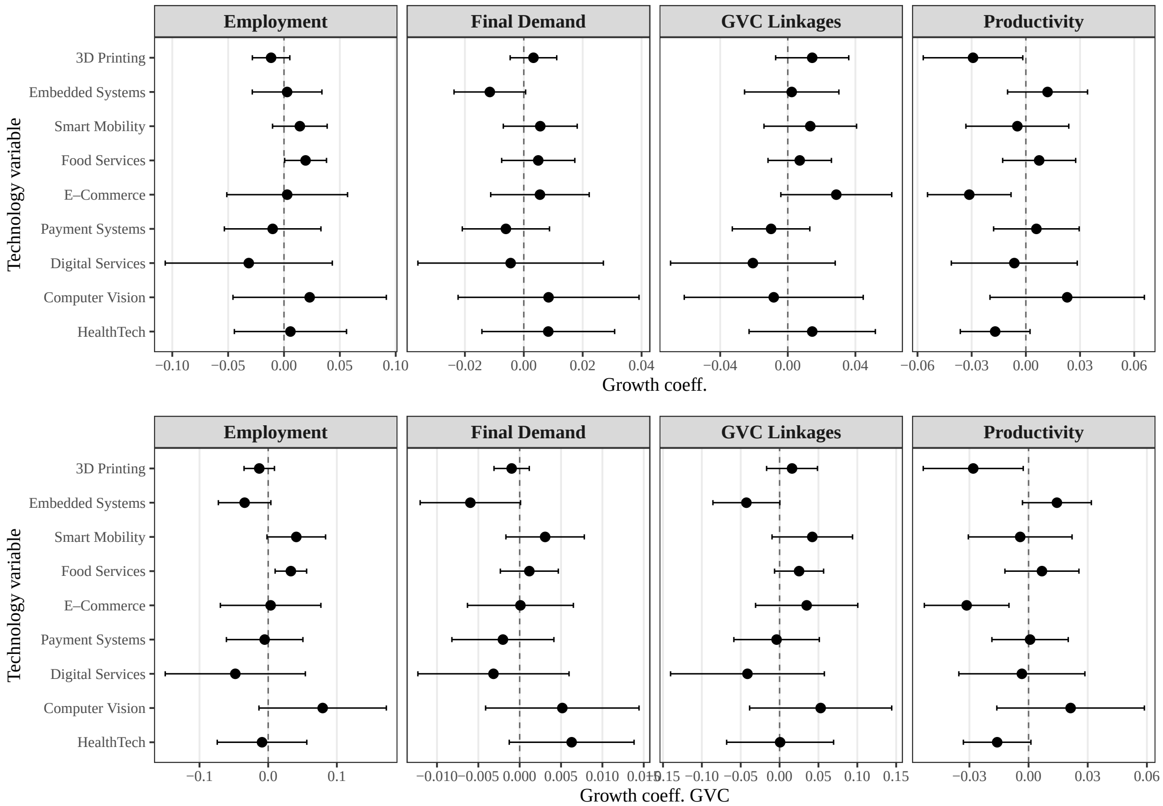


Figure 9: Marginal effects for each technology family – Services and manufacture sectors

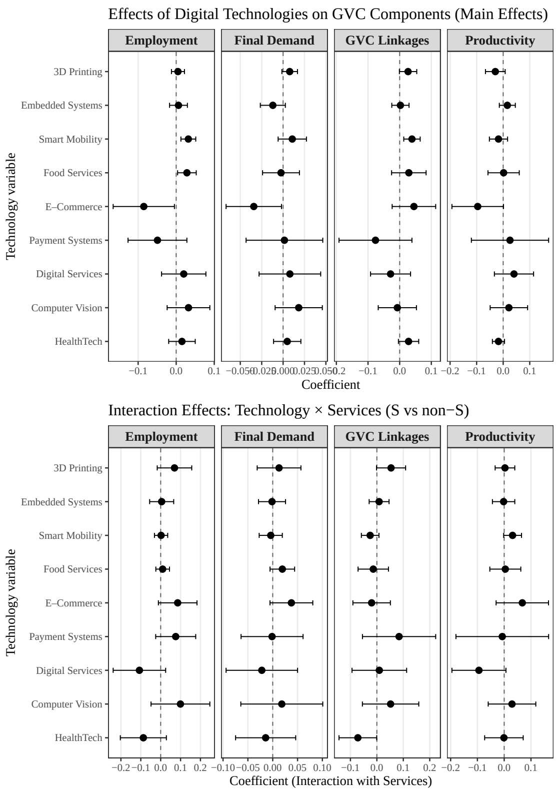
1. We do not find very strong *prima facie* evidence. it seems that the different components compensate one another.

