The Implications of the Interplay between Global Value Chains and Technology for Labour Productivity and Demand*

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Abstract

Leveraging a new sample of 35 industries covering the entire economies of 62 developed and developing countries in 2000–2019, we derive a broad set of insights about the implications of Global Value Chains (GVCs) and their interplay with technology for labour productivity and demand. Participation in GVCs through linkages with suppliers (i.e., backward) and buyers (i.e., forward) increased labour productivity of industries, but the productivity gains from backward participation operated through larger employment losses than output losses, while productivity gains from forward participation operated through output gains or employment losses. Also, GVC participation, especially through backward linkages, was skill-biased, having increased the employment share of workers in high-skilled occupations and decreased the employment shares of young and female workers. By distinguishing between high- and lower-income countries and taking advantage of initial cross-industry differences in the intensities of utilisation of CT, IT, software, and industrial robots, we obtain additional evidence pointing to the critical role of the interplay between GVCs and technology for labour productivity and demand.

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1 Introduction

The concurrent emergence and expansion of Global Value Chains (henceforth, GVCs) and digital industrial technologies since the late 1970s have spawned numerous theoretical and empirical studies on their implications for labour markets in developed and developing countries.[1] Although there is by now a consensus that GVCs and the ensuing trade in intermediates and the widespread use of digital industrial technologies are major drivers of labour market outcomes, their implications are predominantly intertwined and thus hard to be teased apart (Fort et al., 2018). Recent developments in the global economy—most notably, intensifying competition between the US and China, rise in protectionism, geopolitical tensions, and remarkable advancements in ICT, Robotics and Artificial Intelligence—have all rendered this topic even more intriguing and policy-relevant.

Our main goal in this paper is to advance further our knowledge about this topic. Creating a novel sample covering the entire economies of 62 developed and developing countries for the period 2000–2019, we first conduct a comprehensive analysis of how participation in GVCs through the development of linkages with suppliers (i.e., backward) and buyers (i.e., forward) impacts labour productivity and its two components—total value added and total employment—as well as the skill, age, and gender composition of employment. By pooling all countries examined together and then distinguishing these by their income status, we obtain a rich set of results, which not only yield insights about the implications of backward and forward GVC participation for labour productivity and demand but also of technological changes associated with these types of activities. Subsequently, we derive additional pertinent insights by considering the interplay between backward and forward GVC participation and adoption of key technologies with different capabilities—namely, communication technologies (CT), information technologies (IT), software (S/W), and industrial robots.

To create the novel sample, we optimally combine information from four data sources. From the Asian Development Bank (ADB)'s Multi-Region Input-Output (MRIO) database, we retrieve information on backward and forward GVC participation measures and real gross value added. From the International Labour Organization (ILO)'s Harmonized Microdata, we retrieve information on total employment and the employment shares of workers in high-skilled occupations—labeled as high-skilled, workers aged 15–24—labeled as young, and female workers.[2] The third data source is the March 2011 release of the EU KLEMS database, from which we collect information on the real stocks of CT, IT, and software capital, while from Graetz and Michaels (2018) we collect information on robot intensity.

In the first part of the econometric analysis, we estimate long-differenced specifications with

[1] Prominent examples are: Berman et al. (1994), Feenstra and Hanson (1996, 1997, 1999), Goldberg and Pavcnik (2007), Hummels et al. (2018), Autor et al. (2003), Acemoglu and Autor (2011), Autor (2014), and Acemoglu and Restrepo (2019).

[2] The ILO has constructed this database based on its unique collection of national labour force surveys, which are used by national authorities for the production of official statistics. Note that the database includes employment information for two groups per demographic characteristic. Hence, the residual employment shares are held by lower-skilled workers (i.e., those in medium- and low-skilled occupations), older workers (aged 25–64), and male workers, respectively.

the log of labour productivity, value added or total employment, or the employment share of high-skilled, young, or female workers as the dependent variable and the measures of backward and forward GVC participation as the two key regressors. We also include in the specifications the log of value added to control for industry scale and country fixed effects to control for unobserved cross-country heterogeneity in various dimensions (e.g. national wage bargaining and labour market institutions, aggregate labour supply shocks, trade policy and import competition).[3]

Due to the possibility of simultaneously determined key explanatory and outcome variables, measurement errors in the main variables, or omitted variables in the specifications, we interpret the estimates obtained from OLS estimations as conditional correlations. To tackle concerns over endogeneity, we also estimate the specifications by 2SLS, following closely the IV strategy proposed by Michaels et al. (2014) and adapting it to our research question and setting. In particular, considering that initial cross-industry heterogeneity in GVC participation will lead to the differential expansion of industries along this dimension, we instrument the two GVC measures of our specifications using the respective (industry-level) measures for the US in the initial sample year (2000), after excluding this country from the sample. The selection of the US as the benchmark country implies that the average industry in the countries examined emulates the respective industry in the US—arguably, the leading country shaping the global economy since the 1970s based on the idea and practice of global fragmentation of production and the ensuing emergence and expansion of GVCs (World Bank, 2020). As roughly half of the countries in our sample are developing countries whose industries may emulate those of China more closely than those of the US in terms of GVC participation, we also implement a variant of the IV strategy, using as instruments the (industry-level) GVC measures for both the US and China in the year 2000. Although there are strong qualitative similarities between the OLS and 2SLS estimates obtained from the original IV and its variant, the 2SLS estimates are larger, which accords with the possible attenuation bias in the OLS estimates due to measurement error in the data.

To identify differential relationships of backward and forward GVC participation with the outcome variables under consideration in industries with different initial levels of technology intensity, we augment the specifications with interactions of the two GVC measures with a technology variable. The technology variables that we consider for this purpose are the industry-level CT, IT, and software capital intensities (real capital stocks to real gross value added) for the US in 2000 and the industry-level average robot intensity (robot stock in units per million hours worked) of a set of predominantly technologically advanced countries, the US included, in 1993.[4] Similarly to the rationale for the construction of the instruments for the GVC measures, the selection of the technology variables is predicated upon the idea that industries of countries in our sample emulate the respective industries in the US or a group of countries that are close to the global technological frontier.

[3]Estimations of this kind of specifications have been common in the related empirical literature at least since Berman et al. (1994).

[4]Industry-level robot intensity is calculated by Graetz and Michaels (2018) as the unweighted average of robot intensity across countries by industry in 1993.

The econometric analysis yields a rich set of insights about the implications of backward and forward GVC participation and their interplay with technology for labour productivity and demand. Considering only the GVC measures as the key explanatory variables, we find that both backward and forward GVC participation increased labour productivity of industries, but these increases operated through different aggregate output and employment adjustments.[5] In particular, productivity gains from backward GVC participation were driven by larger aggregate employment losses than output losses, while productivity gains from forward GVC participation were driven by output gains (according to the original IV) or employment losses (according to the variant of the IV). Equally importantly, we find that the productivity gains from backward GVC participation and their underlying mechanism were observed in high-income countries, but not in lower-income countries, and that these effects were larger compared to those identified on the whole sample.

The productivity gains of industries from backward GVC participation are consistent with past evidence on productivity-enhancing import activities (Amiti and Konings, 2007; Amiti and Wei, 2009; Topalova and Khandelwal, 2011; Halpern et al., 2015), while their output and employment losses echo past evidence on the downsizing or closure of manufacturing plants in high-income countries like the US due to offshoring to and import competition from lower-income countries—especially China—since the 1980s (Autor et al., 2013, 2021; Autor et al., 2014; Acemoglu et al., 2016; Pierce and Schott, 2016; Fort et al., 2018). The output and employment losses may also reflect the "Solow paradox", that is, the poor productivity and output gains of industries in high-income countries from the utilisation of IT and other labour-saving technologies, which may be associated with backward GVC participation (Acemoglu et al., 2014; Houseman et al., 2015). In a similar vein, this evidence may reflect weak new task creation relative to task displacement due to backward GVC participation and adoption of associated labour-saving technologies, especially when the latter lead to substantial labour cost reductions but poor productivity gains (Acemoglu and Restrepo, 2019, 2022). The two interpretations based on the adoption of labour-saving technologies are likely more relevant than import competition, given that we also find qualitatively similar but larger effects in non-manufacturing industries, which tend to be less exposed to import competition than those in manufacturing, and in IT-using industries, where the Solow paradox is mostly observed.

In sharp contrast to the evidence for high-income countries and the relevant interpretations, we find that backward GVC participation increased the output of industries in lower-income countries. This effect points to complementarities between domestic production of value added and the sourcing of foreign value added and possible adoption of associated labour-saving technologies, and to the generation of a sufficiently high number of tasks. This interpretation also accords with the shift of economic activity of these countries away from the primary sector and towards the manufacturing and service sectors, as we document in this paper. The particular relevance of this interpretation to the manufacturing sector is strengthened by additional evidence showing that the effect of backward GVC participation on output is statistically insignificant in non-manufacturing industries.

[5] In addition to their individual effects, the two GVC measures jointly increased labour productivity more than the actual change of this variable between 2000 and 2019 for the average country-industry pair, implying that there were other factors that pushed labour productivity in the opposite direction.

The productivity gains from forward GVC participation are reminiscent of evidence showing that firms become significantly more productive after they become exporters (De Loecker, 2013) and theories and evidence on industry-level productivity gains from reallocation towards initially more productive firms that have a differential capacity to enter export markets (Clerides et al., 1998; Melitz, 2003). As the productivity gains operated through output gains or employment losses, these effects might have also been driven by the adoption of automation technologies associated with forward GVC participation, such as industrial robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Koch et al., 2021).

We derive more insights about the effects of forward GVC participation on productivity and its two components while distinguishing countries by their income status. In particular, we find that forward GVC participation raised the output and employment of industries of high-income countries, while it raised the productivity of industries of lower-income countries by decreasing their employment more than their output. The effects in high-income countries, which are also very similar but stronger in non-manufacturing industries, point to the generation of value added that is exported through GVCs according to the comparative advantage of these countries in the performance of non-routine cognitive tasks (e.g. R&D, design, engineering, marketing, and management) and the transition of their economies towards market services. The same effects may reflect the "deepening" of forward GVC participation, implying the rise in productivity of production factors (e.g. workers, machines) employed domestically for the generation of outputs that are exported through GVCs. By contrast, the productivity gains and employment losses in lower-income countries, which are larger than those identified on the whole sample and even larger in non-manufacturing and IT-using industries of these countries, likely point to the complementarity between exports of domestic value added through GVCs and adoption of labour-saving technologies (Koch et al., 2021). As the adoption of labour-saving technologies should have also led to output gains, rather than losses (Acemoglu et al., 2014, 2016; Fort et al., 2018), we make sense of the latter effect by documenting that sectors of lower-income countries that increased their forward GVC participation the most were those that grew the least in terms of value added and employment over the period examined, and vice versa. These inconsistencies are smaller among non-manufacturing industries, which likely explains why this effect is not significant in these industries. Combined, this evidence suggests that industries outside manufacturing, especially those in the primary and personal and professional service sectors, failed to adopt output-enhancing technologies as they expanded their forward participation in GVCs.

Regarding the effects on the structure of employment, we find that backward and forward GVC participation reduced the employment share of women, while backward GVC participation reduced the employment share of young workers and increased the employment share of high-skilled workers. The latter two effects are economically significant, accounting for roughly one-fourth and two-thirds, respectively, of the observed changes of the employment shares of these two worker groups between 2000 and 2019 for the average country-industry pair. These effects are largely observed when we also distinguish countries by their income status. We view these effects as reflecting skill upgrading of industries due to their backward and forward participation in GVCs. In particular, sourcing of foreign value added substituted for domestic routine cognitive and manual tasks (e.g. assembly line, administrative support, customer service), which have relatively low skill requirements and are performed primarily by low-skilled, young, and female workers, or complemented (disproportionately) non-routine cognitive tasks (e.g. reasoning, monitoring, direction), which have relatively high skill requirements. However, it is also noteworthy that the backward GVC participation effects are insignificant in non-manufacturing industries, suggesting that skill upgrading due to this activity may be particularly relevant in manufacturing industries of the two country income groups. By contrast, the forward GVC participation effect on the female employment share in lower-income countries is also observed in non-manufacturing industries.

These effects echo past evidence on offshoring-induced skill upgrading of industries or firms in developed countries (Feenstra and Hanson, 1996, 1999; Hijzen et al., 2005; Biscourp and Kramarz, 2007; Mion and Zhu, 2013; Ebenstein et al., 2014; Carluccio et al., 2019; Hummels et al., 2018) and developing ones (Feenstra and Hanson, 1997; Goldberg and Pavcnik (2007); Verhoogen, 2008), as well as recent evidence on less skilled workers bearing the brunt of the decline in the labour share due to forward GVC participation (Reshef and Santoni, 2023). The same effects also relate to theoretical frameworks highlighting offshoring-induced shifts of domestic labour towards more productive uses (Egger et al., 2015) and empirical evidence on labour reallocation towards technology- and innovation-intensive activities induced by offshoring, import competition, or exporting (Becker et al., 2013; Boler et al., 2015; Bloom et al., 2016; Bernard et al., 2023; Pierce and Schott, 2016; Lileeva and Trefler, 2010). As labour reallocation due to offshoring and import competition likely allows firms to compete more effectively in domestic and export markets, these effects can also be viewed through this lens (Aghion et al., 2005; Bernard et al., 2006; Schott, 2003, 2008; Bernard et al., 2011; Khandelwal, 2010; Amiti and Khandelwal, 2013; Hombert and Matray, 2018).

In addition, the effects on employment shares reflect the effects of routine-biased technological changes that may be associated with GVC participation, such as IT and robot adoption (Berman et al., 1994; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014; Graetz and Michaels, 2018; Blanas et al., 2019; Acemoglu et al., 2020; Dauth et al., 2021; Dinlersoz and Wolf, 2023; Blanas, 2023, 2024), and the effects of non-routine-biased technological changes, such as CT adoption (Antràs et al., 2006, 2008; Frydman and Papanikolaou, 2018; Blanas, 2023). We also identify a negative and significant effect of forward GVC participation on the employment share of high-skilled workers in lower-income countries, which may be particularly relevant to manufacturing, as it is insignificant in non-manufacturing industries. We interpret this effect as reflecting the disproportionate creation of tasks and jobs with lower-skill requirements, which may, nevertheless, be relatively skilled from the perspective of these countries, given their relatively low skill abundance. This intuition is very similar to that of Feenstra and Hanson (1997) for their evidence on the offshoring-induced rise in the skill premium in Mexican manufacturing.

Considering interactions between GVC and technology measures, we find smaller productivity gains and aggregate employment losses associated with backward GVC participation and smaller employment share losses of female workers associated with forward GVC participation in initially more CT-capital-intensive industries of high-income countries. Similarly, we find smaller productivity gains and aggregate employment losses associated with forward GVC participation and smaller employment share gains of high-skilled workers associated with both backward and forward GVC participation of initially more CT-capital-intensive industries of lower-income countries. As CT utilisation facilitates investment in and monitoring and coordination of GVCs (Frydman and Papanikolaou, 2018; Antràs et al., 2006, 2008; Fort, 2016; Blanas, 2023), the differential associations suggest that more CT-capital-intensive industries might have had initially higher backward and forward participation in GVCs and adoption of associated labour-saving technologies and thus further increases in their GVC participation in the course of the years led to smaller employment losses and productivity gains and to lower skill upgrading compared to other industries. Another possible interpretation, predicated upon knowledge-based hierarchy theories (e.g. Garicano, 2000; Bloom et al., 2014; Garicano and Rossi-Hansberg, 2015), is that initially more CT-capital-intensive industries faced lower supervision and coordination costs and were thus able to form larger international production teams as they expanded their GVC participation.

In addition, we find smaller aggregate employment losses associated with backward GVC participation in initially more IT-capital-intensive industries of high-income countries and smaller employment share gains of high-skilled workers and employment share losses of female workers associated with the same type of activity in initially more robot-intensive industries of the same group of countries. In lower-income countries, we also find smaller productivity gains and aggregate employment losses associated with forward GVC participation in initially more IT-capital-intensive, software-capital-intensive, or robot-intensive industries, smaller employment share gains of high-skilled workers associated with both backward and forward GVC participation in initially more IT- or software-capital-intensive industries, and smaller employment share losses of female workers associated with forward GVC participation in initially more robot-intensive industries. These findings likely suggest that although more automation-intensive industries continued to adopt automation technologies, such as IT, software and robots, at faster rates as they were increasing their participation in GVCs, they also employed workers who were less amenable to automation thanks to their higher skills and capabilities than workers of other industries (Aghion et al., 2019; Blanas, 2023). This also implies that more automation-intensive industries might have not only automated tasks as they expanded their GVC participation, but also created a larger number of new tasks compared to other industries.

The remainder of the paper proceeds as follows. In Section 2, we describe the data and variables that we use in the main econometric analysis and present useful descriptive statistics for GVC participation and labour productivity and demand. In Section 3, we describe the econometric model and strategy for its estimation. In Section 4, we present and discuss our main findings, while in Section 5, we provide key concluding remarks and some suggestions for further research.

2 Data and descriptive statistics

In this section, we first describe the data sources from which we collect information on the variables that we employ in the main part of the econometric analysis and then present useful descriptive statistics for these variables.

2.1 Data and variables

Combining the Asian Development Bank (ADB)'s Multi-Regional Input-Output (MRIO) Tables with the ILO Harmonized Microdata, which is a database constructed by the International Labour Organization (ILO) based on its collection of harmonised labor-related micro-level data from national labour force surveys, we create a sample of 35 industries in 62 countries in 2000 and 2007–2019.[6] Industries are identified by their ISIC Rev. 3.1 codes and span the entire economies of the countries examined (see relevant list in Appendix Table A.1). Country coverage in our analysis is much broader compared to that in the vast of majority of extant related studies and, on top of that, cross-country heterogeneity in terms of income and development levels is salient. In fact, 33 out of the 62 countries of our sample are classified as upper-middle-, lower-middle-, or low-income, according to World Bank's Historical Country Classification by Income in the initial sample year (2000). We label these countries as lower-income and the rest as high-income and consider this distinction in the descriptive statistics and econometric analyses (see list of countries in Appendix Table A.2). Another advantage of our matched data is that they correspond to a very recent period, which is marked by the significant expansion of trade and investment relations of high-income countries with Eastern European countries and East Asian countries—particularly China, as a result of the rising integration of developing countries into the world economy (e.g. China's accession to the WTO in late 2001, enlargement of the European Union in 2004). This period was also marked by advancements in automation and other digital technologies. To capture empirically recent technological advancements, we use relevant data from the March 2011 release of the EU KLEMS database and from Graetz and Michaels (2018).[7] Judging by these critical features, our dataset is ideally suited for an elucidating analysis on the implications of GVCs and their interactions with different types of technologies for labour markets in both high- and lower-income countries.

From the ADB's database, we draw information on backward and forward GVC participation measures (GVC_b, GVC_f) and real gross value added (VA). GVC participation measures are constructed according to the methodology of Borin and Mancini (2019). The backward GVC participation measure is calculated as the share of foreign value added that is sourced by an industry in its total value added, while the foreign GVC participation measure is calculated as the share of

[6]The ILO's collection of micro-level data comprises essentially the individual- and household-level data that are used for the production of official national statistics (see `https://ilostat.ilo.org/`). Note that the final composition of the sample is determined by data availability in the ADB MRIO Tables, as labour-related information in the ILO Harmonized Microdata is available for more country-industry-year combinations. Also, note that the lack of a match of information for the years 2002–2006 is not a major problem, as we estimate throughout the econometric analysis specifications on long-differenced variables (i.e., values in 2019 subtracted from values in 2000).

[7]As we will explain in more detail later, while information from the EU KLEMS is available for all 35 industries examined, information from Graetz and Michaels (2018) is available for only a sub-set of these industries.

value added that is exported by an industry to the world in its total value added.[8] In doing so, we use variables for GVC participation that capture only the value added that is traded in GVCs, thereby addressing the issue of inflated trade volumes due to multiple border crossings of goods and services (Johnson and Noguera, 2012; Johnson, 2018; Antràs and Chor, 2018, 2022). We use the alternative GVC measures in a robustness exercise. Real gross value added is in 2010 US dollars (USD).