2. 3D printing has a negative contribution through a productivity increase. This is compensated by final demand and GVC linkages

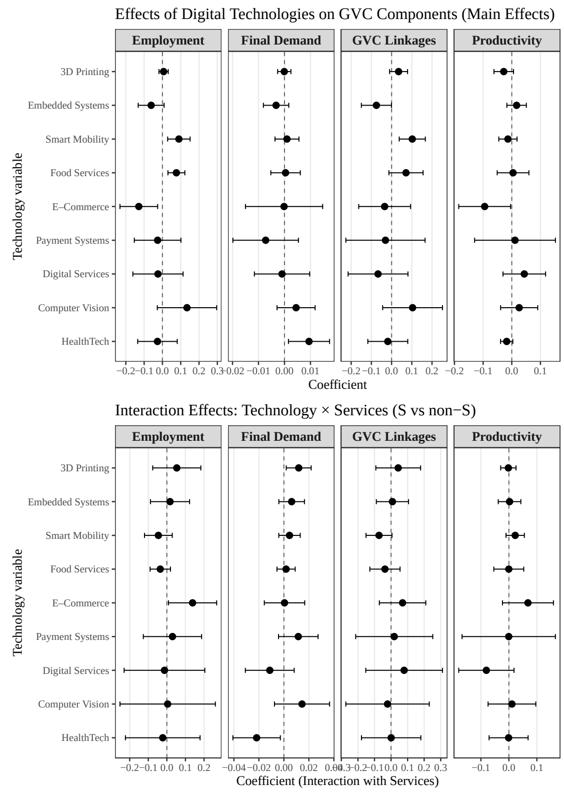
3. Same for e-commerce, although it is only GVC linkages that seem to compensate

4. Embedded system has the opposite pattern: both Final demand and GVC linkages have negative contributions, suggesting that country-industries that are exposed to this tech have seen a contraction in both their scale (final demand) and competitiveness as suppliers (GVC linkages), but this has been offset by an decrease in nominal productivity leaving employment unchanged.

5. The above dynamics apply to both total employment and GVC jobs.



(a) Total jobs



(b) GVC jobs

Figure 10: Marginal effects for each technology family – Service interaction term. Manufacture baseline.

When we look at how technological exposure is related to employment growth and its components across manufacturing (top panels) and services (bottom panels), we find that our aggregate results from Figure **??** hide some heterogeneity:

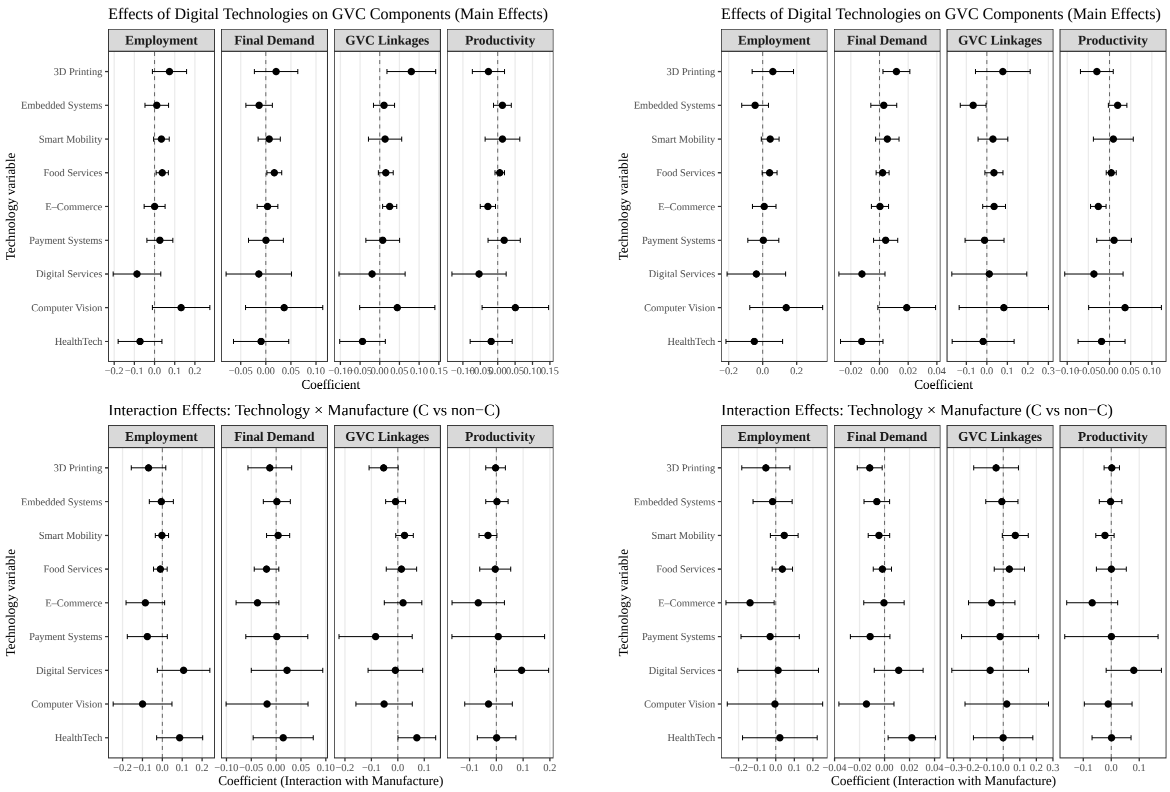
For manufacturing (the benchmark in Figure 10):

1. Smart mobility and food services have an overall positive association with employment growth.

2. We find no distinction between manufacturing and services.

3. Results are similar across total employment and GVC jobs.

Figure 10 is specular to Figure 11 in its interaction term (bottom panels). The services as a baseline does not show a lot of interesting results, except perhaps for 3D printing, which we find hard to relate to services anyways.



(a) Total jobs (b) GVC jobs

Figure 11: Marginal effects for each technology family – Manufacture interaction term. Service baseline.

References

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Baldwin, R. (2022). Globotics and macroeconomics: Globalisation and automation of the service sector. NBER Working Papers 30317, National Bureau of Economic Research, Inc.

Bank, W. (2025). Global trends in ai governance. evolving countries' approach. Technical report, World Bank Group.

Bontadini, F., Evangelista, R., Meliciani, V., and Savona, M. (2024). Technology, global value chains and functional specialisation in europe. *Research Policy*, 53(2):104908.

Bontadini, F., Meliciani, V., Savona, M., and Wirkierman, A. (2023). Nearshoring and farsharing in europe within the global economy. *EconPol Forum*, 23(5).

Bontadini, F., Meliciani, V., Savona, M., and Wirkierman, A. (2025a). Nearshoring and farsharing in europe within the global economy: regional trends, structural components and sectoral patterns. *Economia e Politica Industriale: Journal of Industrial and Business Economics*, 52(3):559–597.

Bontadini, F., Meliciani, V., Urbani, R., and Wirkierman, A. (2025b). Reshaping global value chains: Nearshoring and re-shoring in emerging markets. Technical report, Luiss Research Institute for European Analysis and Policy.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour economics*, 66:101885.