From the ILO's database, we retrieve information on total employment (E), which is measured as the total number of workers, and the employment shares of high-skilled workers (Esh^{HS}), young workers (Esh^{Y}), and female workers (Esh^{F}). As information on employment is available for two groups per worker characteristic, the other groups are the lower-skilled, older, and male workers. Skill allocation is based on the skill requirements of individuals' occupations. Specifically, workers are classified as high-skilled, if they work in major occupational groups 1, 2, or 3 (i.e., managerial, professional, or technical and associate professional) according to the International Standard Classification of Occupations (ISCO). This approach provides more accurate definitions of skill levels than the crude distinction between production and non-production occupations or workers' educational attainment.[9] In fact, heterogeneity in skills in production and non-production occupations and in different education groups is salient and determines how exposed workers are to changes induced by GVC participation and technology adoption (Cortes, 2016; Black et al., 2021). Furthermore, capturing skills based on occupations' skill requirements facilitates comparisons of industry-level employment shares across countries, which is of particular importance in our analysis given the substantial differences in education systems of the developed and developing countries that we examine.[10] In accord with these remarks and related studies (Michaels et al., 2014; Graetz and Michaels, 2018; Blanas, 2023), we will present later not only statistics for these variables in the initial year, but also statistics for their percentage changes, as the latter are more appropriate for comparisons across countries. Young workers are those aged 15–24 (and older workers are those aged 25–64). In addition, we construct a variable for labour productivity as the ratio of value added to total employment.[11]

The underlying concept of the technology measures that we create and use in conjunction with

[8]In fact, the original forward GVC participation measure of Borin and Mancini (2019) is calculated as the share of the value added that is exported by an industry to a country and then re-exported to a third country in total gross exports of the industry. However, this measure disregards the value added that is exported by an industry to a country to meet its final demand, which should also be deemed as GVC-related trade. The methodology of Wang et al. (2017), which has also been adopted by the ADB, considers both cases as GVC-related trade. For this reason and to eliminate inconsistencies in the forward GVC participation measure between the two methodologies, the ADB also provides information on an adjusted Borin and Mancini (2019) forward GVC participation measure. As for the construction of the backward GVC participation measure, there are no inconsistencies between the two methodologies.

[9]Mostly due to data constraints, the latter approaches have been very common in the extant literature. See among others: Berman et al. (1994), Feenstra and Hanson (1996), Hijzen et al. (2005), Michaels et al. (2014), Graetz and Michaels (2018), and Blanas (2023).

[10]This is also particularly important because of the lack of information on wage bill shares, which allow for worker traits to be adjusted for the corresponding wage.

[11]Note that we have detected a few extraordinarily high percentage changes of labour productivity, its two components, and the employment shares, even compared to the majority of the percentage change values above the 99^{th} percentile. We have assigned missing values to these variables for the corresponding country-industry-year combinations.

the GVC measures is that industries that make initially more intensive use of certain types of technologies will continue to do so compared to other industries in subsequent years (Michaels et al., 2014). Hence, we generate industry-level technology variables for the US in the initial sample year (2000). We select the US as the benchmark country, as it is arguably the global technological leader. To this end, we draw relevant information from the 2011 March release of the EU KLEMS on real stocks of three types of capital, namely: communication technologies (CT), information technologies (IT), and software (S/W). Real stocks of capital are in 1995 USD. Dividing the stocks by real gross value added yields CT, IT, and S/W capital intensities. To create real gross value added in 1995 USD, we deflate *nominal* value added from the ADB MRIO Tables using the value added deflator from the EU KLEMS database.[12] To capture one more type of technology, we use the unweighted average of robot intensity (ratio of robot stock in units to million hours worked) across some of the most developed—and thus technologically advanced—countries in the world by industry in 1993, as calculated by Graetz and Michaels (2018) based on data from the International Federation of Robotics (IFR) and EU KLEMS (see Panel A of their Online Appendix Table A3). Note that information on robot intensity is available for only a sub-set of the 35 industries examined due to missing information in the IFR database.[13] Variation in the initial levels of all four technology variables across industries is substantial (Appendix Table C.1).

2.2 Descriptive statistics

2.2.1 Backward and forward GVC participation

Panels (a) and (b) of Figure 1 display the mean values of backward and forward GVC participation measures, respectively, for the whole sample over the period examined. Given that these measures vary by country-industry-year cell, we calculate their annual sample mean values by implementing the methodology of Graetz and Michaels (2018).[14] According to the two panels, backward and forward GVC participation of the average country-industry pair exhibited upward trends overall, resulting in increases of 32% and 108%, respectively, between the start and end years (see bottom of Panel B in Appendix Table C.2). The rise of both backward and forward GVC participation

[12]Information on the real stocks of the three types of capital is also available in the February 2023 release of the EU KLEMS, but only for 31 of the 35 industries examined of the US and other technologically advanced countries. We create capital intensities based on this version of the database in robustness checks.

[13]The list of developed countries considered by the authors comprises Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, South Korea, Spain, Sweden, UK, and US. Industries for which information is available correspond to the following ISIC Rev. 3.1 codes: AtB, C, 15t16, 17t18, 20, 21t22, 24, 26, 27t28, 30t33, 34t35, F, and M. Note that information on the stock of robots in the IFR database for the year 2000 and earlier is unavailable for the US and if we were to use this information for other major robot-producing countries such as Japan or Germany, we would have to restrict industry coverage further. Relatedly, Graetz and Michaels (2018) calculate robot stocks for a panel of countries, industries and years using available information from the same database on robot *sales* and implementing a perpetual inventory method similar to that implemented by the EU KLEMS for calculations of stocks of different types of capital.

[14]To save on space, we relegate to Appendix B the description of this methodology and the methodologies for the production of statistics by country and by industry, following Graetz and Michaels (2018), as well as statistics by country income group, by sector, and by country income group and sector. For the steps taken for the production of statistics for the whole sample, by country, and by industry, see also Blanas (2023, 2024).

is particularly strong until the financial crisis, which is likely to have been particularly driven by bilateral and multilateral trade and investment liberalisation episodes of that and the previous decades, such as the transformation of the General Agreement on Tariffs and Trade (GATT) into the World Trade Organization (WTO) in 1995 and China's entry into the WTO in 2001, and technological advances, such as containerisation and information and communication technologies (Antràs, 2020, 2021; World Bank, 2020). Interestingly, though, forward GVC participation rose much faster than backward GVC participation over the second decade. This might have been driven by the acceleration of the adoption of CT and automation technologies (e.g. IT, robots) during that decade, especially in developing countries such as those in South-East Asia (Cheng et al., 2019).

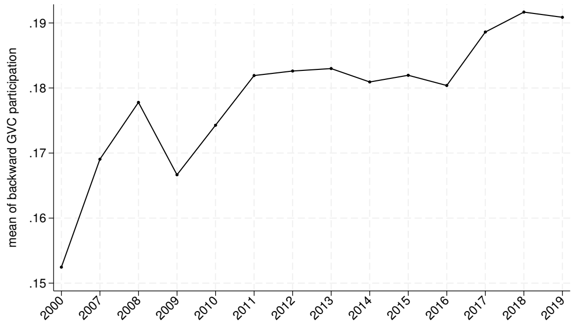
Evidence on the high overall similarity between the trends of backward and forward GVC participation is strengthened by the very high correlation (94%) between their sample means (see Panel (a) of Appendix Figure C.1), which is consistent with existing evidence on the complementarity between importing and exporting activities of firms (Bernard et al., 2007). Judging by these facts, one may view these measures as reflecting a common trend of participation in GVCs, regardless of whether this takes place through backward or forward linkages. However, their relatively low correlation (40%), when these vary by country-industry-year cell, likely suggests that the two measures capture the two different modes of participation in GVCs (see Panel (b) of Appendix Figure C.1).

Table 1: Backward and forward GVC participation by country income group and sector

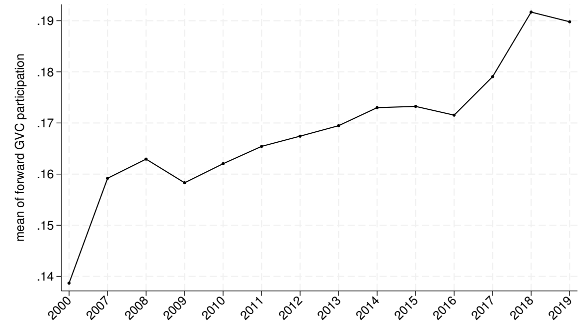
Country income group	Sector	Mean level 2000		Mean % ch. 2000–2019	
		GVC_b	GVC_f	GVC_b	GVC_f
High-income (HI)	Primary	0.179	0.202	52.447	67.996
High-income (HI)	Manufacturing	0.302	0.302	29.667	57.643
High-income (HI)	Utilities & Construction	0.224	0.054	29.996	157.204
High-income (HI)	Market services	0.143	0.176	39.603	72.016
High-income (HI)	Pers. & prof. services	0.090	0.029	37.139	188.590
Lower-income (LMI)	Primary	0.125	0.140	33.739	120.793
Lower-income (LMI)	Manufacturing	0.253	0.212	29.088	67.099
Lower-income (LMI)	Utilities & Construction	0.229	0.070	73.402	105.344
Lower-income (LMI)	Market services	0.137	0.176	24.091	41.710
Lower-income (LMI)	Pers. & prof. services	0.100	0.045	4.130	191.216

Notes: GVC_b and GVC_f denote backward and forward GVC participation, respectively. For the calculation of the means of GVC variables by country income group, sector and year, we first average the variables across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group, sector and year without using country weights. For the calculation of the mean percentage changes of GVC variables by country income group and sector, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and sector without using country weights. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Author's calculations based on ADB MRIO Tables.

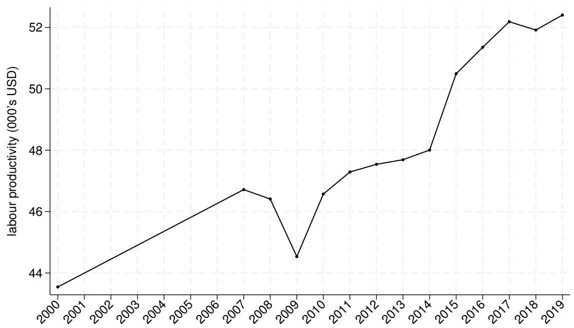
Figure 1: GVC participation, labour productivity, and employment shares



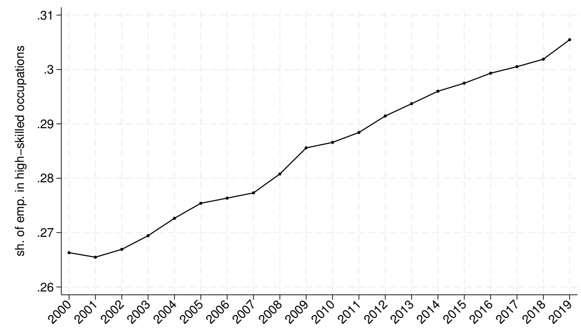
(a) Backward GVC participation



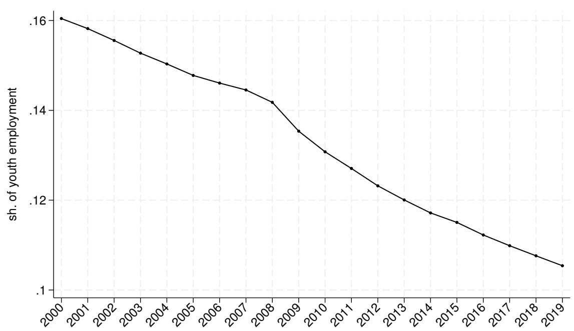
(b) Forward GVC participation



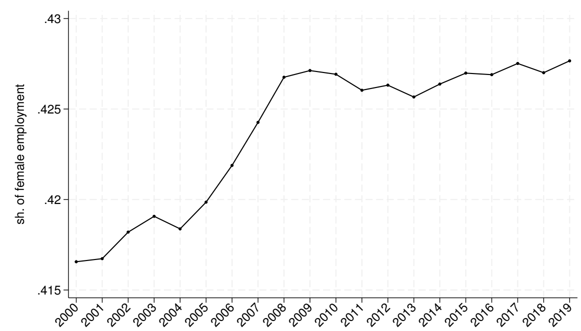
(c) Labour productivity



(d) Employment share of high-skilled



(e) Employment share of young (aged 15–24)



(f) Employment share of female

Notes: Labour productivity is calculated as the ratio of real gross value added to total employment. For the calculation of the sample means of GVC and labour variables by year, we first average the variables across industries within each country and year using as weights each industry's employment in economy-wide employment in 2000. Then, we average across countries by year without using country weights. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Author's calculations based on ADB MRIO Tables and ILO Harmonized Microdata.

In line with the documented trends for the whole sample, high- and low-income countries and almost all sectors in the two country income groups increased rapidly their backward and forward GVC participation over the period examined, as indicated by their mean growth rates in Panels

Table 2: Labour productivity and employment shares by country income group and sector

Panel A: Labour productivity and its decomposition

Country income group	Sector	Mean level 2000			Mean % ch. 2000–2019		
		LP	VA	E	LP	VA	E
High-income (HI)	Primary	108.090	1.8e+04	517.805	69.999	19.722	-20.991
High-income (HI)	Manufacturing	68.572	1.6e+04	276.054	109.480	51.720	-22.848
High-income (HI)	Utilities & Construction	84.361	8.8e+04	1071.692	-2.318	12.686	19.280
High-income (HI)	Market services	102.002	7.4e+04	1026.323	33.784	70.045	40.137
High-income (HI)	Pers. & prof. services	62.206	6.7e+04	1108.837	2.715	39.860	39.390
Lower-income (LMI)	Primary	5.871	3.4e+04	2.3e+04	117.011	50.788	-20.197
Lower-income (LMI)	Manufacturing	11.185	5387.597	1196.060	224.607	300.786	61.368
Lower-income (LMI)	Utilities & Construction	16.534	1.9e+04	1866.618	32.924	196.936	143.497
Lower-income (LMI)	Market services	18.717	1.2e+04	2634.518	127.256	281.907	100.603
Lower-income (LMI)	Pers. & prof. services	11.253	1.1e+04	1577.169	63.819	135.499	50.666

Panel B: Employment shares

Country income group	Sector	Mean level 2000			Mean % ch. 2000–2019		
		Esh^{HS}	Esh^{Y}	Esh^{F}	Esh^{HS}	Esh^{Y}	Esh^{F}
High-income (HI)	Primary	0.101	0.103	0.282	130.088	-17.887	2.331
High-income (HI)	Manufacturing	0.238	0.132	0.301	52.460	-26.480	9.486
High-income (HI)	Utilities & Construction	0.171	0.141	0.095	77.245	-35.087	37.511
High-income (HI)	Market services	0.354	0.153	0.425	7.371	-26.612	7.336
High-income (HI)	Pers. & prof. services	0.522	0.109	0.601	69.385	-25.084	9.584
Lower-income (LMI)	Primary	0.040	0.180	0.370	107.870	-40.155	-7.845
Lower-income (LMI)	Manufacturing	0.130	0.221	0.415	74.236	-39.721	31.309
Lower-income (LMI)	Utilities & Construction	0.140	0.174	0.114	103.620	-36.108	7.592
Lower-income (LMI)	Market services	0.231	0.175	0.389	19.049	-31.730	20.079
Lower-income (LMI)	Pers. & prof. services	0.498	0.138	0.497	31.408	-29.549	26.117

Notes: LP denotes labour productivity (ratio of real gross value added to total employment) and is measured in thousands of USD per worker. VA denotes total real gross value added and is measured in millions of USD. E denotes total employment and is measured in thousands of workers. Esh^{HS}, Esh^{Y}, and Esh^{F} denote employment shares of high-skilled, young, and female workers, respectively. For the calculation of the means of variables by country income group, sector and year, we first average these across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group, sector and year without using country weights. For the calculation of the mean percentage changes of these variables by country income group and sector, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and sector without using country weights. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Author's calculations based on ILO Harmonized Microdata.

A and B of Table 1, although the increases of forward GVC participation were larger. It is also noteworthy that heterogeneity in quantitative terms across individual countries, including those pertaining to the same income group, is salient (see Panel B of Appendix Table C.2). By contrast, there is very little heterogeneity in qualitative terms, as there are very few countries that exhibited negative growth of backward or forward GVC participation. Similarly, heterogeneity in initial levels and growth rates across sectors or industries is salient in quantitative, but not qualitative, terms (Panels A and B of Table C.3).

2.2.2 Labour productivity and its decomposition

Panel (c) of Figure 1 shows the evolution of the annual sample mean values of labour productivity (in thousands of USD). Except for a dip during the global financial crisis (2008–2009), labour productivity was upward-trending for the average country-industry pair, increasing by roughly 80% between the start and end years and driven by higher value added growth than total employment growth (see also bottom of Panel B in Table C.4). Similarly to the trend in Panel (c) of Figure 1, all sectors in lower-income countries and all sectors except for utilities and construction in high-income countries experienced positive labour productivity growth (Panel A of Table 2). Positive labour productivity growth rates are also largely observed by country income group, by country, by sector, and by industry (Panels A and B of Appendix Tables C.4 and C.5). Labour productivity growth rates differed across sectors, with the highest ones being exhibited by the manufacturing, primary, and market service sectors of either country income group.

Except for the primary sector of lower-income countries, where productivity increased because of an increase in value added and a decrease in employment, productivity growth of the other sectors was driven by higher value added growth than employment growth, as is the case in the whole sample. Also, value added growth of the primary sector in the same group of countries was at least two times smaller than the respective growth rates of the other sectors. These facts are consistent with the structural transformation that has been taking place in lower-income countries in recent decades, implying the shift of economic activity away from agriculture and towards other sectors. Indeed, the primary sector is the only sector in lower-income countries that decreased its shares in both total employment and total value added over the period examined, while the other sectors—except for personal and professional services—gained higher shares in both total employment and total value added (Appendix Table C.6).[15]

In high-income countries, the positive labour productivity growth of the primary and manufacturing sectors was driven by positive value added growth and negative employment growth, while the positive labour productivity growth of market services and personal and professional services was driven by (marginally) higher value added growth than employment growth. The negative labour productivity growth of utilities and construction was driven by higher employment growth than value added growth. Also, the value added growth rates of manufacturing, market services, and personal and professional services were at least twice as high as those of the other sectors, while the employment growth rates of the latter two sectors were at least twice as high the respective rate of utilities and construction. These patterns and trends are consistent with the employment share losses of the primary and manufacturing sectors and the value added share losses of the first sector in this group of countries (Appendix Table C.6) and point to the secular shift of economic activity of high-income countries away from the primary sector, which commenced in the late 19th and early 20th centuries (Tombe, 2015), and the de-industrialisation and shift of their economies

[15]The mean employment and value added shares of sectors in high- and lower-income countries are calculated as unweighted averages of the sectoral shares across countries by country income group and year. The respective mean percentage changes are calculated as unweighted averages of the percentage changes of the sectoral shares between 2000 and 2019 across countries by country income group.

towards services in recent decades (e.g. Autor et al., 2013; Pierce and Schott, 2016; Fort et al., 2018).

2.2.3 Employment shares

The last three panels of Figure 1 display the evolution of annual sample means of the employment shares of high-skilled (Panel (d)), young (Panel (e)), and female (Panel (f)) workers. In contrast to the continuous rise of the employment share of the high-skilled and continuous decline of the employment share of the young between 2000 and 2019, female employment share increased only in the first decade, especially between 2004 and 2008, and remained rather stable from 2010 onwards. Despite their relative gains, high-skilled and female workers held lower shares in total employment throughout the period examined than lower-skilled and male workers, respectively, while, in addition to their relative losses, the young held already in the initial year lower shares in total employment than older workers. Consistent with the trends in the three panels, the sample mean percentage changes of the employment shares of the three worker groups are 71%, -33%, and 11%, respectively (bottom of Panel B in Appendix Table C.7). These trends largely hold by country income group and sector (Panel B of Table 2), as well as by country income, by country, by sector, and by industry (Panels A and B of Appendix Tables C.7 and C.8). In addition, according to Panel B of Table 2, while there is little cross-sector variation in the (negative) employment share growth rates of the young by country income group, cross-sector variation per country income group in the (positive) employment share growth rates of high-skilled and female workers is quite high.

As we will explain in Section 3.1, aggregate labour supply shocks are always controlled for in the econometric analysis, allowing us to interpret employment shares as measures of relative labour demand. However, in addition to labour demand shifters such as GVC participation and its interaction with technology, which are of particular interest to us, the trends of the employment shares that we document in this section are likely driven by supply factors, such as education attainment. In fact, total years of education of young (aged 15–24) and older (aged 25–64) individuals increased between 2000 and 2020 in both high- and lower-income countries (Panels (a) and (c) and Panels (b) and (d), respectively, of Appendix Figure C.2), which might have partly contributed to the employment share gains of the high-skilled and women and employment share losses of the young. Hence, on condition that the young postponed their labour market entry in order to spend more years in education, their employment share losses may not be reflecting a deterioration of their labour market position. By contrast, as women of both high- and lower-income countries are likely to have improved their education, the stagnation of their employment share as of 2010 should be concerning and may be attributed to additional factors, including the labour demand shifters that we focus on in this paper.[16] Demographic aging is another possible factor impacting labour supply,

[16]As extra evidence of the potentially crucial role of education attainment, we document that while the years of primary education among young and older individuals remained largely unchanged in high-income countries and declined in lower-income countries between 2000 and 2020 (Panels (e) and (g) and Panels (f) and (h), respectively, of Appendix Figure C.2), their years of secondary and tertiary education increased remarkably in both country income groups (Panels (i), (k), (m), (o) and Panels (j), (l), (n), (p) of the same figure). For the production of these trends, we calculate unweighted averages of years of education of the two age groups across countries by country income group

particularly that of the young. In fact, while the shares of young individuals (aged 15–24) decreased sharply in both high- and lower-income countries between 2000 and 2019 (Panels (a) and (b) of Appendix Figure C.3), the share of older individuals (aged 25–64) in lower-income countries rose significantly and that in high-income countries exhibited an inverted-U-shaped trend (Panels (c) and (d) of Appendix Figure C.3).

3 Econometric model and estimation strategy

In this section, we describe the specifications that we estimate in the econometric analysis and the IV strategy that we devise for the GVC variables.

3.1 Econometric model

To identify the long-run effects of GVC participation on labour productivity and demand, we estimate long-differenced specifications of the following form:

$$\Delta Y_{ci} = \beta_{GVC} * \Delta GVC_{ci} + \beta_{VA} * \Delta \log VA_{ci} + \alpha_c + \epsilon_{ci}, \tag{1}$$

where Δ indicates the difference between 2019 and 2000 and c and i denote countries and industries, respectively. The dependent variable (Y) is the log of labour productivity (Log(LP_{ci})), each of its two components—the log of value added (Log(VA_{ci})) or log of total employment (Log(E_{ci})), or the employment share of high-skilled workers (Esh_{ci}^{HS}), young workers (Esh_{ci}^{Y}), or female workers (Esh_{ci}^{F}).[17]

GVC_{ci} is a vector comprising the measures of backward and forward participation of country-industry pairs in GVCs (GVC_b and GVC_f), which are the two main regressors in the specifications. Hence, we are particularly interested in the estimates of β_{GVC_b} and β_{GVC_f}, capturing the effects of these regressors on the outcome variables under consideration. In addition to the two key regressors, we include in the specification the log of value added to control for industry scale. Obviously, this control is omitted when it is used as the dependent variable or when the dependent variable is the log of labour productivity.[18] As common in related empirical studies, we would ideally include aggregate capital intensity in the set of controls, but we only have information on capital stock at the country, not industry, level for our large panel of developed and developing countries. Constructing

and year. Information on years of education is retrieved from Barro and Lee (2013).

[17] As common in the literature, employment share specifications are derived from the minimisation of a translog cost function, which exhibits constant returns to scale and is thus linearly homogeneous in wages. See, for instance, Berman et al. (1994), Feenstra and Hanson (1996), Hijzen et al. (2005), Michaels et al. (2014), Blanas (2023, 2024). Because of this, the coefficient estimates of each explanatory variable in the specifications by skill, age, and gender add up to zero. Therefore, it is sufficient to estimate the specification corresponding to one of the two groups per worker characteristic.

[18] As the backward and forward GVC measures that we employ aim at capturing sourcing of foreign value added and exporting of domestic value added, respectively, we estimate in a robustness exercise the log of total employment and employment share specifications without controlling for the log of value added.

country-level capital intensity, though, is redundant as the specifications always include country fixed effects, α_c.[19]

In addition to capital intensity, country fixed effects control for other country-level factors that could potentially impact labour productivity and demand, such as factor endowments and levels of technological sophistication, occupational structure, education systems and enrollment and human capital accumulation, demographic ageing, social policies for different segments of the population, innovation policies, trade policies and import competition, and labour market institutions and regulations. Controlling for country-level import competition is particularly important, given that its effects may be confounded with the effects of GVC measures (Autor et al., 2013, 2014).[20] Equally importantly, assuming that wage bargaining takes place at the national level, country fixed effects also absorb variation in the average wage in the productivity, value added, and total employment specifications, and in relative wages in employment share specifications.[21] Due to the factors controlled for by country fixed effects, we interpret the log of total employment and the employment shares as measures of absolute and relative labour demand, respectively.

Considering the interplay between GVC participation and technology, we add to the specifications in (1) interactions of the two GVC measures with a variable capturing industries' initial intensity of utilisation of a certain type of technology ($\Delta GVC_{ci} * TECH_i$):

$$\begin{aligned} \Delta Y_{ci} =& \beta_{GVC} * \Delta GVC_{ci} + \beta_{GVC,TECH} * \Delta GVC_{ci} * TECH_i \\ &+ \beta_{TECH} * TECH_i + \beta_{VA} * \Delta \log VA_{ci} + \alpha_c + \epsilon_{ci}. \end{aligned} \tag{2}$$

In particular, as already mentioned in Section 2.1, we consider the industry-level CT, IT, or software capital intensity for the country that is admittedly at the forefront of global technological innovation, the US, in the initial sample year (2000), or the industry-level average robot intensity of predominantly technologically advanced countries, including the US, in 1993 (Michaels et al., 2014; Blanas, 2023). In addition to the estimates of the coefficients in β_{GVC}, we are particularly interested in these specifications in the estimates of the coefficients in $\beta_{GVC,TECH}$, which capture the differential relationships of backward and forward GVC participation with the outcome variables under consideration in industries with different initial technology intensities. Using initial values of these variables implies that we take advantage of pre-determined—and thus exogenous—cross-industry differences in these dimensions.[22]

[19]On condition that capital accumulation of industries is very similar or varies little across countries, capital intensity can be captured, at least to some extent, by industry (or sector) fixed effects. We will come back to this issue in our robustness analysis in Section 4.1.1.

[20]Note that we can only create import competition measures for goods-producing industries, which would substantially reduce industry coverage in our analysis. We will elaborate more on this issue in the robustness analysis in Section 4.1.1.

[21]This approach is common for the estimation of wage bill or employment share specifications (e.g. Michaels et al., 2014; Graetz and Michaels, 2018; Blanas, 2023, 2024). Although we lack information on wages, making this approach is more appropriate as the presence of wages in the specifications would raise concerns over endogeneity.

[22]In a robustness exercise, we also consider using industry-level CT, IT, and software capital intensity for the US in 1985, rather than 2000, in order to account for historical and persistent differences across industries along

Taking advantage of heterogeneity in initial CT capital intensity across industries is motivated by theories and evidence showing that CT induces the emergence and expansion of GVCs by facilitating coordination among their production stages (Antràs et al., 2006, 2008; Fort, 2016). Technology, and especially CT, also facilitate managers' search for new investment and growth opportunities for their firms, some of which may be related to participation in GVCs (Frydman and Papanikolaou, 2018). Relatedly, theoretical frameworks show that firms self-select into offshoring by incurring the relevant fixed cost, which is determined by industries' technological intensities, among other factors (Egger et al., 2015). Unlike CT, IT, software, and robots represent automation technologies, but the first two typically undertake routine cognitive tasks, such as arithmetic calculations and book-keeping, while the latter typically undertake routine manual tasks, such as welding, assembly, and packaging (Autor et al., 2003; Acemoglu and Autor, 2011; Michaels et al., 2014; Graetz and Michaels, 2018; Blanas, 2023). Be that as it may, there exists evidence on complementarities between firms' export activities and adoption of automation technologies, such as industrial robots (Koch et al., 2021), while business functions, such as computer-controlled assembly lines, demonstrate that all four types of technologies that we consider may be complementary with each other (Blanas, 2023).

3.2 IV strategy

OLS estimates of the two GVC measures that we initially produce may suffer from at least three types of biases. First, the simultaneity bias implies that while changes in GVC participation may induce changes in labour productivity and absolute and relative labour demand, changes in the latter variables may also induce changes in GVC participation. For instance, GVC participation may boost labour productivity, but also more productive industries may find it more profitable to increase their participation in GVCs. Similarly, while participation in GVCs may lead to skill upgrading, industries with higher shares of high-skilled workers may increase faster their participation in GVCs. Second, although we control for various factors that may determine the key regressors and outcome variables, there may still be factors (e.g. cross-industry labour mobility) that remain unaccounted for and may thus introduce an omitted variable bias in the specifications. Another possible type of bias in the OLS estimates is the attenuation bias, stemming from measurement errors in the explanatory and outcome variables.[23] To address these plausible concerns and allow for the causal interpretation of the estimates, we implement a similar IV strategy to that of Michaels et al. (2014). In particular, we instrument the two GVC measures using the values of the same variables for the US in 2000 (IV–GVC–USA). Formally, we use: $IV^{GVC,USA}_{c\neq USA,i} = GVC_{USA,i,2000}$, $GVC \in \{GVC_b, GVC_f\}$.

The rationale for this IV, which is underpinned by relevant evidence (e.g. World Bank, 2020), is that the average US industry leads globally in terms of participation in GVCs. Using the initial sample year ensures that we take advantage of pre-determined—and thus exogenous—differences

these dimensions. This approach is similar to that of Acemoglu and Restrepo (2020), who construct instruments for the exposure of US commuting zones to industrial robots using the employment shares of industries in 1990 as the benchmark and the shares in 1970 as a robustness check. We cannot do this robustness exercise for robot intensity, as information on this variable for a year earlier than 1993 is not available.

[23] For similar discussions about these types of biases in OLS estimates using similar industry-level data, see Michaels et al. (2014), Graetz and Michaels (2018), and Blanas (2023, 2024).

across industries in backward and forward GVC participation.[24] To ensure exogeneity of the instruments, the selection of the US as the benchmark country requires its elimination from the estimating sample. In a variant of this IV strategy (IV–GVC–USA–CHN), we add to the set of instruments the industry-level GVC measures for China in 2000: $IV^{GVC,USA,CHN}_{c\neq j,i} = GVC_{ji,2000},\ \ j \in \{USA, CHN\},\ GVC \in \{GVC_b, GVC_f\}$. We do so because the spectacular trade growth of this country since the 1990s, mostly through GVC participation, implies that its average industry is likely to be emulated in this regard by industries of other countries, especially developing ones. Using the US and China as the benchmark countries implies the elimination of both from the estimating sample.[25] In the robustness analysis in Section 4.1.1, we consider additional variants of the IV strategy.

Although we confirm the relevance of the selected instruments in the econometric analysis based on first-stage results and statistics, the positive and significant raw correlations of the two GVC measures with the respective main instruments already give us an idea about this (Appendix Figure C.4). These instruments are also significantly correlated with most of the (long-differenced) dependent variables (Appendix Figure C.5).[26]

4 Econometric results

In this section, we first identify the effects of backward and forward GVC participation on labour productivity and demand, confirm their robustness to numerous checks, and quantify them. Then, we conduct a series of exercises that help us to detect the underlying mechanisms of these effects, highlighting particularly the interplay between GVC participation and technology adoption. Lastly, we present results obtained from exercises with interactions between GVC and technology measures.

4.1 GVC participation and labour productivity and demand

Table 3 displays the results obtained from OLS estimations (Panel A) and 2SLS estimations of Eq. (1) based on the original IV strategy (Panel B) and its variant (Panel C). Starting with OLS, the coefficient estimates of backward and forward GVC participation in column (1) are positive and significant at 1% and 5%, respectively, pointing to positive associations of the two key regressors with the log of labour productivity. These efficiency gains were driven by employment losses, as indicated by the negative and significant associations of the two key regressors with the log of total employment (column (3)) and their statistically insignificant associations with the log of value added (column (2)). Apart from a negative and significant association of forward GVC participation with the

[24]This holds on condition that initial sources of cross-industry differences (e.g. demand or technological shocks) do not persist over time.

[25]As the focus of our analysis is on the identification of the effects of the two GVC measures, we do not instrument the log of value added in the log of employment and employment share specifications. We acknowledge, though, that this variable may also be endogenous, as it is likely to adjust to shocks rather than remain fixed (Egger and Egger, 2005; Hijzen, 2005; Blanas, 2023). For this reason, we interpret the relevant coefficient estimates throughout the analysis as conditional correlations of this control variable with the outcome variables under consideration.

[26]Notably, we obtain similar scatterplots when we use the instruments based on China (available upon request).

employment share of female workers (column (6)), there are no statistically significant associations of the two key regressors with the employment shares of workers differing by skill, age, or gender (columns (4)–(6)). As for the log of value added acting as a control in the specifications of columns (3)–(6), while it is positively associated with the log of total employment and the employment share of young workers, its associations with the employment shares of high-skilled and female workers are statistically insignificant.

Looking at Panels B and C, the 2SLS estimates are largely similar to the respective OLS estimates in terms of sign and significance, but mostly of larger size. The latter is consistent with a possible attenuation bias in the OLS estimates due to measurement error in the variables, as discussed in Section 3.2.[27] Another notable difference is that the 2SLS estimates of the two GVC measures are statistically distinguishable from each other in almost all columns of the two panels, while this never holds for the OLS estimates. According to the two panels, backward and forward GVC participation impacted positively the log of labour productivity, but the underlying mechanisms of these effects are different. Productivity gains due to backward GVC participation were driven by the positive and significant effect of this key regressor on the log of value added and an even stronger positive and significant effect on the log of total employment. By contrast, productivity gains due to forward GVC participation were driven by the positive and significant effect of this key regressor on the log of value added along with its insignificant effect on the log of total employment (Panel B) or the negative and significant effect of this key regressor on the log of total employment along with its insignificant effect on the log of value added (Panel C).

The productivity gains from backward GVC participation are consistent with past evidence on productivity gains from importing of material inputs (Amiti and Konings, 2007; Topalova and Khandelwal, 2011; Halpern et al., 2015) and service inputs (Amiti and Wei, 2009). However, had this really been a cost-reducing and productivity-enhancing activity, it should have increased, rather than decreased, value added. Hence, the value added losses due to backward GVC participation likely point to the substitutability between the sourcing of foreign value added and creation of domestic value added and along with the greater employment losses are consistent with the downsizing or closure of production facilities—especially in the manufacturing sector of high-income countries—due to relocation of production abroad—especially in lower-income countries (Autor et al., 2013, 2021; Autor et al., 2014; Acemoglu et al., 2016; Pierce and Schott, 2016; Fort et al., 2018). On condition that backward GVC participation is associated with technological changes such as IT adoption, its negative effects on both output and employment are consistent with evidence on the lack or meagre productivity and output gains of IT-using manufacturing industries in developed countries like the US in recent decades, a phenomenon dubbed as the "Solow paradox" (Acemoglu et al., 2014; Houseman et al., 2015).

Because of the latter evidence, backward GVC participation itself and technological changes that this activity is associated with might have not generated a sufficiently high number of new tasks,

[27]Past studies estimating similar specifications on similar industry-level data also obtain larger 2SLS estimates (Michaels et al., 2014; Graetz and Michaels, 2018; Blanas, 2023, 2024).

Table 3: GVC participation and labour productivity and demand, OLS and 2SLS

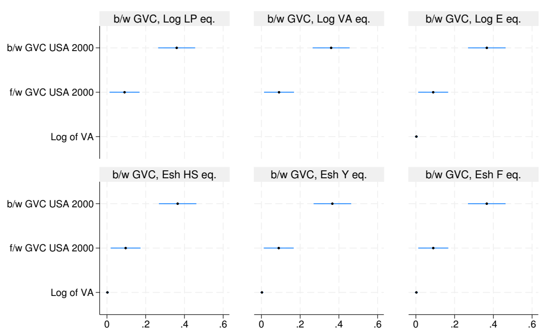
Panel A: OLS	$Log(LP)$	$Log(VA)$	$Log(E)$	Esh^{HS}	Esh^{Y}	Esh^{F}
GVC_b	0.91***	-0.069	-0.96***	0.045	-0.000071	-0.061
	[0.3]	[0.3]	[0.3]	[0.04]	[0.02]	[0.04]
GVC_f	0.35**	-0.16	-0.46***	0.0055	-0.014	-0.049**
	[0.2]	[0.2]	[0.1]	[0.02]	[0.01]	[0.02]
Log(VA)			0.36***	0.0041	0.0059**	0.0039
			[0.03]	[0.005]	[0.003]	[0.004]
Constant	0.33***	0.51***	0.0025	0.037***	-0.056***	0.013***
	[0.02]	[0.02]	[0.02]	[0.005]	[0.002]	[0.004]
Observations	2096	2097	2096	2089	2097	2096
R^2	0.227	0.255	0.305	0.196	0.535	0.197
F-test (p-value): $\beta_{GVC_b} = \beta_{GVC_f}$	0.123	0.794	0.112	0.412	0.514	0.834
Panel B: IV–GVC–USA	$Log(LP)$	$Log(VA)$	$Log(E)$	Esh^{HS}	Esh^{Y}	Esh^{F}
GVC_b	6.46***	-6.14***	-10.5***	1.01***	-0.34***	-0.50***
	[1.5]	[1.5]	[1.5]	[0.2]	[0.08]	[0.2]
GVC_f	2.76**	2.32**	-1.23	-0.22	-0.0017	-0.35***
	[1.2]	[1.2]	[1.2]	[0.2]	[0.06]	[0.1]
Log(VA)			0.34***	0.0041	0.0054*	0.0013
			[0.05]	[0.007]	[0.003]	[0.005]
Observations	2061	2062	2061	2054	2062	2061
R^2	-0.662	-0.645	-1.454	-0.392	-0.383	-0.338
F-test (p-value): $\beta_{GVC_b} = \beta_{GVC_f}$	0.135	0.000473	0.000191	0.00132	0.00598	0.550
Kleibergen-Paap rk LM	29.66	29.66	30.83	29.50	30.83	30.86
Kleibergen-Paap rk LM (p-value)	5.14e-08	5.14e-08	2.82e-08	5.60e-08	2.82e-08	2.77e-08
Kleibergen-Paap Wald rk F	14.42	14.42	15.15	14.46	15.15	15.17
Hansen J	N/A	N/A	N/A	N/A	N/A	N/A
Hansen J (p-value)	N/A	N/A	N/A	N/A	N/A	N/A
Panel C: IV–GVC–USA–CHN	$Log(LP)$	$Log(VA)$	$Log(E)$	Esh^{HS}	Esh^{Y}	Esh^{F}
GVC_b	5.47***	-2.63**	-7.76***	1.05***	-0.33***	-0.37**
	[1.5]	[1.2]	[1.3]	[0.2]	[0.08]	[0.2]
GVC_f	4.04***	1.18	-2.79***	-0.51**	-0.025	-0.44***
	[1.2]	[0.9]	[1.0]	[0.2]	[0.06]	[0.1]
Log(VA)			0.33***	0.0022	0.0049	0.0011
			[0.04]	[0.008]	[0.003]	[0.006]
Observations	2028	2029	2028	2021	2029	2028
R^2	-0.841	-0.140	-1.024	-0.608	-0.373	-0.397
F-test (p-value): $\beta_{GVC_b} = \beta_{GVC_f}$	0.553	0.0505	0.0181	0.000171	0.0156	0.779
Kleibergen-Paap rk LM	33.22	33.22	33.76	32.24	33.76	33.79
Kleibergen-Paap rk LM (p-value)	2.9e-07	2.9e-07	2.2e-07	4.7e-07	2.2e-07	2.2e-07
Kleibergen-Paap Wald rk F	8.088	8.088	8.337	7.971	8.337	8.344
Hansen J	7.904	66.11	41.64	19.92	1.881	8.481
Hansen J (p-value)	0.0192	4.42e-15	9.08e-10	0.0000473	0.390	0.0144

Notes: OLS estimations in Panel A and 2SLS estimations in Panels B and C. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. Asterisks denote significance at 1% (***), 5% (**), and 10% (*), based on robust standard errors.