Dietzenbacher, E. and Los, B. (1998). Structural decomposition techniques: Sense and sensitivity. *Economic Systems Research*, 10(4):307–323.

Domini, G., Grazzi, M., Moschella, D., and Treibich, T. (2022). For whom the bell tolls: the firm-level effects of automation on wage and gender inequality. *Research Policy*, 51(7):104533.

Giunta, A., Marvasi, E., and Sforza, M. (2025). Digitalization and regionalization of global value chains in european industries. *Journal of Industrial and Business Economics*, pages 1–30.

Juhász, S., Elekes, Z., Ilyés, V., and Neffke, F. (2024). Colocation of skill related suppliers – Revisiting coagglomeration using firm-to-firm network data.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ict polarized skill demand? evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, 96(1):60–77.

Miller, R. E. and Blair, P. D. (2022). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press, 3rd edition.

Pahl, S., Timmer, M. P., Gouma, R., and Woltjer, P. J. (2022). Jobs and productivity growth in global value chains: new evidence for twenty-five low-and middle-income countries. *The World Bank Economic Review*, 36(3):670–686.

Prytkova, E., Petit, F., Li, D., Chaturvedi, S., and Ciarli, T. (2025). The employment impact of emerging digital technologies.

Stapleton, K. and Webb, M. (2025). Automation, Trade and Multinational Activity: Micro Evidence from Spain.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. J. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, 28(2):99–118.

World Development Report (2020). World development report 2020 : trading for development in the age of global value chains. Technical report, World Bank, Washington, DC.

Annex

Technologies

Table 1: Emerging Digital Technologies (1/3)

	Technology	Description
		[F1] 3D Printing
1	3D Printer Hardware	Three-dimensional printers and their components, such as printing heads, pens, nozzles, platforms, and devices for printing, extruding, cleaning, recycling, heating, and cooling.
2	3D Printing	Printing systems for creating three-dimensional objects using a variety of materials and techniques, like photocuring and powder spreading.
3	Additive Manufacturing	Technologies and processes for additive manufacturing, with applications such as prostheses and building materials.
		[F2] Embedded Systems
4	Smart Agriculture & Water Management	Various Internet of Things (IoT) technologies for intelligent and remote management in agriculture, and water and sewage systems.
5	Internet of Things (IoT)	Systems and devices interconnected via IoT for data collection, remote control, and real-time monitoring in diverse applications, including agriculture, home automation, and environmental monitoring.
6	Predictive Energy Management and Distribution	A combination of network, data management, and AI technologies for monitoring, distribution, and efficient use of electrical power and energy, including renewable energy sources, and for consumption prediction in intelligent power management.
7	Industrial Automation & Robot Control	Industrial process automation, including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.
8	Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.
9	Smart Home & Intelligent Household Control	Various IoT technologies for the intelligent control of homes and buildings, including household appliances, home environments, and smart home integrations, often utilizing wireless communication and monitoring.
		[F3] Smart Mobility
10	Intelligent Logistics	A combination of monitoring, remote control technologies, data acquisition, and mobile robot technologies for logistics and delivery applications, including supply chain management, warehouse operations, package tracking, and courier services.
11	Autonomous Vehicles & UAVs	Developments in unmanned aerial vehicles (UAVs), drones, and autonomous driving technologies, with an emphasis on vehicle control, navigation, and sensor integration.
12	Parking & Vehicle Space Management	Networking technologies for parking management, including systems for monitoring available spaces and intelligent parking solutions.
13	Vehicle Telematics & Electric Vehicle Management	Technologies for intra-vehicle information management, especially in electric vehicles, including aspects of real-time monitoring, traffic information, and vehicle diagnostics.
14	Passenger Transportation	Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization.