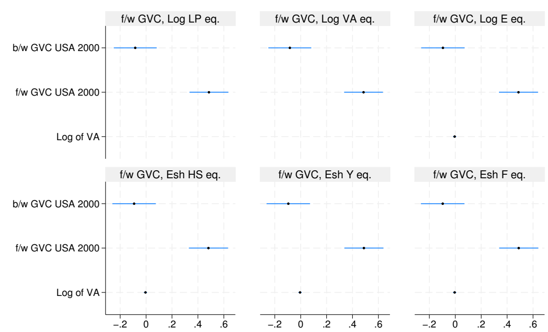
which would more than offset the number of tasks relocated abroad and/or undertaken domestically by automation technologies. In fact, there exists evidence for the US showing that new task creation has fallen considerably behind task displacement since the 1980s—especially in the manufacturing sector, and that this may be partly attributed to the adoption of "so-so" technologies, that is, technologies that lead to substantial labour cost reductions but poor productivity gains (Acemoglu and Restrepo, 2019, 2022).

The productivity gains from forward GVC participation are consistent with evidence on firms' substantial productivity gains from export market entry, a result that is dubbed as "learning by exporting" (e.g. De Loecker, 2013), but also with theoretical frameworks and empirical evidence on firms' self-selection into exporting and industry-level productivity gains from trade-induced reallocation towards initially more productive firms (Clerides et al., 1998; Melitz, 2003). The value added gains or employment losses through which the aforementioned productivity gains were achieved suggest that this type of activity had an output-enhancing or labour-saving aspect, similar to those of technology adoption and especially automation. At least for developed countries, where the use of automation technologies such as IT and industrial robots is more widespread, such evidence abounds.[28] Hence, it is plausible to think that backward and forward GVC participation might have also exerted indirect effects on labour productivity and its two components by driving the adoption of such technologies and/or being driven by them (Fort et al., 2018).

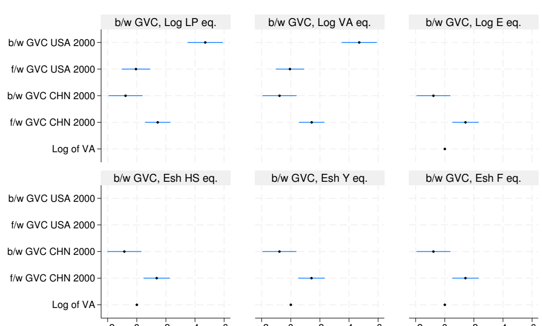
Figure 2: First stages of estimations in Table 3



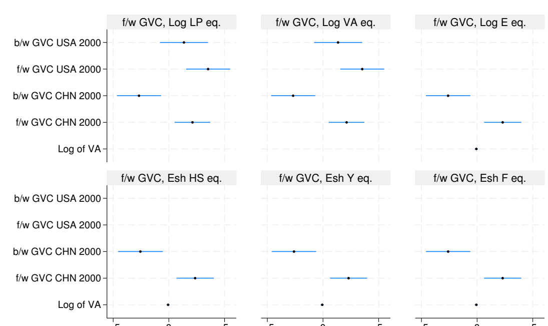
(a) GVC_b, IV–GVC–USA



(b) GVC_f, IV–GVC–USA



(c) GVC_b, IV–GVC–USA–CHN



(d) GVC_f, IV–GVC–USA–CHN

Notes: Panels (a)–(b) and (c)–(d) display the first-stage results of 2SLS estimations in Panels B and C, respectively, of Table 3.

[28] See, for instance, Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Dauth et al. (2021), and Koch et al. (2021).

Regarding the effects on employment shares, backward GVC participation impacted positively the employment share of the high-skilled (column (4)) and negatively the employment shares of the young and women (columns (5) and (6)). These effects suggest that sourcing of foreign value added substituted for domestic routine cognitive and manual (e.g. assembly line, customer service) tasks, which are primarily undertaken by less skilled, young, and female workers, or was more complementary to domestic non-routine cognitive analytical and interactive tasks (e.g. management, R&D), which are primarily undertaken by high-skilled, older, and male workers.[29] The skill bias of backward GVC participation is consistent with voluminous evidence based on data of different aggregation levels for high- and lower-income countries showing that offshoring increased the demand for high-skilled workers relative to the lower-skilled (Goldberg and Pavcnik, 2007; Hummels et al., 2018). As for the age bias of backward GVC participation, this is consistent with existing evidence based on industry-level data for a group of developed countries (Blanas, 2024). Similarly to backward GVC participation, forward GVC participation impacted negatively the employment share of women, likely suggesting that exporting of domestic value added complemented (disproportionately) domestic non-routine cognitive tasks. This evidence is consistent with the industry-level analysis of Reshef and Santoni (2023), showing that the reduction in the labour share due to forward GVC participation was borne disproportionately by less skilled workers.

In a similar vein, the effects on employment shares are in accord with frameworks featuring offshoring-induced shifts of domestic labour towards more productive uses (Egger et al., 2015) and econometric evidence showing that offshoring has led to reallocation towards more non-routine and more interactive tasks and towards highly-educated workers (Becker et al., 2013), higher R&D investments bringing about technological changes (Boler et al., 2015), higher IT capital intensity and TFP (Bloom et al., 2016), and the shedding of production workers along with increases in the absolute and relative demand for workers in innovation- and technology-related occupations aiming at the production of higher-quality varieties of the same products that are sourced from abroad (Bernard et al., 2023). Domestic production upgrading in the form of higher capital intensity has also occurred due to intensified import competition facing firms in high-income countries (e.g. US) from China (Pierce and Schott, 2016), although there also exists evidence on lower R&D expenditures and patent production by such firms, especially those that were initially less profitable and capital-intensive (Autor et al., 2020). In addition, there is evidence showing that the intensification of firms' export activities has led to the upgrade of their domestic production through higher product innovation, advanced manufacturing technology adoption, and labour productivity (Lileeva and Trefler, 2010).

On condition that backward and forward GVC participation are associated with technology adoption, their effects are consistent with the effects of technologies undertaking routine tasks, such as IT and robots (Berman et al., 1994; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014; Graetz and Michaels, 2018; Blanas et al., 2019;

[29] For evidence based on US data on the task content of occupations, which workers with different education, age, or gender profiles find themselves in, see Acemoglu and Autor (2011), Michaels et al. (2014), Blanas et al. (2019), Blanas (2024), among others.

Acemoglu et al., 2020; Dauth et al., 2021; Dinlersoz and Wolf, 2023; Blanas, 2023, 2024), and the effects of technologies allowing workers to perform non-routine cognitive interactive tasks, such as CT (Frydman and Papanikolaou, 2018; Blanas, 2023). Note, though, that in contrast to this evidence and the relevant effect of backward GVC participation, forward GVC participation exerted a negative and significant effect on the employment share of the high-skilled, which is identified only when implementing the variant of the IV strategy. This effect suggests that the generation and exporting of domestic value added through GVCs shifted production disproportionately towards tasks and occupations with lower-skill requirements. We shed more light on the identified effects and their underlying mechanisms in additional exercises further below, including by distinguishing between high- and lower-income countries, considering only non-manufacturing or IT-using industries of the two country income groups, and using interactions between GVC participation and technology measures on samples of high- and lower-income countries.

As for the first-stage results of the 2SLS estimations, they indicate that the instruments are strongly correlated with the respective GVC measures (Panels (a)–(b) and (c)–(d) of Figure 2). The relevance of the selected instruments is also evident from the first-stage statistics. The p-value of the under-identification test is below 10% and the F value of the weak identification test is above 10 (see bottom of Panel B of Table 3) or below, but close to, 10 (see bottom of Panel C of the same table). For the variant of the IV, some caution is also required from the test for over-identifying restrictions, as the p-values of the Hansen J statistic are below 10% in all columns.[30]

4.1.1 Robustness

Additional variant of the IV strategy: In the first exercise of this section, our goal is to test the robustness of the main 2SLS results to the implementation of an additional variant of the IV strategy. For the production of the main results, we have constructed instruments for backward and forward GVC participation using China alongside the US as the benchmark countries. Arguably, one could also deem China primarily as "the world's factory" for the production of intermediate inputs and final outputs and the US primarily as the leading country in sourcing of intermediate inputs and final outputs from abroad, especially from lower-income countries (e.g. Autor et al., 2013). Therefore, in the additional variant of the IV strategy, we consider using the values of backward (forward) GVC participation for the US (China) in 2000 as an instrument for the backward (forward) GVC participation measure. Apart from a positive effect of forward GVC participation on the log of total employment, second-stage results from these estimations bear a very close resemblance to the main ones (Panel (a) of Appendix Figure D.1), while first-stage results (Panels (b) and (c) of the same figure) and statistics (available upon request) suggest that the selected instruments are relevant, albeit weak.

Industry fixed effects controlled for: As discussed earlier, we control for aggregate labour supply shocks and other factors by incorporating in the main long-differenced specifications country

[30]This test is not applicable in the original IV, as the number of instruments equals the number of instrumented variables.

fixed effects. However, shifts of different types of workers across industries affecting employment shares and total employment or industry shocks, such as capital accumulation and import competition, affecting labour productivity and demand are not accounted for in these specifications. To control for these factors, we re-estimate the main specifications by OLS after adding industry fixed effects (see Appendix Figure D.2). The OLS estimates obtained largely maintain their signs, but are almost always insignificant, which likely suggests that the two GVC measures are highly collinear with the set of industry dummies. In other words, there may be little variation of an industry's backward and forward GVC participation across the countries examined. This issue becomes even more severe when applying our IV strategy, rendering 2SLS estimations as inappropriate (recall that we use as instruments industry-level GVC measures for the US (and China) in 2000). Other studies estimating similar specifications have also faced a drop or loss of statistical significance of their estimates because of the incorporation of industry fixed effects on long-differenced data (Michaels et al., 2014) or industry-year fixed effects on annual data (Blanas, 2023).

Clustered standard errors: For the production of the main results, we have estimated the specifications with non-clustered robust standard errors. Although this typically reduces the significance of the estimates, related empirical studies also estimate specifications similar to ours with two-way clustered standard errors by country and industry to account for correlated shocks (e.g. TFP, demand) across industries within a country or correlated shocks (e.g. TFP, income) across countries impacting a given industry (Graetz and Michaels, 2018; Blanas, 2023). Following suit and in accord with this evidence, we obtain OLS and 2SLS that are largely statistically insignificant (Appendix Figure D.3). This is also the case when we cluster standard errors only by industry (Appendix Figure D.4). By contrast, statistical significance is largely maintained when we cluster standard errors only by country (Appendix Figures D.5). Taken together, these results suggest that while the main effects of GVC participation are likely captured by correlated shocks to countries for a given industry, they are unlikely to be captured by correlated shocks to industries by country.

Alternative weighting schemes: In our main specifications, we use as weights the shares of industries' employment in economy-wide employment of countries in the initial sample year (2000) to account for the size of each industry relative to the total economy of each country. These weights, however, do not capture changes in the industrial structure of countries over the years. To check the insensitivity of the main results to accounting for such changes, we re-estimate the specifications using as weights the unweighted averages of industries' economy-wide employment shares across the years in 2000–2019 (see Graetz and Michaels, 2017; Blanas, 2023). Relying on the alternative weighting scheme barely changes the main results (Appendix Figure D.6).

Mean reversion controlled for: Emulating related empirical studies, we check whether our main results are affected by mean reversion (Michaels et al., 2014; Acemoglu and Restrepo, 2020; Blanas, 2023). For instance, it is not uncommon in our sample that initially more productive or skill-intensive industries are also among those that experienced faster productivity growth or upgraded skills more rapidly over the period examined (Panel B of Table C.5). To control for that, we augment the main specifications with the initial (2000) values of the corresponding dependent variables. Reassuringly, the estimates obtained bear a very close resemblance to the main ones (Appendix Figure D.7).

Alternative backward and forward GVC measures: As stressed in Section 2.1, while there is no inconsistency in the definition of backward GVC participation between Borin and Mancini (2019) and Wang et al. (2017), the original forward GVC participation measure of the first study excludes an important component of GVC-related trade and therefore, the ADB has adjusted this measure to reconcile it with that of Wang et al. (2017), who take the aforementioned component into consideration. Indeed, re-estimating the specifications with the GVC measures of Wang et al. (2017) yields almost identical OLS and 2SLS estimates to the main ones (Appendix Figure D.8).

Use of the backward or forward GVC participation measure as the single key regressor: In Section 2.2.1, we have shown that the backward and forward GVC participation measures exhibited similar trends for the whole sample, which may raise concerns that the two measures represent a common trend of participation of industries in GVCs. In that section, we have argued against this interpretation, showing that the raw correlation between the two variables is not very high (roughly 40%), while in the description of the main results table, we have shown that the 2SLS estimates of the two key regressors are statistically different from each other in almost all specifications. To remove any remaining concerns about the possibility of multi-collinearity in the specifications, we re-estimate these using the backward or forward GVC measure as the single key regressor. Indeed, the OLS and 2SLS estimates obtained are very similar to the main ones (Figure D.9).

Log of value added not controlled for: Another possible source of multi-collinearity in the log of employment and employment share specifications is that while the backward and forward GVC measures that we use as the key regressors capture the foreign value added that is sourced and the domestic value added that is exported, respectively, through participation in GVCs, the log of value added, acting as a measure of industry scale, is controlled for. To ensure that that the results are not affected by this, we re-estimate these specifications without controlling for the log of value added. The OLS and 2SLS estimates of the two GVC measures largely maintain their signs and levels of significance. Equally importantly, their magnitudes also change very little, without a clear pattern of inflated or deflated estimates (Appendix Figure D.10).

Sample period 2000–2020: Information on all variables that we employ in the main specifications is also available for 2020 in the relevant databases. However, we have decided to conduct the main analysis until 2019, as all main variables may have been affected by the COVID-19 pandemic outbreak, which started in the first few weeks of 2020. Adding the year 2020 to the sample and taking long differences of variables by subtracting their values for that year from those for 2000, we show that the main results continue to hold (Appendix Figure D.11).

Stacked differences: Estimating the specifications in long differences implies that possible differences in the trends of variables between sub-periods are not accounted for. For instance, we have shown in Section 2.2.1 that backward GVC participation increased only a little as of 2011 relative to the pre-2011 period, while forward GVC participation rose faster in the second half of the period than in the first half. Similarly, the employment share of female workers rose rapidly until 2008, but it was almost stable thereafter. On top of that, our period covers the years of the credit crunch and ensuing global financial crisis and trade collapse (2007–2010), which have likely affected our main variables, as evident, for instance, from the dips and recoveries of backward and forward GVC participation and labour productivity in those years.

Motivated by this evidence, we estimate the main specifications in stacked differences for the sub-periods 2000–2010 and 2010–2019 and for the sub-periods 2000–2007 and 2007–2019 (Acemoglu and Restrepo, 2020). The results are very similar to the main ones, suggesting that not accounting for different trends of variables in sub-periods does not bias the long-run effects that we have identified (Appendix Figure D.12).

Annual data in 2000–2019: Throughout the econometric analysis, we have looked into long-run effects of GVC participation. Taking advantage of annual variation in the data is also useful, as it allows for the identification of short-run effects. This approach also has the advantage of capturing possible changes in the trends of the main variables over the period examined and is thus closer to estimations of the specifications in stacked differences. To this end, we estimate the following specifications on annual data:

$$Y_{cit} = \beta_{GVC} * GVC_{cit} + \beta_{VA} * \log VA_{cit} + \alpha_{ci} + \alpha_{ct} + \epsilon_{cit}, \tag{3}$$

where country-industry (α_{ci}) and country-year (α_{ct}) fixed effects are akin to long-differenced variables and country fixed effects, respectively, in the main specifications. Estimating the specifications by OLS yields very similar estimates to those obtained on long-differenced data (Panel (a) of Appendix Figure D.13). To deal with endogeneity, we implement a Bartik-type IV strategy that is tailored to the use of annual data. In particular, we instrument for the backward and forward GVC measures using the same variables in 2000 multiplied by the per-capita number of broadband subscriptions ($BBND$) in the US, while dropping this country from the sample: $IV^{GVC,USA}_{c \neq USA,i} = GVC_{ci,2000} \cdot \Delta BBND_{USA}, \;\; GVC \in \{GVC_b, GVC_f\}$. The rationale for this IV strategy is that industries with higher initial GVC participation that are located in countries with higher broadband penetration rates—comparable to those of the global technological leader, the US—will expand faster in terms of participation in GVCs. Communication technologies and infrastructure propping up broadband use tend to facilitate GVC participation (Fort, 2016; Gopalan et al., 2022; Blanas, 2024). Thus, the instruments are expected to be relevant. Also, backward and forward GVC participation in the initial sample year are deemed as pre-determined and thus exogenous, while using the per-capita number of broadband subscriptions in the US likely captures global—and thus exogenous—progress in communication technologies and infrastructure. Implementing this IV strategy yields very similar estimates to the 2SLS estimates obtained on long-differenced data (Panel (b) of Appendix Figure D.13), while the first-stage results (Panel (c) of the same figure) and statistics (available upon request) point to the relevance of the IV.[31]

[31] Using the per-capital number of mobile cellular subscription of the US for the construction of the instruments also yields very similar results to those obtained on long differences. These additional robustness results are available

4.1.2 Quantification

Thus far, we have identified, rationalised, and confirmed the robustness of the main effects of backward and forward GVC participation on labour productivity and demand. But are the identified effects also significant in terms of magnitude? To answer this question, we identify the joint effects of the two GVC participation measures and calculate the fractions of the changes in the outcome variables these measures might have accounted for. As a first step, we multiply the 2SLS estimates of the two GVC participation measures obtained from the IV strategy (IV–GVC–USA) and its variant (IV–GVC–USA–CHN), shown in Panels B and C of Table 3, by their sample mean percentage point changes between 2000 and 2019 to calculate the individual effects of the two key regressors. Next, we sum the individual effects to calculate their joint effects, divide the summations by the respective sample mean percentage point changes of the outcome variables between 2000 and 2019, and multiply these ratios by 100 to calculate the joint percentage contributions of the two key regressors to the changes in the outcome variables. The p-values of the relevant F-tests, shown below the magnitudes of individual and joint effects, indicate their statistical significance (Panels A and B of Table 4).[32]

The joint effects of backward and forward GVC participation on the log of labour productivity and the employment share of the high-skilled are positive and significant at 1%, while their joint effects on the log of employment and the employment shares of young and female workers are negative and significant at 1% and their joint effect on the log of value added is negative and significant at 5%. Backward and forward GVC participation accounted jointly for 66% or 32% of the rise in the employment share of high-skilled workers and for 24% or 25% of the decline in the employment share of young workers. As the percentage point changes of the logs of value added and total employment and of the employment share of female workers between the start and end years are positive, there were other factors that more than offset the negative effects exerted on them jointly by backward and forward GVC participation. Conversely, as the joint contribution of backward and forward GVC participation to the rise in the log of labour productivity exceeded 100%, there were other factors that drove this outcome variable downwards.[33]

upon request. Information on the per-capita number of broadband subscriptions and per-capita number of mobile cellular subscriptions is retrieved from the World Bank's World Development Indicators.

[32] For this methodology, see Michaels et al. (2014) and Blanas (2023, 2024). Also note that in this exercise, unlike Table 2 and other tables in the appendix showing statistics for labour productivity and its two components, we calculate the sample mean percentage point changes of the *logs* of labour productivity, value added and total employment, as this is how they enter the specifications.

[33] According to the second and third variants of our IV strategy (IV–GVC–CHN and IV–GVC–USA for GVC_b and IV–GVC–CHN for GVC_f), the joint effects of the two GVC participation measures on the log of total employment and the shares of high-skilled and female workers are statistically insignificant or exerted significant effects in opposite directions from the realised shifts of these outcome variables. Also, the joint effect of the two measures on the log of value added is insignificant or accounted for slightly more than 100% of the rise in the log of value added over the period examined. By contrast, the joint effect of the two measures on the log of labour productivity is positive and significant at 1%, accounting for 71% or 98% of the increase of this outcome variable over the period examined and their joint effect on the employment share of the young is negative and significant at 1%, accounting for 24% or 25% of the decline of this variable over the period examined.

Table 4: Quantification of the joint effects of backward and forward GVC participation

Panel A: IV–GVC–USA

	(1) $Log(LP)$	(2) $Log(VA)$	(3) $Log(E)$	(4) Esh^{HS}	(5) Esh^{Y}	(6) Esh^{F}
Coefficient estimate of GVC_b	6.464***	-6.137***	-10.522***	1.010***	-0.342***	-0.500***
Coefficient estimate of GVC_f	2.763**	2.316**	-1.232	-0.223	-0.002	-0.350***
Sample mean change of GVC_b (2000–2019)	0.038	0.038	0.038	0.038	0.038	0.038
Sample mean change of GVC_f (2000–2019)	0.052	0.052	0.052	0.052	0.052	0.052
Magnitude of GVC_b effect (row 1 * row 3)	0.246	-0.233	-0.400	0.038	-0.013	-0.019
F-test H_0: row 1 * row 3 = 0 (p-value)	0.000	0.000	0.000	0.000	0.000	0.002
Magnitude of GVC_f effect (row 2 * row 4)	0.144	0.120	-0.064	-0.012	-0.000	-0.018
F-test H_0: row 2 * row 4 = 0 (p-value)	0.019	0.046	0.294	0.220	0.977	0.004
Magnitude of joint effect of GVC_b and GVC_f	0.389	-0.113	-0.464	0.027	-0.013	-0.037
F-test H_0: row 5 + row 7 = 0 (p-value)	0.000	0.023	0.000	0.001	0.000	0.000
Sample mean change of $Log(LP)$ (2000–2019)	0.381	–	–	–	–	–
Sample mean change of $Log(VA)$ (2000–2019)	–	0.502	–	–	–	–
Sample mean change of $Log(E)$ (2000–2019)	–	–	0.119	–	–	–
Sample mean change of Esh^{HS} (2000–2019)	–	–	–	0.041	–	–
Sample mean change of Esh^{Y} (2000–2019)	–	–	–	–	-0.055	–
Sample mean change of Esh^{F} (2000–2019)	–	–	–	–	–	0.011
Fraction of magnitude of joint effect of GVC_b and GVC_f (%)	102.178	N/A	N/A	66.078	23.778	N/A

Panel B: IV–GVC–USA–CHN

	(1) $Log(LP)$	(2) $Log(VA)$	(3) $Log(E)$	(4) Esh^{HS}	(5) Esh^{Y}	(6) Esh^{F}
Coefficient estimate of GVC_b	5.470***	-2.631**	-7.759***	1.048***	-0.331***	-0.371**
Coefficient estimate of GVC_f	4.037***	1.175	-2.788***	-0.510**	-0.025	-0.440***
Sample mean change of GVC_b (2000–2019)	0.038	0.038	0.038	0.038	0.038	0.038
Sample mean change of GVC_f (2000–2019)	0.052	0.052	0.052	0.052	0.052	0.052
Magnitude of GVC_b effect (row 1 * row 3)	0.208	-0.100	-0.295	0.040	-0.013	-0.014
F-test H_0: row 1 * row 3 = 0 (p-value)	0.000	0.025	0.000	0.000	0.000	0.018
Magnitude of GVC_f effect (row 2 * row 4)	0.210	0.061	-0.145	-0.027	-0.001	-0.023
F-test H_0: row 2 * row 4 = 0 (p-value)	0.001	0.209	0.006	0.010	0.690	0.000
Magnitude of joint effect of GVC_b and GVC_f	0.418	-0.039	-0.440	0.013	-0.014	-0.037
F-test H_0: row 5 + row 7 = 0 (p-value)	0.000	0.287	0.000	0.085	0.000	0.000
Sample mean change of $Log(LP)$ (2000–2019)	0.381	–	–	–	–	–
Sample mean change of $Log(VA)$ (2000–2019)	–	0.502	–	–	–	–
Sample mean change of $Log(E)$ (2000–2019)	–	–	0.119	–	–	–
Sample mean change of Esh^{HS} (2000–2019)	–	–	–	0.041	–	–
Sample mean change of Esh^{Y} (2000–2019)	–	–	–	–	-0.055	–
Sample mean change of Esh^{F} (2000–2019)	–	–	–	–	–	0.011
Fraction of magnitude of joint effect of GVC_b and GVC_f (%)	109.655	N/A	N/A	32.826	25.225	N/A

Notes: Rows (1) and (2) of Panels A and B replicate the coefficient estimates of GVC_b and GVC_f in Panels B and C, respectively, of Table 3. Rows (3) and (4) of each panel display the sample mean percentage point changes of the GVC_b and GVC_f between 2000 and 2019. For the calculations of sample mean percentage point changes of variables varying by country-industry-year cell, see Appendix B. Rows (11), (12) and (13) of each panel display the sample mean percentage point changes of $Log(LP)$, $Log(VA)$, $Log(E)$, Esh^{HS}, Esh^{Y}, and Esh^{F} between 2000 and 2019. For the calculation of the magnitudes of the individual effects of GVC_b and GVC_f in rows (5) and (7) of each panel, I multiply the coefficient estimates of these variables (rows (1) and (2)) by their respective sample mean percentage point changes (rows (3) and (4)). The joint effects of GVC_b and GVC_f in row (9) of each panel are the summations of their individual effects in rows (5) and (7). P-values below the magnitudes of the individual and joint effects indicate their statistical significance. The fractions of the magnitudes of the joint effects in row (14) of each panel are calculated as ratios of the magnitudes of the effects to the sample mean percentage point changes of the outcome variables, multiplied by 100. "N/A" denotes that the joint effects are statistically significant but shift the outcome variables in opposite directions from the realised shifts or are statistically insignificant.

4.2 GVC participation and labour productivity and demand in high- Vs lower-income countries

The interpretations for some of the main results that we have obtained in the previous section may be more relevant to industries of certain groups of countries. Besides, the setting of global fragmentation of production that has marked the global economy since the 1970s implies that routine production tasks (e.g. final assembly) have been relocated predominantly to lower-income countries, while complex pre-production tasks (e.g. design, engineering) have been mostly retained in high-income countries and in-house (Antràs et al., 2006, 2008; Feenstra, 2010; Baldwin, 2016; Fort et al., 2018; Arkolakis et al., 2018; Fort, 2023; Bloom et al., 2019).[34]

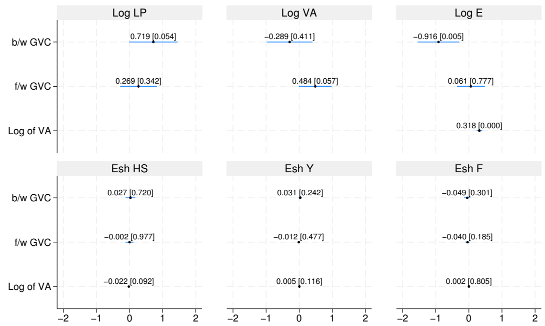
Hence, to be able to better understand possible mechanisms of the main effects, we take advantage of the broad coverage of high- and lower-income countries in our sample and estimate the specifications in Eq. (1) separately for these country groups. As in Section 2.2, we distinguish countries by their income status in the year 2000 according to the World Bank's Historical Country Classification by Income. Results obtained from OLS and 2SLS estimations on the samples of high- and lower-income countries are shown in Panels (a)–(d) of Figure 3. In 2SLS estimations, we rely primarily on the variant of the IV strategy (IV–GVC–USA–CHN), as we expect lower-income countries to emulate China more closely than the US in terms of GVC participation over the period examined. Despite a few differences in significance and sign, the OLS and 2SLS estimates paint a similar picture.[35] As interpretations for some of the main results presented in the previous section may also be more relevant to certain industries or sectors, we present in this section 2SLS results obtained from the variant of the IV while considering further only non-manufacturing or IT-using industries of each country income group.[36]

[34]The extreme case of this setting is the documented emergence of the so-called "factory-less goods-producing firms" (FGPFs) in high-income countries (Bernard and Fort, 2015, 2017; Fort et al., 2018; Fort, 2023). The documented increasing number of manufacturing firms owning an increasing number of non-manufacturing establishments domestically is also part of this setting (Fort et al., 2018; Fort, 2023; Bloom et al., 2019).

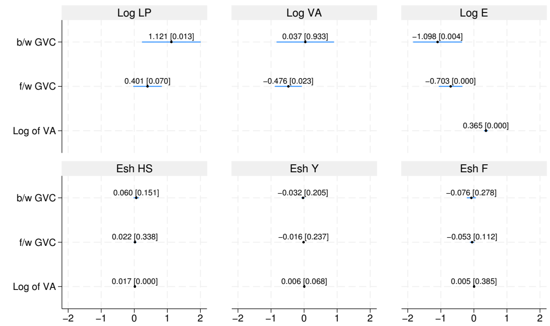
[35]First-stage results, shown in Appendix Figure D.14, point to the relevance of the IV strategy on either sample. The weak identification test is always passed successfully, but the F values of the weak identification test are smaller than those obtained on the whole sample. Also, similarly to the IV estimations on the whole sample, the p-values of the F-test for over-identifying restrictions are smaller than 10%. The first-stage statistics are available upon request. In addition, note that we obtain very similar estimates when we implement the original IV on the sample of high-income countries (Panel (a) of Figure D.15), while a few inconsistencies in terms of significance and sign obtained from the original IV on the sample of lower-income countries do not prevent us from deriving the key insights that we derive based on the variant of the IV (Panel (b) of the same figure). The first-stage results (Panels (c)–(f) of the same figure) and statistics (available upon request) point to the relevance of the original IV on the two samples.

[36]Coverage of non-manufacturing or IT-using industries per country group implies that we eliminate from the relevant samples the manufacturing (ISIC Rev. 3.1 codes 15–39) and IT-producing (ISIC Rev. 3.1 codes 29–33) industries, respectively. We also estimate the specifications on these samples by OLS and by 2SLS based on the original IV. The results are largely similar to those that we will describe next based on the variant of the IV (Panels (a)–(b) and (c)–(d) of Appendix Figures D.16 and D.17).

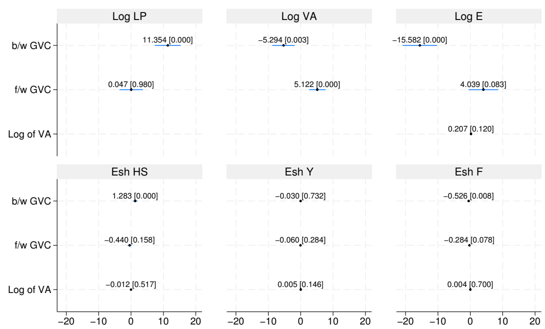
Figure 3: GVC participation and labour productivity and demand by country income group



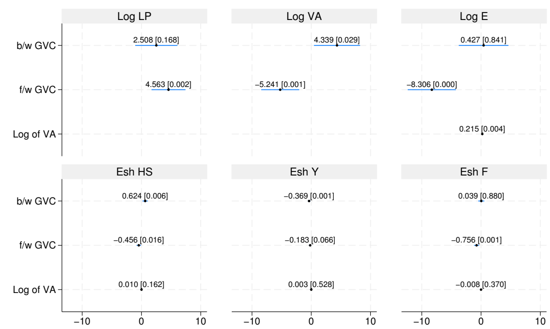
(a) HI countries, OLS



(b) LMI countries, OLS



(c) HI countries, IV–GVC–USA–CHN



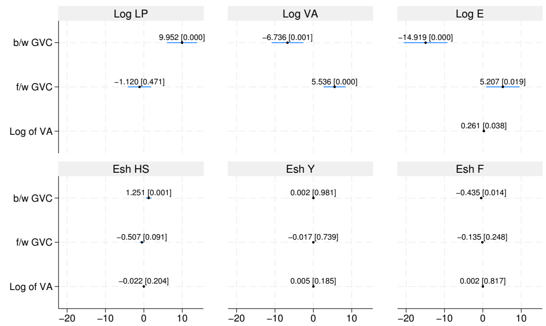
(d) LMI countries, IV–GVC–USA–CHN

(e) HI, Non-manufacturing, IV–GVC–USA–CHN

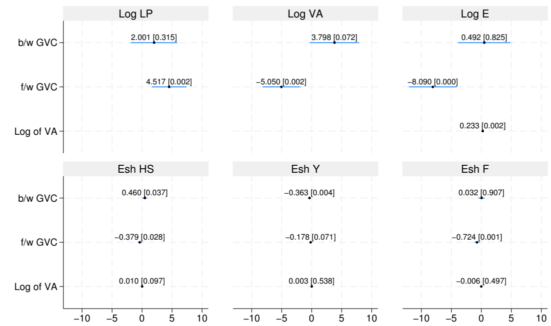
(f) LMI, Non-manufacturing, IV–GVC–USA–CHN

4.2.1 Backward GVC participation effects

Comparing estimates of backward GVC participation between the two country income groups reveals that the productivity gains and output and employment losses identified when all countries are pooled together are driven only by high-income countries (Panels (c) and (d)). On top of that, the productivity gains and output and employment losses are much larger in high-income countries than those estimated on the whole sample. By contrast, backward GVC participation exerted no statistically significant effects on productivity and total employment in lower-income countries, but



(g) HI, IT-using industries, IV–GVC–USA–CHN



(h) LMI, IT-using industries, IV–GVC–USA–CHN

Notes: OLS with robust standard errors in Panels (a)–(b) and 2SLS estimations with robust standard errors in Panels (c)–(h). The equations in all panels include country fixed effects. The equations in Panels (a)–(d) are weighted by the share of each industry's employment in economy-wide employment in 2000, while the equations in Panels (e)–(f) and (g)–(h) are weighted by the share of each industry's employment in economy-wide employment net of employment in manufacturing (ISIC Rev. 3.1: 15–39) and IT-producing (ISIC Rev. 3.1: 29 and 30–33) industries, respectively, in 2000. The estimating samples in Panels (a), (c), (e), and (g) comprise high-income (HI) countries, while the estimating samples in Panels (b), (d), (f), and (h) comprise lower-income (LMI) countries, according to the World Bank's Historical Country Classification By Income in 2000.

had an output-enhancing effect, as indicated by the relevant positive and significant coefficient estimate.[37] These notable differences confirm the relevance, highlighted in the previous section, of the effects of backward GVC participation to key evidence for high-income countries in the extant literature. Namely, evidence on output and employment losses of industries, especially in manufacturing, of these countries due to offshoring to and import competition from lower-income countries like China (e.g. Autor et al., 2013; Acemoglu et al., 2016) and their meagre productivity and output gains and ensuing insufficient new task creation from technological changes associated with backward GVC participation, such as IT and robot adoption (Acemoglu et al., 2014; Acemoglu and Restrepo, 2019, 2022).

The effects of backward GVC participation on productivity and its two components in non-manufacturing of high-income countries are qualitatively very similar, suggesting that these effects may not be capturing primarily import competition from lower-income countries, given that the most exposed industries in high-income countries to this factor are those of the manufacturing sector (Panel (e)). Rather, the adoption of labour-saving technologies associated with backward GVC participation may be a more relevant interpretation, indicating further that the inter-related problems of insufficient new task creation and adoption of "so-so" automation technologies in high-income countries may not be present only in the manufacturing sector, but also in other sectors. Besides, manufacturing is the only sector in high-income countries along with market services that experienced positive value added share growth over the period examined (Appendix Table C.6). This is also evident from the much larger output and employment losses and much smaller produc-

[37]Note that, albeit insignificant, the coefficient estimate of the backward GVC participation measure in the log of total employment specification has a positive sign, which also contrasts with the respective estimates on the whole sample and the sample of high-income countries.

tivity gains of non-manufacturing industries in high-income countries due to backward GVC participation than the respective effects obtained when all sectors in high-income countries are taken into consideration. The qualitatively similar and larger, albeit to a lesser extent, backward GVC participation effects in IT-using industries of high-income countries lend extra support to this argumentation, considering evidence of Acemoglu et al. (2014) showing, at least for US manufacturing, that the adoption of labour-saving technologies such as IT is output- and productivity-enhancing in IT-producing industries, but not in IT-using industries (Panel (g)).

The interpretations that we have put forward are consistent with the shift of employment from manufacturing to services that has occurred in high-income countries in recent decades, including over the period examined, as indicated by our evidence on structural transformation by country income group (Appendix Table C.6). By contrast, lower-income countries were transitioning in the years examined from the primary sector to other sectors—primarily, manufacturing and market services. Hence, the output-enhancing effect of backward GVC participation identified on the sample of lower-income countries suggests that this type of activity and the technological changes that is associated with are likely to have generated more tasks than they destroyed in this group of countries (Panel (d)). This rationale tallies with the rapid expansion of backward GVC participation of almost all main sectors of high- and lower-income countries along with the considerably higher productivity, value added, and employment growth rates of sectors in lower-income countries compared to those in high-income countries, as we document in this paper (Table 1 and Panel A of Table 2). The effect of backward GVC participation on output is also observed in IT-using industries of lower-income countries, albeit with reduced significance (Panel (h)), but it is statistically insignificant and switches sign in non-manufacturing industries of the same country group (Panel (f)). Its effect on productivity also switches sign and becomes marginally significant. The evidence in Panels (f) and (h) suggests that our rationale for the output-enhancing effect of backward GVC participation in Panel (d) may be particularly relevant to manufacturing industries.

In addition, the positive and significant effect of backward GVC participation on the employment share of high-skilled workers and its negative and significant effect on the employment share of female workers in Panel (c) suggest that the brunt of output and employment losses due to this type of activity was borne primarily, if not exclusively, by lower-skilled and female workers. In lower-income countries, it is the high-skilled and older workers who benefited mostly from output gains due to backward GVC participation, as indicated by the positive and significant effect of this type of activity on the employment share of the high-skilled and its negative and significant effect on the employment share of the young (Panel (d)). Hence, despite the opposite effects on output and employment, backward GVC participation led to skill upgrading of the average industry in both high- and lower-income countries. As stressed in the previous section, this is consistent with a wealth of evidence and theories on the routine and skill bias of offshoring (e.g. Goldberg and Pavcnik, 2007; Hummels et al., 2018) and the reallocation of domestic labour towards more productive uses due to offshoring and import competition (e.g. Egger et al., 2015; Becker et al., 2013). Note that these effect hold in IT-using industries (Panels (g) and (h)), but are insignificant in non-manufacturing industries (Panels (e) and (f)), suggesting that skill upgrading due to backward GVC participation may be particularly relevant in manufacturing industries of the two country income groups.