Table 2: Emerging Digital Technologies (2/3)

	[F4] Food Ordering	
15	Food Ordering & Vending Systems	Wireless infrastructures, encryption, monitoring, and remote control technologies for food order management, such as automatic vending, self-service ordering, meal preparation, and delivery.
	[F5] E-Commerce	
16	Digital Advertising	Automated tracing and tagging, and AI technologies for digital advertisements, including targeted delivery on mobile devices.
17	Electronic Trading and Auctions	Online trading platforms, financial instrument exchanges, and auction mechanisms, focusing on real-time bidding, trading, and market data.
18	Online Shopping Platforms	Wireless technologies (e.g., RFID and mobile terminals), encryption (e.g., blockchain), and AI technologies for e-commerce transactions, and digital tools related to the purchase, sale, and display of product information, including recommendation systems.
19	E-Coupons & Promotion Management	Data management platforms for electronic coupon distribution, management, redemption, and associated loyalty programs.
	[F6] Payment Systems	
20	Electronic Payments & Financial Transactions	A combination of wireless (e.g., mobile) and encryption (e.g., blockchain) technologies for processing electronic payments (e.g., credit card transactions) and interfacing with financial institutions.
21	Mobile Payments	A combination of mobile technologies for processing electronic payments.
22	Gaming & Wagering Systems	A combination of user interface and data management technologies for gaming, both online and physical, including gambling and gaming machines.
	[F7] Digital Services	
23	Digital Authentication	Encryption and robotic processing technologies for verifying user identities, securing transactions, and safeguarding data through various authentication mechanisms, such as biometrics and cryptographic methods.
24	E-Learning	A combination of AI and data management technologies for digital platforms and systems in education, including teaching, learning, and classroom management.
25	Location-Based Services & Tracking	Technologies that provide location-based content and services, often relying on global positioning and navigation systems and related communication technology.
26	Voice Communication	Technologies focusing on voice communication, including communication protocols and user interfaces.
27	Electronic Messaging	Digital communication methods, infrastructure, and user interfaces for services such as email and conferences.
28	Workflow Management	A combination of AI and network technologies for management applications, including workflow automation, recruitment, event scheduling, and building and property management.

Table 3: Emerging Digital Technologies (3/3)

		[F7] Digital Services (continued)
29	Cloud Storage & Data Security	Cloud-based data storage, distributed data management, encryption, and backup, often integrated with blockchain technology.
30	Information Processing	Systems for managing, processing, and delivering data and information across various domains, potentially including content generation, transmission, and verification.
31	Cloud Computing	Cloud computing and virtual machines, focusing on cloud platforms and resource allocation in cloud environments.
32	Recommender Systems	Algorithms and systems for providing recommendations and personalized content delivery based on user behavior, search queries, and similarity metrics.
33	Social Networking & Media Platforms	User interfaces for online social networking services, content sharing, and recommendation systems.
34	Digital Media Content	Tools and platforms for digital media content creation, management, distribution, and access.
		[F8] Computer Vision
35	Augmented and Virtual Reality (AR/VR)	Augmented reality (AR) and virtual reality (VR) models, devices, interfaces, and experiences, including head-mounted displays and interactions in virtual environments.
36	Machine Learning & Neural Networks	Machine learning training techniques, model architectures, and data processing for computer vision applications.
37	Medical Imaging & Image Processing	Diverse applications for acquiring and analyzing medical images from various modalities, such as computed tomography (CT), ultrasound, magnetic resonance imaging (MRI), and virtual reality (VR), for purposes including diagnosis, surgical planning, and the design of prostheses.
		[F9] HealthTech
38	Health Monitoring	Wearable and implantable devices and systems for real-time health monitoring that track vital signs such as blood pressure, heart rate, and temperature, coupled with comprehensive medical data management.
39	Medical Information	A combination of data sharing, encryption, and Natural Language Processing (NLP) technologies for the storage, retrieval, and management of medical and patient information, encompassing electronic medical records, prescription management, and remote healthcare services.
40	E-Healthcare	An integration of data sharing, wireless communication, monitoring, and user interface technologies for healthcare and health management systems, including those used in hospitals and cloud-based platforms.