4.2.2 Forward GVC participation effects

Looking at the effects of forward GVC participation, we detect important differences in these between the two country income groups and with respect to the effects of backward GVC participation per country income group. Although forward GVC participation exerted no significant effect on the log of labour productivity of industries in high-income countries, it impacted positively their logs of output and employment, albeit the second effect is weaker and significant only at 10% (Panel (c)). These effects are in sharp contrast to those of backward GVC participation and suggest that exports of domestic value added through GVCs led to output and employment gains. These gains accord with the relative abundance in human capital and cutting-edge technologies of this group of countries and their ensuing comparative advantage in activities involving the intensive execution of non-routine cognitive tasks (e.g. R&D, design, engineering, marketing, management) for the production of outputs that are exported through GVCs (Fort, 2023). Also, these gains may suggest that as forward GVC participation expanded, the productivity of production factors (e.g. workers, machines) in performing tasks for the generation of these outputs rose. This can be dubbed as "deepening" of forward GVC participation. In line with these interpretations and the documented disproportionate shift of employment in high-income countries away from manufacturing and towards services, we identify output- and employment-enhancing effects of forward GVC participation of non-manufacturing and ICT-using industries of high-income countries (Panels (e) and (g)). On top of that, the effects are larger than those identified in Panel (c), although those in ICT-using industries are only slightly so.

These interpretations are also relevant to the identified employment share losses incurred by female workers in high-income countries due to forward GVC participation, albeit this effect is significant only at 10% (Panel (c)). Also, this effect is insignificant in non-manufacturing industries (Panel (e)), but significant at 5% in IT-using industries (Panel (g)). In particular, male workers are more likely to perform the aforementioned non-routine cognitive tasks that are closely aligned with the comparative advantage of high-income countries and their productivity in executing these tasks might have risen disproportionately due to the expansion of forward GVC participation. As stressed in the previous section, these effects also relate to evidence on the link between exporting and domestic production upgrading through, for instance, product quality and technology upgrading (Lileeva and Trefler, 2010). In addition, technological changes associated with forward GVC participation, such as communication technology adoption, might have been (more) complementary to male workers, as they are more likely to perform tasks relying on the utilisation of such technologies, such as monitoring and coordination of production and search for new investment opportunities for their firms (Antràs et al., 2006, 2008; Fort, 2016; Frydman and Papanikolaou, 2018; Blanas, 2023).

In lower-income countries, the effects of forward GVC participation on productivity and its components are very different. This type of activity exerted a negative and significant effect on the log of value added and a larger negative and significant effect on the log of total employment, which explains its positive and significant effect on the log of labour productivity (Panel (d)). Hence, the effects of forward GVC participation on productivity and employment identified earlier on the whole sample are driven mostly by lower-income countries, while its effect on output is driven mostly by high-income countries. It is also noteworthy that these effects are larger than the respective effects identified on the whole sample. As mentioned in the discussion of the results produced on the whole sample, a possible explanation for the productivity gains and employment losses in lower-income countries is that exporting of domestic value added through GVCs is associated with the adoption of labour-saving technologies (e.g. computer-controlled assembly line). For instance, Koch et al. (2021) find evidence on the complementarity between firms' export activities and robot adoption, which raises their productivity. As these technologies typically undertake routine tasks, this interpretation also provides the context for the negative and significant effects of the same type of activity on the employment shares of young and female workers, who are more likely to perform such tasks. These effects also hold in non-manufacturing or IT-using industries (Panels (f) and (h)). As also mentioned earlier, an additional interpretation for these effects is that other types of technological changes associated with forward GVC participation, such as communication technology adoption, were (more) complementary to older and male workers, who are more likely to undertake supervisory, coordination, and managerial roles requiring the utilisation of such technologies.

Interestingly, we also find that forward GVC participation exerted a negative and significant effect on the employment share of high-skilled workers. This seems to be counter-intuitive at first sight. A plausible interpretation which reconciles this effect with the negative effects on the employment shares of young and female workers is as follows. In line with the comparative advantage of lower-income countries, the generation of domestic value added that is exported through GVCs likely led to the generation of new tasks related to a wide range of occupations, but disproportionately so to lower-skilled occupations. The new tasks, though, might have had predominantly high skill requirements relative to skill abundance of lower-income countries and were thus performed primarily by older and male workers and were also complementary to tasks undertaken by associated labour-saving technologies. A similar interpretation has provided the context for the increase in wage inequality between high- and less skilled workers in lower-income countries such as Mexico due to offshoring to these countries (Feenstra and Hanson, 1997). On condition that the effects of forward GVC participation on the employment shares of the high-skilled, young, and female workers reflect labour reallocation aiming at the upgrade of the quality of products exported through GVCs, then these effects also relate to evidence on the rise in wage inequality between high- and lower-skilled workers of manufacturing plants in Mexico due to their engagement in exporting (Verhoogen, 2008). The rationale that we have put forward and its pertinence to the aforementioned empirical evidence are strengthened by the evidence in Panels (h) and (f) showing that the negative effect on the employment share of the high-skilled holds in IT-using industries of lower-income countries, but is insignificant in non-manufacturing industries.

Despite these interpretations, the negative effect of forward GVC participation on domestic value added remains a puzzling finding, as one would expect that this type of activity and the adoption of labour-saving technologies that may be associated with it would have the opposite effect (Acemoglu et al., 2014, 2016; Fort et al., 2018). A possible explanation for this finding, which may also explain the negative effect on total employment and supplement the other interpretations, is the inconsistencies between structural transformation lower-income countries underwent over the period examined and their sectoral forward GVC participation trends. In particular, while the primary and personal and professional service sectors increased their forward participation in GVCs at faster rates than other sectors (Table 1), their value added and employment grew the least (Panel A in Table 2), resulting in negative value added share growth rates and negative or the lowest positive employment share growth rates between 2000 and 2019 (Appendix Table C.6). This may also suggest that industries such as those of the primary and personal and professional service sectors failed to incorporate in their production processes technologies that would be output-enhancing.

In line with Panel (d), productivity gains and employment losses due to forward GVC participation are also observed in non-manufacturing and IT-using industries of lower-income countries, lending extra support to the complementarity between exporting through GVCs and adoption of labour-saving technologies in these countries (Panels (f) and (h)). In non-manufacturing industries, however, these effects are much larger, suggesting that productivity gains from the introduction of labour-saving technologies associated with exporting through GVCs may be particularly relevant in non-manufacturing sectors—most notably perhaps, the primary sector, from which workers were shifting away over the period examined (Appendix Table C.6). Equally importantly, in contrast to Panel (d), the effect of forward GVC participation on output of non-manufacturing industries in lower-income countries is not statistically significant. In line with the corresponding interpretation above, this effect likely becomes insignificant because of the smaller inconsistencies between structural transformation in lower-income countries and the sectoral forward GVC participation trends after the elimination of manufacturing industries, which had the second lowest forward GVC participation growth but highest value added growth, likely partly due to the utilisation of better technologies (Table 1 and Panel A in Table 2).

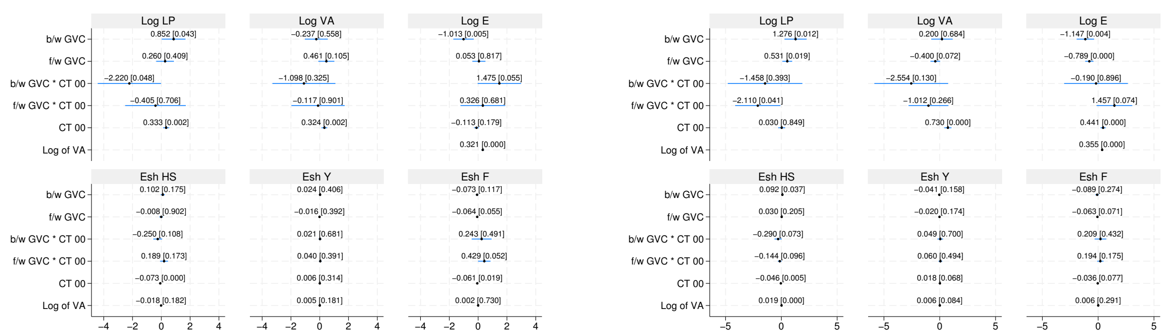
As some of the insights that we have derived in this and the previous sections highlight the potential of the interplay between GVC participation and technology adoption to determine labour productivity and demand, our next step in the econometric analysis is to estimate specifications with interactions between GVC and technology measures.

4.3 Interplay between GVC participation and technology and labour productivity and demand

In this section, we present results obtained from estimations of the specifications in Eq. (2) separately for high- and lower-income countries. As described earlier, $TECH_i$ includes industry-level communication technology (CT), information technology (IT), or software (S/W) capital intensity for the US in 2000, or industry-level robot intensity for a set of predominantly technologically advanced countries in 1993. We estimate the specifications by OLS and interpret the coefficient estimates as conditional correlations.[38]

Cross-industry differences in initial levels of CT capital intensity: Results obtained when taking advantage of cross-industry variation in initial CT capital intensity are displayed in Panels (a) and (b) of Figure 4. By and large, the coefficient estimates of the non-interacted GVC measures obtained on the two samples are very similar to the respective estimates obtained from earlier estimations without interaction terms (Panels (a) and (b) of Figure 3). However, the corresponding coefficient estimates of the interaction terms, especially when they are statistically significant, have opposite signs. In particular, results suggest that the productivity gains and aggregate employment losses associated with backward GVC participation and the employment share losses of female workers associated with forward GVC participation are smaller in initially more CT-capital-intensive industries of high-income countries. Similarly, in lower-income countries, the productivity gains and aggregate employment losses associated with forward GVC participation and the employment share gains of high-skilled workers associated with both backward and forward GVC participation are smaller in industries that are initially more CT-capital-intensive.[39]

Figure 4: Interplay between GVC participation and CT and labour productivity and demand



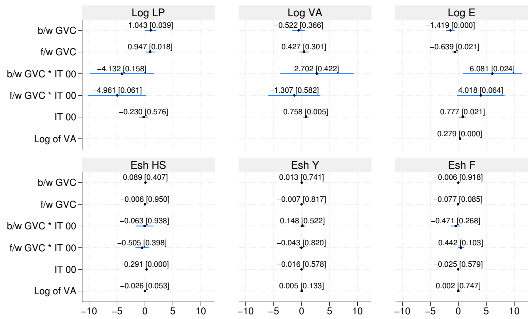
(a) HI countries (b) LMI countries

Notes: OLS estimations with robust standard errors in both panels. The equations include interactions of the backward and forward GVC measures with the real stock of communication technology (CT) capital to real gross value added for the US in 2000 and country fixed effects, and are weighted by the share of each industry's employment in economy-wide employment in 2000. The estimating sample in Panel (a) comprises high-income (HI) countries, while the estimating sample in Panel (b) comprises lower-income (LMI) countries, according to the World Bank's Historical Country Classification By Income in 2000.

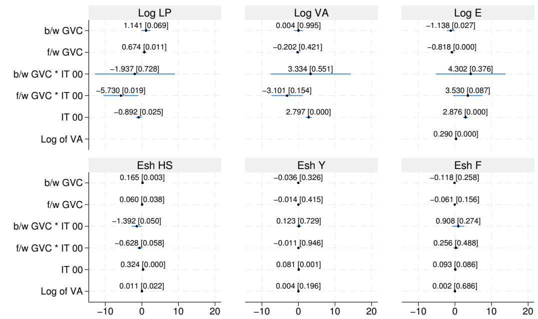
[38]When estimating Eq. (2) by 2SLS, the second-stage results are quite similar to the OLS ones, but the first-stage results are unsatisfactory, which prevents us from making a discussion based on these results. A possible reason for this is that the construction of variables that we use as instruments for the GVC participation measures (i.e., initial values of the measures for the US) is conceptually similar to the construction of the technology variables.

[39]In line with these results, the OLS estimates obtained on the whole sample suggest that forward GVC participation of initially more CT-capital-intensive industries is associated with smaller productivity gains, aggregate employment losses and female employment share losses and backward GVC participation of this type of industries is associated with smaller employment share gains of high-skilled workers (Panel (a) of Appendix Figure D.18).

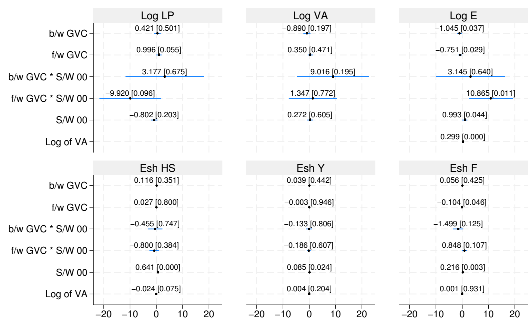
Figure 5: Interplay between GVC participation and automation technologies and labour productivity and demand



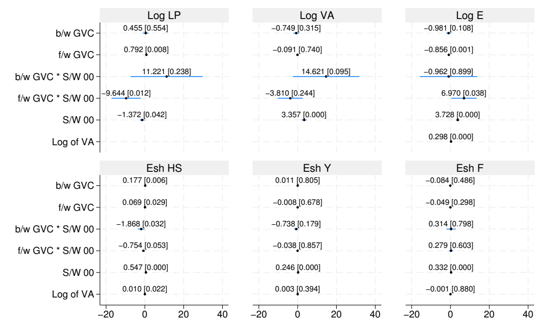
(a) IT – HI countries



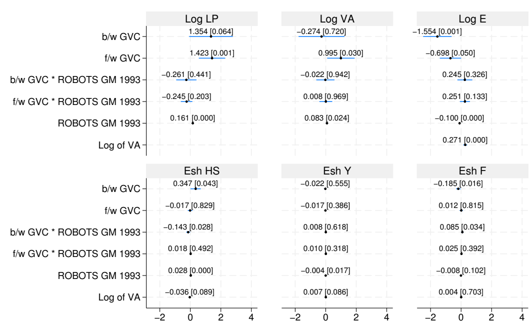
(b) IT – LMI countries



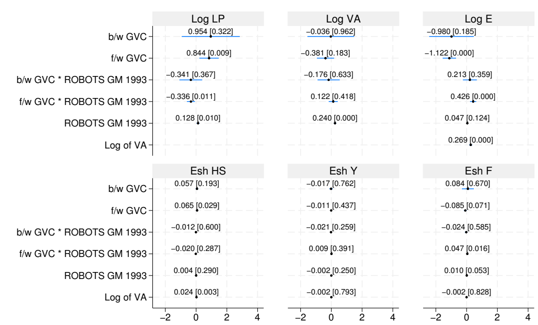
(c) S/W – HI countries



(d) S/W – LMI countries



(e) ROBOTS – HI countries



(f) ROBOTS – LMI countries

Notes: OLS estimations with robust standard errors in all panels. The equations include interactions of the backward and forward GVC measures with a technology measure and country fixed effects, and are weighted by the share of each industry's employment in economy-wide employment in 2000. The technology measure is the ratio of the real stock of information technology (IT) or software (S/W) capital to real gross value added for the US in 2000 (Panels (a)–(b) and Panels (c)–(d)), or the unweighted cross-country average of robot intensity by industry (ROBOTS) in 1993, as constructed by Graetz and Michaels (2018) (Panels (e)–(f)). The estimating samples in Panels (a), (c), and (e) comprise high-income (HI) countries, while the estimating samples in Panels (b), (d), and (f) comprise lower-income (LMI) countries, according to the World Bank's Historical Country Classification By Income in 2000.

As already discussed in Section 4.1, the adoption of CT decreases the costs of monitoring and coordination of GVCs (Antràs et al., 2006, 2008; Fort, 2016; Blanas, 2023) and the cost of search for new opportunities for investments in these (Frydman and Papanikolaou, 2018). Hence, industries that were initially more CT-capital-intensive might have also been more engaged in GVCs and made more intensive use of associated labour-saving technologies in the initial year. In turn, further expansions of these industries in terms of GVC participation led to smaller employment losses and labour productivity gains and to the lower upgrade of skills over the years. Another closely-related interpretation draws on key insights from knowledge-based hierarchy theories (e.g. Garicano, 2000; Bloom et al., 2014; Garicano and Rossi-Hansberg, 2015). As CT adoption renders monitoring and direction and identification of opportunities for business expansion less costly, managers in initially more CT-capital-intensive industries might have been able to supervise a higher number of (lower-skilled) production workers more easily and might have thus formed larger international production teams over the years through GVC participation.

Cross-industry differences in initial levels of automation technology intensity: By taking advantage of cross-industry variation in initial IT capital, software capital or robot intensity, we obtain the results shown in Panels (a)–(b), (c)–(d), and (e)–(f), respectively, of Figure 5. Again, the coefficient estimates of the non-interacted GVC measures are largely similar to those obtained from estimations without interactions, while the corresponding statistically significant coefficient estimates of the interaction terms always have opposite signs.[40] In particular, the aggregate employment losses associated with both backward GVC participation are smaller in initially more IT-capital-intensive industries of high-income countries and the employment share gains of high-skilled workers and employment share losses of female workers associated with the same type of activity are smaller in initially more robot-intensive industries. The negative and significant association of forward GVC participation with the log of employment and its positive and significant differential association with the same outcome variable in initially more software-intensive industries suggest that the positive effect on aggregate employment identified in the previous section may hold only in this type of industries. There are also differential associations of forward GVC participation with the log of productivity in initially more software-intensive industries and with the logs of productivity and employment in initially more IT-intensive industries, but these are significant only at 10%. In lower-income countries, the productivity gains and aggregate employment losses associated with forward GVC participation are smaller in industries that are initially more IT-capital-intensive, software-capital-intensive, or robot-intensive. Also, the employment share gains of high-skilled workers associated with both backward and forward GVC participation are smaller in initially more IT- or software-capital-intensive industries, and the employment share losses of female workers associated with forward GVC participation are smaller in initially more robot-intensive industries.[41]

[40]Note that as information on the robot intensity measure is available for a limited number of industries, we first ensure that we obtain very similar results to the main ones when we estimate the specifications without interaction terms on this restricted sample (Appendix Figure D.19).

[41]The OLS estimates obtained on the whole sample yield very similar insights. In particular, forward GVC participation of initially more IT-capital-intensive, software-capital-intensive, or robot-intensive industries is associated with

The great similarities in the associations across panels per country income group suggest that while IT, software and robots are different types of automation technologies undertaking different types of tasks, they are highly complementary with each other. A possible interpretation for these findings is that industries of high- and lower-income countries that make initially more intensive use of IT, software, or robots likely continued to adopt routine-biased, labour-saving technologies at faster rates as they expanded their participation in GVCs than other industries, but at the same time, employed workers that have, on average, higher human capital and thus performed tasks that are better shielded from automation and contributed more to the generation of value added that was exported through GVCs (Aghion et al., 2019; Blanas, 2023). In other words and in relation to the discussion in Section 4.2, initially more automation-technology-intensive industries might have been able to create more new tasks and/or retain higher numbers of less routine tasks as GVC participation expanded.

Robustness: Results presented in this section are robust to considering historical and persistent differences across industries in CT, IT, and software capital intensities (Acemoglu and Restrepo, 2020). To perform this check, we use in interaction terms these measures for the US in 1985, rather than 2000 (Appendix Figures D.20 and D.21).[42] In addition, our results are robust to the construction of CT, IT and software capital intensities for the US in 2000 using information on real capital stocks from the latest (February 2023) release of the EU KLEMS database (Appendix Figures D.22 and D.23). This exercise is conducted on a sample comprising 31 out of the 35 industries examined, which is the reason why we have not relied on this version of the database for the construction of our benchmark technology variables.[43]

Cross-industry differences in initial levels of R&D capital intensity: Relying on information on the real stock of R&D capital from the February release of the EU KLEMS, we calculate industry-level R&D capital intensity for the US in 2000. On condition that this variable captures different types of innovations (e.g. process, product) and the intensity of utilisation of the four types of technologies that we have considered in the analysis (CT, IT, S/W, robots), it is a broader technology measure. Therefore, estimating the specifications while interacting this variable with the GVC measures is an equally useful exercise.

smaller productivity gains and aggregate employment losses. Also, forward GVC participation of initially more IT- or software-capital-intensive industries and backward GVC participation of initially more robot-intensive industries are associated with smaller employment share gains of high-skilled workers, and forward GVC participation of the latter type of industries is associated with smaller employment share losses of female workers (Panels (b)–(d) of Appendix Figure D.18).

[42] Using the same measures for the US in 1982, 1990, or 1995 also yields very similar results to the main ones. These results are available upon request. Note that we cannot perform this check using the robot intensity measure as 1993, which is our benchmark, is the earliest year for which relevant information is available in the IFR database and, subsequently, in Graetz and Michaels (2018).

[43] In particular, the latest release of the EU KLEMS database does not provide information on stocks of different types of capital in 2000 or another year prior to that for industries with ISIC Rev. 3.1 codes 24, 50, 64, and L in any technologically advanced country, the US included. Relatedly, we show that the change in the industry composition of the sample does not affect the main results by estimating the specifications without interaction terms on this restricted sample (Appendix Figure D.24). Also, note that real capital stocks in the EU KLEMS database are in 2015 USD. Hence, for the calculation of capital intensities as ratios of real capital stocks to real gross value added, we first deflate *nominal* value added from the ADB MRIO Tables using the corresponding deflator from the latest release of the EU KLEMS database.

Indeed, this conjecture is supported by the OLS results obtained from these additional estimations, while the interpretations that we have provided in the previous paragraphs of this section are still relevant (Panels (b) and (c) of Figure D.25). In particular, there are positive, albeit significant only at 10%, differential associations of forward GVC participation with aggregate output and employment of initially more R&D-intensive industries in high-income countries. Hence, similarly to the differential association in initially more software-intensive industries, the effects on aggregate output and employment identified in the previous section may hold in initially more, but not less, R&D-intensive industries. In lower-income countries, the productivity gains and aggregate employment losses associated with forward GVC participation are smaller in initially more R&D-intensive industries, while there are also negative and significant differential associations of both backward and forward GVC participation with the employment share of high-skilled workers and a negative and significant differential association of backward GVC participation with the employment share of female workers.

In addition, the negative, albeit significant only at 10%, differential association of forward GVC participation with the employment share of the young in initially more R&D-intensive industries of high-income countries and the negative and significant differential associations of both backward and forward GVC participation with the employment share of the same age group of workers in initially more R&D-intensive industries of lower-income countries likely point to disproportionate complementarities between GVC participation and key characteristics associated with age, such experience and tenure, in industries undertaking R&D activities more intensively.[44]

5 Conclusion

In this paper, we have conducted an elucidating analysis on the long-run implications of GVCs and their interplay with technology for labour productivity and demand. Leveraging a novel sample of 35 industries, covering all economic sectors, in 62 developed and developing countries from 2000 to 2019 and implementing a relevant and valid IV strategy, we have first identified the effects of participation in GVCs through linkages with suppliers (backward) and buyers (forward) on labour productivity, its two components (aggregate output and employment), and the skill, age, and gender structure of employment. Considering further countries' different structures of economic activity and comparative advantages based on their distinction by income status, we have identified striking differences in the effects between high- and lower-income countries, allowing us to detect possible underlying mechanisms and derive insights not only about the labour market implications of GVCs, but also of various types of technological changes that likely drive or are driven by the emergence

[44]From estimations on the whole sample, we find positive and significant differential associations of forward GVC participation with aggregate output and employment of initially more R&D-intensive industries, which are consistent with relevant evidence for high-income countries, negative and significant differential associations of forward and backward GVC participation with the employment share of high-skilled and young workers, respectively, which are consistent with relevant evidence for lower-income countries, and a negative and significant differential association of forward GVC participation with the employment share of young workers, which is consistent with relevant evidence for both country income groups (Panel (a) of Figure D.25).

and expansion of GVCs. In this light, our analysis extends strong support to the view that the labour market effects of trade-related activities and technology adoption are tightly intertwined (Fort et al., 2018). We have derived additional insights in favour of this view by providing novel evidence on differential associations of backward and forward GVC participation with labour productivity, aggregate output and employment, and the employment shares of high-skilled, young, and female workers in industries with different initial technology intensities per country income group. Crucially, we have considered four types of technologies—CT, IT, software, and industrial robots—that have different capabilities and are used in all or a large set of industries.

According to our analysis, while skill upgrading of industries brought about by both backward and forward participation in GVCs is a common pattern in high- and lower-income countries, their effects on productivity and aggregate output and employment of industries in the two country income groups paint a picture with various nuances. In accord with the structures of economic activity and comparative advantages of the two country groups, industries of high-income countries gained from forward GVC participation in terms of output and employment and industries of lower-income countries gained in terms of output from backward GVC participation. Industries of high- and lower-income countries also gained in terms of productivity from backward and forward GVC participation, respectively.

These productivity gains, however, operated through larger employment losses than output losses. Given that all three effects were stronger in industries outside the manufacturing sector and in IT-using industries of high-income countries, we have argued that they are unlikely to represent primarily import competition effects and put forward instead as the main explanations the adoption of pertinent labour-saving technologies, which might have reduced labour costs substantially but yielded poor productivity gains, and the weak new task creation relative to task displacement. Further research along the lines of Acemoglu et al. (2014), Acemoglu and Restrepo (2019, 2022), and Autor et al. (2023) on the potential of GVCs and associated technological changes to not only save on labour costs, but to be primarily output- and productivity enhancing and strong new task generators in industries of high-income countries would be more than welcome and could inform economic policy further. Regarding the productivity gains and employment losses of industries in lower-income countries, we have interpreted these as reflecting the adoption of labour-saving technologies associated with forward GVC participation. As for the output losses, these are explained by inconsistencies that we have documented between sectors' forward GVC participation and output trends. The fact that this effect is insignificant in non-manufacturing industries, where these inconsistencies are less pronounced, lends extra support to this interpretation and also likely points to the failure of non-manufacturing industries, particularly those in the primary and personal and professional service sectors, to adopt output-enhancing technologies. The micro- and macro-level factors hindering some industries and sectors in lower-income countries to adopt output- and productivity-enhancing technologies, despite being disproportionately involved in GVCs, are of great relevance to the growth and development prospects of these countries and merit an in-depth investigation.

Equally importantly, additional evidence reveals the mitigating role played by the utilisation of

CT, IT, software, robots, and R&D for the aforementioned productivity gains, employment losses, and skill upgrading of industries in high- and lower-income countries. This evidence suggests that more technology-, automation-, and innovation-intensive industries may enjoy lower productivity gains from backward and forward GVC participation, but this is because of the greater complementarities between their relatively skilled labour and these activities and the labour-saving and other technologies they are associated with.

In conclusion, although our analysis highlights some clear benefits from GVC participation and the adoption of associated technologies for industries in both high- and lower-income countries, it also highlights some key challenges facing primarily less technology- and innovation-intensive industries in countries of either group. Further research in the direction indicated by Aghion et al. (2019) is likely to be particularly useful.

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Appendix

A Classifications

A.1 Classification of industries

Table A.1: Industries

ISIC Rev. 3.1	Industry Name	Sector Name
AtB	Agriculture, Hunting, Forestry and Fishing	Primary
C	Mining and Quarrying	Primary
15t16	Food, Beverages and Tobacco	Manufacturing
17t18	Textiles and Textile Products	Manufacturing
19	Leather, Leather and Footwear	Manufacturing
20	Wood and Products of Wood and Cork	Manufacturing
21t22	Pulp, Paper, Paper , Printing and Publishing	Manufacturing
23	Coke, Refined Petroleum and Nuclear Fuel	Manufacturing
24	Chemicals and Chemical Products	Manufacturing
25	Rubber and Plastics	Manufacturing
26	Other Non-Metallic Mineral	Manufacturing
27t28	Basic Metals and Fabricated Metal	Manufacturing
29	Machinery, Nec	Manufacturing
30t33	Electrical and Optical Equipment	Manufacturing
34t35	Transport Equipment	Manufacturing
36t37	Manufacturing, Nec; Recycling	Manufacturing
E	Electricity, Gas and Water Supply	Utilities
F	Construction	Construction
50	Sale, Maintenance and Repair of Motor-vehicles & -cycles; Retail Sale of Fuel	Market services
51	Wholesale Trade and Commission Trade, Except of Motor-vehicles & -cycles	Market services
52	Retail Trade, Except of Motor-vehicles & -cycles; Repair of Household Goods	Market services
H	Hotels and Restaurants	Market services
60	Inland Transport	Market services
61	Water Transport	Market services
62	Air Transport	Market services
63	Other Supporting and Aux. Transport Activities; Activities of Travel Agencies	Market services
64	Post and Telecommunications	Market services
J	Financial Intermediation	Market services
70	Real Estate Activities	Market services
71t74	Renting of M&Eq and Other Business Activities	Market services
L	Public Admin and Defence; Compulsory Social Security	Pers. & prof. services
M	Education	Pers. & prof. services
N	Health and Social Work	Pers. & prof. services
O	Other Community, Social and Personal Services	Pers. & prof. services
P	Private Households with Employed Persons	Pers. & prof. services

Source: ADB MRIO Tables and ILO Harmonized Microdata.

A.2 Classification of countries by income

To classify countries as high- or lower-income in the initial sample year (2000), we rely on the World Bank's Historical Country Classification by Income. Of the 62 countries examined, 29 are classified as high-income. The rest, classified as upper-middle, lower-middle-, or low-income, form the lower-income group. The list of countries with high-income (HI) status in 2000 comprises Australia, Austria, Belgium, Brunei Darussalam, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Korea, Luxembourg, Malta, Netherlands, Norway, Portugal, Singapore, Slovenia, Spain, Sweden, Switzerland, Taiwan, United Kingdom, United States of America. The list of countries with lower-income (LMI) status in 2000 comprises Bangladesh, Bhutan, Brazil, Bulgaria, Cambodia, China, Croatia, Czech Republic, Estonia, Fiji, Hungary, India, Indonesia, Kazakhstan, Kyrgyzstan, Lao PDR, Latvia, Lithuania, Malaysia, Maldives, Mexico, Mongolia, Nepal, Pakistan, Philippines, Poland, Romania, Russian Federation, Slovakia, Sri Lanka, Thailand, Turkey, Viet Nam.

B Calculation of descriptive statistics for the main variables

The main variables in our analysis are the backward and forward GVC participation measures, labour productivity and its components (value added and total employment), and the employment shares of the high-skilled, the young, and women. As these variables vary by country, industry and year, we produce statistics for these for the whole sample, by country, and by industry emulating the relevant methodologies implemented by Graetz and Michaels (2018). The description of these methodologies can also be found in Blanas (2023, 2024). In line with these methodologies, we also calculate in this paper statistics for the main variables by country income group (high- and lower-income countries), by sector (primary, manufacturing, utilities and construction, market services, personal and professional services), and by country income group and sector.

Calculation of mean levels for the whole sample by year We first average the main variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by year without using country weights.

Calculation of mean levels by country and year: We average the main variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000.

Calculation of mean levels by industry and year: We average the main variables across countries by industry and year without using country weights.

Calculation of mean levels by country income group and year: We first average the main variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and year without using country weights.

Calculation of mean levels by sector and year: We first average the main variables across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector and year without using country weights.

Calculation of mean levels by country income group, sector and year: We first average the main variables across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group, sector and year without using country weights.

Calculation of mean percentage changes between the start and end years for the whole sample: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. In the second step, we average the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries without using country weights.

Calculation of mean percentage changes between the start and end years by country: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. Then, we calculate the weighted averages of the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000.

Calculation of mean percentage changes between the start and end years by industry: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. Then, we average the percentage changes across countries by industry without using country weights.

Calculation of mean percentage changes between the start and end years by country income group: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. In the second step, we average the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group without using country weights.

Calculation of mean percentage changes between the start and end years by sector: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. In the second step, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector without using country weights.

Calculation of mean percentage changes between the start and end years by country income group and sector: We first calculate the percentage changes of the main variables between 2000 and 2019 by country-industry pair. In the second step, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and sector without using country weights.

C Additional descriptive statistics

Table C.1: Technology variables by industry

	1985			2000			1993
Industry	CT	IT	S/W	CT	IT	S/W	ROBOTS
15t16	0.006	0.002	0.005	0.024	0.068	0.063	0.34
17t18	0.006	0.001	0.003	0.010	0.031	0.031	0.12
19	0.006	0.001	0.003	0.010	0.031	0.031	–
20	0.001	0.001	0.002	0.010	0.034	0.028	0.77
21t22	0.004	0.002	0.006	0.034	0.077	0.086	0.06
23	0.004	0.002	0.013	0.019	0.074	0.088	–
24	0.007	0.002	0.007	0.017	0.093	0.102	1.16
25	0.003	0.001	0.004	0.005	0.023	0.026	–
26	0.011	0.005	0.011	0.018	0.048	0.052	0.34
27t28	0.009	0.003	0.007	0.011	0.042	0.045	2.37
29	0.020	0.004	0.012	0.032	0.128	0.186	–
30t33	0.114	0.023	0.070	0.006	0.021	0.033	0.95
34t35	0.008	0.004	0.013	0.023	0.064	0.115	5.36
36t37	0.007	0.003	0.005	0.017	0.069	0.065	–
50	0.011	0.003	0.003	0.029	0.052	0.021	–
51	0.024	0.009	0.006	0.041	0.083	0.025	–
52	0.012	0.003	0.004	0.031	0.053	0.023	–
60	0.084	0.001	0.003	0.408	0.115	0.091	–
61	0.084	0.001	0.003	0.408	0.115	0.091	–
62	0.084	0.001	0.003	0.408	0.115	0.091	–
63	0.084	0.001	0.003	0.408	0.115	0.091	–
64	0.638	0.002	0.007	0.982	0.224	0.138	–
70	0.004	0.000	0.000	0.008	0.010	0.005	–
71t74	0.008	0.005	0.014	0.069	0.267	0.129	–
AtB	0.001	0.000	0.000	0.005	0.012	0.006	0.01
C	0.065	0.009	0.027	0.044	0.129	0.154	0.07
E	0.066	0.005	0.014	0.040	0.061	0.079	–
F	0.000	0.000	0.000	0.039	0.036	0.055	0.01
H	0.006	0.001	0.001	0.019	0.021	0.015	–
J	0.010	0.007	0.017	0.036	0.312	0.094	–
L	0.006	0.001	0.007	0.034	0.063	0.098	–
M	0.005	0.001	0.005	0.031	0.081	0.105	0.02
N	0.006	0.001	0.002	0.030	0.052	0.043	–
O	0.014	0.001	0.002	0.038	0.042	0.023	–

Notes: CT, IT, S/W: Ratios of real stocks of communication technology, information technology, and software capital to real gross value added for the US in 1985 or 2000. ROBOTS: Unweighted averages of ratios of stocks of robots in units to hours worked in millions across a set of countries (Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, South Korea, Spain, Sweden, UK, and US) by industry in 1993, as calculated by Graetz and Michaels (2018).
Source: Columns (2)–(7): Authors' calculations based on the EU KLEMS March 2011 release and ADB MRIO Tables. Column (8): Calculations of Graetz and Michaels (2018) based on the IFR database and the EU KLEMS March 2011 release.

Table C.2: Backward and forward GVC participation by country income group or by country

Panel A: By country income group				
Country	Mean level 2000		Mean % ch. 2000–2019	
	GVC_b	GVC_f	GVC_b	GVC_f
High-income (HI)	0.164	0.147	38.121	116.624
Lower-income (LMI)	0.143	0.132	27.710	101.521

Panel B: By country				
Country	Mean level 2000		Mean % ch. 2000–2019	
	GVC_b	GVC_f	GVC_b	GVC_f
Australia	0.110	0.121	7.813	13.545
Austria	0.157	0.167	57.585	51.724
Bangladesh	0.049	0.019	84.265	-0.718
Belgium	0.206	0.215	50.724	68.255
Bhutan	0.066	0.052	61.828	0.223
Brazil	0.059	0.061	42.446	175.530
Brunei Darussalam	0.231	0.084	48.846	694.683
Bulgaria	0.187	0.069	26.047	465.250
Cambodia	0.134	0.069	41.699	533.952
Canada	0.138	0.163	11.834	-3.988
China	0.080	0.055	-4.547	36.640
Croatia	0.171	0.167	24.831	97.025
Cyprus	0.172	0.116	61.142	330.226
Czech Republic	0.207	0.206	18.665	37.522
Denmark	0.155	0.129	48.132	95.031
Estonia	0.252	0.177	10.784	131.600
Fiji	0.102	0.164	94.536	169.085
Finland	0.140	0.165	44.816	5.552
France	0.112	0.111	50.738	34.282
Germany	0.118	0.123	27.122	124.509
Greece	0.108	0.060	63.630	208.429
Hong Kong	0.179	0.161	-1.523	77.394
Hungary	0.260	0.160	1.324	82.309
India	0.049	0.045	34.525	18.889
Indonesia	0.104	0.133	-37.342	0.726
Ireland	0.257	0.236	60.428	16.148
Italy	0.109	0.097	27.811	86.275
Japan	0.050	0.045	95.718	72.584
Kazakhstan	0.158	0.217	-40.920	-27.177
Republic of Korea	0.135	0.118	43.373	48.129
Kyrgyzstan	0.127	0.196	139.242	55.267
Lao PDR	0.066	0.180	15.789	119.216
Latvia	0.187	0.153	25.530	211.954
Lithuania	0.129	0.112	120.226	236.891
Luxembourg	0.279	0.319	59.754	45.107
Malaysia	0.309	0.387	-26.104	-29.039
Maldives	0.197	0.240	11.895	57.171
Malta	0.317	0.187	30.973	285.696
Mexico	0.104	0.063	23.467	98.754
Mongolia	0.199	0.145	10.217	141.637
Nepal	0.091	0.051	15.880	-18.508
Netherlands	0.162	0.192	50.894	79.463
Norway	0.123	0.150	37.312	-8.214
Pakistan	0.058	0.062	42.746	-21.584
Philippines	0.116	0.085	-17.840	19.136
Poland	0.161	0.113	23.490	102.227
Portugal	0.160	0.067	16.173	303.071
Romania	0.162	0.137	23.466	145.288
Russian Federation	0.094	0.187	18.534	21.723
Singapore	0.292	0.309	20.534	21.687
Slovakia	0.215	0.130	22.427	190.023
Slovenia	0.208	0.148	47.679	262.206
Spain	0.136	0.096	-1.329	110.016
Sri Lanka	0.173	0.144	-33.517	0.499
Sweden	0.147	0.159	7.251	43.538
Switzerland	0.151	0.169	54.375	45.365
Taiwan (Province of China)	0.206	0.175	17.516	93.317
Thailand	0.186	0.168	1.061	165.965
Turkey	0.105	0.076	20.949	49.085
United Kingdom	0.114	0.114	50.122	58.183
United States of America	0.055	0.043	21.328	51.394
Viet Nam	0.172	0.138	103.179	137.037
Unweighted mean	0.152	0.139	32.412	108.342

Notes: GVC_b and GVC_f denote backward and forward GVC participation, respectively. For the calculation of the means of GVC variables by country income group and year in Panel A, we first average these variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and year without using country weights. For the calculation of the mean percentage changes of the GVC variables by country income group in Panel A, we first average the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group without using country weights. For the calculation of the means of GVC variables by country and year in Panel B, we average these variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. For the calculation of the mean percentage changes of the GVC variables by country in Panel B, we calculate the weighted averages of the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ADB MRIO Tables.

Table C.3: Backward and forward GVC participation by sector or by industry

Panel A: By sector

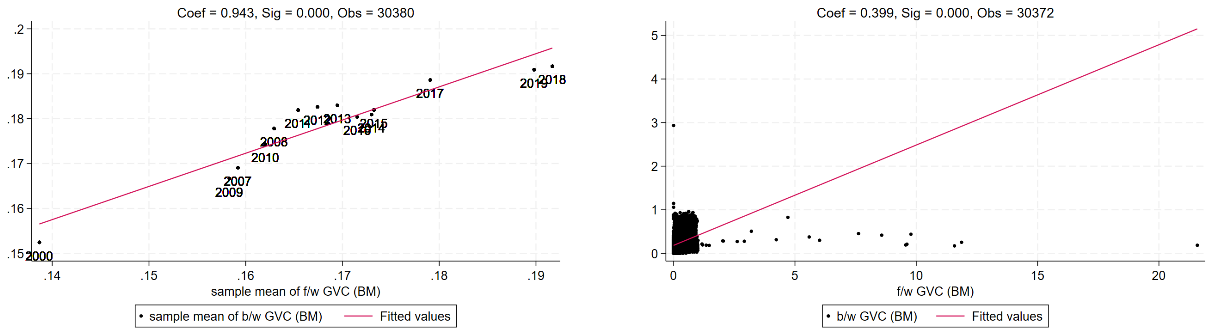
Sector	Mean level 2000		Mean % ch. 2000–2019	
	GVC_b	GVC_f	GVC_b	GVC_f
Primary	0.150	0.168	42.187	96.949
Manufacturing	0.275	0.252	29.349	62.829
Utilities & Construction	0.227	0.063	53.799	128.765
Market services	0.140	0.176	31.096	55.396
Personal and professional services	0.095	0.038	19.037	190.030

Panel B: By industry

Industry	Mean level 2000		Mean % ch. 2000–2019	
	GVC_b	GVC_f	GVC_b	GVC_f
15t16	0.216	0.095	34.558	105.986
17t18	0.276	0.209	25.966	51.355
19	0.264	0.172	42.793	201.074
20	0.241	0.353	21.658	48.976
21t22	0.244	0.284	33.208	49.086
23	0.410	0.301	31.995	67.369
24	0.297	0.364	27.064	58.807
25	0.329	0.349	22.859	59.579
26	0.243	0.255	31.120	91.792
27t28	0.316	0.411	37.097	39.579
29	0.303	0.243	28.770	22.241
30t33	0.335	0.293	27.433	42.174
34t35	0.345	0.201	34.082	40.467
36t37	0.271	0.131	23.771	106.169
50	0.170	0.158	22.747	50.104
51	0.129	0.235	27.489	31.819
52	0.102	0.143	29.792	49.692
60	0.185	0.228	39.501	45.552
61	0.257	0.440	47.375	28.385
62	0.281	0.319	61.412	45.671
63	0.170	0.306	41.021	48.331
64	0.142	0.150	60.641	75.119
70	0.062	0.054	35.036	98.969
71t74	0.136	0.219	32.193	85.710
AtB	0.151	0.144	40.657	98.939
C	0.176	0.397	43.381	47.377
E	0.216	0.179	126.737	54.235
F	0.232	0.043	22.304	136.661
H	0.154	0.086	28.028	87.241
J	0.115	0.178	31.616	40.753
L	0.104	0.038	10.825	266.971
M	0.066	0.017	22.051	229.651
N	0.122	0.015	19.178	157.102
O	0.136	0.114	30.921	65.566
P	0.007	0.009	-66.020	497.272

Notes: GVC_b and GVC_f denote backward and forward GVC participation, respectively. For the calculation of the means of GVC variables by sector and year in Panel A, we first average these variables across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector and year without using country weights. For the calculation of the mean percentage changes of the GVC variables by sector in Panel A, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector without using country weights. For the calculation of the means of GVC variables by industry and year in Panel B, we average these across countries by industry and year without using country weights. For the calculation of the mean percentage changes of GVC variables by industry in Panel B, we average the percentage changes across countries by industry without using country weights. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ADB MRIO Tables.

Figure C.1: Correlation between backward and forward GVC participation



(a) Yearly sample means (b) Country-industry-year variation

Notes: GVC_b and GVC_f denote backward and forward GVC participation, respectively. Panel (a) displays the raw correlation of the yearly sample means of backward and forward GVC participation measures. For the calculation of the sample means of GVC variables by year, we first average these across industries within each country and year using as weights each industry's employment in economy-wide employment in 2000. Then, we average across countries by year without using country weights. Panel (b) displays the raw correlation of backward and forward GVC participation measures that vary by country-industry-year cell.
Source: Authors' calculations based on ADB MRIO Tables.

Table C.4: Labour productivity and its decomposition by country income group or by country

Panel A: By country income group

Country income group	Mean level 2000 LP	Mean level 2000 VA	Mean level 2000 E	Mean % ch. 2000–2019 LP	Mean % ch. 2000–2019 VA	Mean % ch. 2000–2019 E
High-income (HI)	81.763	6.2e+04	923.846	38.323	52.012	22.552
Lower-income (LMI)	12.069	2.3e+04	1.3e+04	113.404	147.394	31.583

Panel B: By country

Country	Mean level 2000 LP	Mean level 2000 VA	Mean level 2000 E	Mean % ch. 2000–2019 LP	Mean % ch. 2000–2019 VA	Mean % ch. 2000–2019 E
Australia	103.148	4.5e+04	562.586	17.771	58.530	43.120
Austria	79.827	1.4e+04	199.987	25.893	36.614	19.675
Bangladesh	1.355	9151.045	1.8e+04	114.464	176.594	44.939
Belgium	88.828	2.0e+04	260.667	23.053	32.072	19.000
Bhutan	2.966	167.865	122.326	79.255	149.331	41.782
Brazil	20.322	5.9e+04	5242.778	37.802	51.853	31.360
Brunei Darussalam	77.860	644.640	19.436	110.700	123.386	36.231
Bulgaria	10.629	1360.605	169.523	66.140	78.034	14.114
Cambodia	0.931	1811.762	3023.148	95.052	152.851	66.359
Canada	86.549	6.0e+04	959.366	34.663	60.724	28.825
China	3.270	2.5e+05	1.9e+05	268.386	269.897	7.854
Croatia	27.064	1801.997	100.410	69.882	47.904	7.990
Cyprus	38.325	854.540	24.856	28.668	69.561	39.301
Czech Republic	32.076	6465.354	222.758	89.554	95.966	13.105
Denmark	98.481	1.5e+04	191.942	24.530	21.190	4.850
Estonia	23.070	563.547	28.899	77.567	78.469	14.396
Fiji	8.014	132.798	26.937	152.375	144.282	15.922
Finland	81.055	9887.326	138.140	57.267	49.358	11.831
France	87.352	1.2e+05	1357.899	28.603	30.734	13.507
Germany	77.949	1.4e+05	2006.597	11.047	25.520	18.886
Greece	51.936	1.0e+04	320.431	27.889	-0.419	-11.281
Hong Kong, China	47.874	7117.990	216.666	91.851	84.576	20.947
Hungary	25.915	4324.461	199.284	32.684	44.912	16.092
India	2.385	1.5e+05	1.4e+05	117.772	150.193	22.737
Indonesia	5.499	4.8e+04	2.2e+04	90.140	138.634	40.708
Ireland	98.646	7864.141	105.285	38.208	54.958	28.332
Italy	90.200	8.5e+04	1091.585	-0.127	2.540	13.280
Japan	79.131	2.4e+05	4476.331	28.812	23.074	4.009
Kazakhstan	9.856	3673.514	1087.947	162.762	188.504	31.661
Republic of Korea	28.764	2.9e+04	1344.431	77.692	92.300	23.090
Kyrgyzstan	2.030	553.589	578.623	121.925	107.100	23.382
Lao PDR	1.326	1278.624	1600.718	21.662	100.192	56.552
Latvia	16.635	736.112	62.345	126.941	94.872	-3.014
Lithuania	15.694	1066.678	110.516	148.432	106.870	-3.910
Luxembourg	234.618	2850.799	12.483	9.333	46.872	61.198
Malaysia	17.928	8666.668	738.864	114.236	189.869	63.576
Maldives	12.155	93.223	7.759	198.575	498.016	158.255
Malta	46.621	288.496	7.467	23.202	86.989	52.301
Mexico	21.204	3.6e+04	3083.095	17.075	62.777	45.597
Mongolia	3.732	501.634	227.209	177.982	295.135	44.038
Nepal	0.840	2792.311	6329.509	109.962	147.301	37.117
Netherlands	82.668	4.1e+04	565.205	31.569	39.263	12.180
Norway	148.715	1.6e+04	170.291	49.312	59.645	18.036
Pakistan	2.723	1.6e+04	9534.622	41.654	117.345	66.948
Philippines	5.045	1.1e+04	4887.272	52.527	133.975	54.112
Poland	19.413	1.4e+04	1054.428	109.968	142.120	18.451
Portugal	39.220	9405.704	319.041	40.857	12.311	-2.788
Romania	11.521	6165.752	2385.688	223.881	106.666	-19.826
Russian Federation	13.082	3.7e+04	4139.432	63.760	58.392	8.339
Singapore	59.153	5438.846	121.802	84.765	156.350	67.683
Slovakia	27.776	2643.109	104.599	186.949	212.202	23.682
Slovenia	35.300	1294.780	43.453	68.858	64.026	9.445
Spain	68.876	5.6e+04	888.658	7.066	25.335	25.437
Sri Lanka	5.250	3013.011	1228.632	393.057	456.546	12.513
Sweden	79.048	2.0e+04	302.813	68.727	67.532	16.178
Switzerland	124.940	2.4e+04	229.002	22.161	39.247	23.274
Taiwan, China	30.481	1.2e+04	534.282	57.942	99.766	21.979
Thailand	6.138	1.8e+04	9591.740	50.719	61.282	13.428
Turkey	24.226	3.5e+04	3217.968	94.561	145.835	40.763
United Kingdom	61.116	9.5e+04	1744.170	36.969	50.036	21.257
United States	91.454	6.8e+05	8997.256	23.455	36.559	14.751
Viet Nam	1.521	9478.407	1.7e+04	70.338	115.177	41.715
Unweighted mean	43.544	4.0e+04	7635.459	79.496	104.318	27.504

Notes: LP denotes labour productivity (ratio of real gross value added to total employment) and is measured in thousands of USD per worker. VA denotes total real gross value added and is measured in millions of USD. E denotes total employment and is measured in thousands of workers. For the calculation of the means of variables by country income group and year in Panel A, we first average these across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and year without using country weights. For the calculation of the mean percentage changes of these variables by country income group in Panel A, we first average the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group without using country weights. For the calculation of the means of variables by country and year in Panel B, we average these variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. For the calculation of the mean percentage changes of these variables by country in Panel B, we calculate the weighted averages of the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ILO Harmonized Microdata and ADB MRIO Tables.

Table C.5: Labour productivity and its decomposition by sector or by industry

Panel A: By sector

Sector	Mean level 2000			Mean % ch. 2000–2019		
	LP	VA	E	LP	VA	E
Primary	52.034	2.7e+04	1.3e+04	95.780	36.758	-20.556
Manufacturing	37.102	1.0e+04	780.573	172.614	188.305	23.335
Utilities & Construction	47.165	5.0e+04	1507.619	17.008	113.726	87.399
Market services	56.330	4.0e+04	1908.236	85.043	186.227	73.296
Personal and professional services	34.264	3.7e+04	1365.664	36.223	92.308	45.574

Panel B: By industry

Industry	Mean level 2000			Mean % ch. 2000–2019		
	LP	VA	E	LP	VA	E
15t16	34.468	1.4e+04	893.776	175.454	211.125	26.182
17t18	25.248	6204.992	1288.628	127.306	75.709	-7.664
19	16.344	1139.679	207.636	113.261	46.270	3.920
20	20.009	2251.544	302.484	198.341	161.091	-4.072
21t22	74.138	9464.710	188.921	208.191	190.268	13.889
23	132.113	2999.718	27.585	515.878	312.003	5.584
24	68.022	1.1e+04	208.271	169.837	230.241	33.059
25	35.248	4587.602	177.348	199.484	246.339	59.552
26	349.014	4595.000	346.196	189.110	190.375	19.920
27t28	33.874	1.3e+04	449.589	146.586	204.154	47.721
29	52.871	1.0e+04	238.728	299.907	163.888	12.812
30t33	49.162	1.6e+04	306.696	101.355	148.560	46.025
34t35	33.722	1.1e+04	225.976	227.934	382.869	77.466
36t37	23.151	5295.649	468.363	87.234	166.872	57.216
50	30.014	1.2e+04	396.707	220.454	338.714	53.726
51	100.656	4.5e+04	492.039	42.466	135.698	82.901
52	20.711	3.7e+04	3142.961	94.059	170.252	46.720
60	34.948	1.7e+04	1016.337	78.082	160.096	49.616
61	78.627	2144.243	42.997	183.854	137.730	14.906
62	69.051	2677.769	44.466	352.200	324.507	19.637
63	69.777	5944.928	130.426	105.892	371.901	202.775
64	69.258	1.4e+04	239.844	70.634	156.415	54.154
70	1123.328	7.4e+04	136.913	-12.909	92.277	229.896
71t74	61.483	8.0e+04	925.297	-10.526	175.572	227.714
AtB	15.881	3.0e+04	1.3e+04	96.235	36.274	-24.121
C	228.098	2.2e+04	179.937	192.768	218.357	16.918
E	109.637	1.5e+04	227.434	39.454	151.650	115.144
F	41.467	5.6e+04	1657.715	13.990	117.549	89.771
H	26.096	2.0e+04	891.363	50.637	204.661	124.355
J	108.570	4.6e+04	437.138	47.422	162.240	137.841
L	50.986	6.6e+04	1366.676	44.436	83.731	31.143
M	31.997	2.7e+04	1415.439	25.461	90.890	52.317
N	30.144	3.9e+04	1149.818	30.269	127.438	82.988
O	43.811	3.0e+04	1043.950	30.005	88.902	54.446
P	115.167	3367.573	452.661	45.715	79.645	47.324

Notes: LP denotes labour productivity (ratio of real gross value added to total employment) and is measured in thousands of USD per worker. VA denotes total real gross value added and is measured in millions of USD. E denotes total employment and is measured in thousands of workers. For the calculation of the means of variables by sector and year in Panel A, we first average these across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector and year without using country weights. For the calculation of the mean percentage changes of these variables by sector in Panel A, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector without using country weights. For the calculation of the means of variables by industry and year in Panel B, we average these across countries by industry and year without using country weights. For the calculation of the mean percentage changes of these variables by industry in Panel B, we average the percentage changes across countries by industry without using country weights. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ILO Harmonized Microdata and ADB MRIO Tables.

Table C.6: Employment and value added shares of sectors by country income group

Country income group	Sector	Mean level 2000		Mean % ch. 2000–2019	
		Esh	VAsh	Esh	VAsh
High-income (HI)	Primary	0.054	0.057	-35.460	-18.019
High-income (HI)	Manufacturing	0.180	0.143	-35.878	8.338
High-income (HI)	Utilities & Construction	0.086	0.087	-2.424	-20.424
High-income (HI)	Market services	0.388	0.484	14.270	10.231
High-income (HI)	Pers. & prof. services	0.292	0.229	13.768	-4.303
Lower-income (LMI)	Primary	0.359	0.183	-40.511	-28.676
Lower-income (LMI)	Manufacturing	0.150	0.159	20.566	55.594
Lower-income (LMI)	Utilities & Construction	0.062	0.101	76.027	2.810
Lower-income (LMI)	Market services	0.243	0.388	52.017	21.846
Lower-income (LMI)	Pers. & prof. services	0.186	0.168	14.779	-6.279

Notes: Esh and VAsh denote shares of employment and value added, respectively, of a sector in economy-wide employment. For the calculation of the means of variables by country income group, I average these across countries by country income group without using country weights.
Source: Authors' calculations based on ILO Harmonized Microdata and ADB MRIO Tables.

Table C.7: Employment shares by country income group or by country

Panel A: By country income group

Country	Mean level 2000 Esh^{HS}	Mean level 2000 Esh^{Y}	Mean level 2000 Esh^{F}	Mean % ch. 2000–2019 Esh^{HS}	Mean % ch. 2000–2019 Esh^{Y}	Mean % ch. 2000–2019 Esh^{F}
High-income (HI)	0.350	0.132	0.422	46.651	-26.429	10.014
Lower-income (LMI)	0.198	0.184	0.412	90.332	-38.222	11.406

Panel B: By country

Country	Mean level 2000 Esh^{HS}	Mean level 2000 Esh^{Y}	Mean level 2000 Esh^{F}	Mean % ch. 2000–2019 Esh^{HS}	Mean % ch. 2000–2019 Esh^{Y}	Mean % ch. 2000–2019 Esh^{F}
Australia	0.387	0.178	0.438	10.704	-17.185	11.774
Austria	0.378	0.133	0.438	4.350	-9.858	9.372
Bangladesh	0.050	0.259	0.235	6.843	-43.422	74.171
Belgium	0.382	0.090	0.422	34.477	-21.406	16.861
Bhutan	0.074	0.245	0.420	95.142	-58.465	9.698
Brazil	0.217	0.238	0.387	-16.897	-38.738	10.065
Brunei Darussalam	0.228	0.170	0.401	106.475	-43.961	15.906
Bulgaria	0.347	0.081	0.462	-22.675	-48.709	1.950
Cambodia	0.041	0.288	0.514	163.143	-32.192	7.617
Canada	0.396	0.154	0.460	12.950	-13.999	5.352
China	0.171	0.177	0.452	-18.021	-45.109	1.952
Croatia	0.291	0.090	0.448	25.075	-19.773	-1.330
Cyprus	0.270	0.143	0.392	78.188	-33.898	18.554
Czech Republic	0.312	0.123	0.436	19.077	-58.400	-2.146
Denmark	0.393	0.151	0.466	25.581	-8.297	-2.606
Estonia	0.367	0.101	0.496	24.850	-28.048	12.337
Fiji	0.175	0.212	0.314	96.335	-35.366	28.611
Finland	0.377	0.101	0.471	28.562	6.184	0.828
France	0.391	0.091	0.449	158.087	-6.570	3.606
Germany	0.388	0.115	0.439	12.944	-14.154	3.124
Greece	0.233	0.102	0.364	136.349	-64.975	27.638
Hong Kong, China	0.301	0.116	0.419	47.448	-43.705	22.918
Hungary	0.322	0.127	0.451	3.287	-50.203	3.608
India	0.079	0.205	0.256	468.441	-46.082	0.372
Indonesia	0.073	0.196	0.381	-10.790	-26.920	2.690
Ireland	0.295	0.235	0.407	48.740	-51.467	12.320
Italy	0.337	0.082	0.369	15.031	-48.641	7.527
Japan	0.241	0.106	0.405	19.102	-21.438	5.217
Kazakhstan	0.212	0.167	0.481	46.639	-39.920	1.772
Republic of Korea	0.308	0.099	0.407	-1.416	-49.806	4.445
Kyrgyzstan	0.185	0.211	0.438	-58.834	-32.620	0.068
Lao PDR	0.048	0.303	0.501	1051.641	-18.422	4.269
Latvia	0.319	0.108	0.486	30.410	-48.269	2.171
Lithuania	0.299	0.093	0.509	75.107	-28.131	0.591
Luxembourg	0.398	0.086	0.394	250.769	-13.523	22.426
Malaysia	0.220	0.189	0.357	1.466	-22.724	10.915
Maldives	0.253	0.254	0.339	50.380	-40.088	-30.381
Malta	0.338	0.208	0.303	38.968	-46.268	44.756
Mexico	0.177	0.254	0.335	3.530	-32.727	14.159
Mongolia	0.196	0.210	0.469	-20.432	-46.603	28.066
Nepal	0.101	0.310	0.489	602.456	-6.816	27.024
Netherlands	0.446	0.161	0.430	8.231	-8.321	3.531
Norway	0.421	0.137	0.467	30.070	-10.142	3.407
Pakistan	0.112	0.265	0.155	228.648	-15.792	68.836
Philippines	0.203	0.217	0.384	14.258	-23.734	1.157
Poland	0.293	0.109	0.448	28.518	-37.108	1.373
Portugal	0.247	0.122	0.449	47.396	-50.847	7.426
Romania	0.164	0.112	0.469	28.527	-49.744	-8.862
Russian Federation	0.340	0.121	0.484	30.631	-56.923	-1.787
Singapore	0.451	0.106	0.387	32.688	-26.392	4.578
Slovakia	0.321	0.126	0.458	-2.810	-54.552	-1.162
Slovenia	0.322	0.101	0.461	17.056	-37.216	-0.998
Spain	0.261	0.120	0.365	23.340	-58.176	24.241
Sri Lanka	0.149	0.168	0.316	63.390	-53.221	62.346
Sweden	0.413	0.114	0.479	33.695	-13.896	-1.878
Switzerland	0.393	0.139	0.440	45.022	-6.438	7.131
Taiwan, China	0.269	0.135	0.397	3.878	-45.130	9.239
Thailand	0.095	0.156	0.458	-40.048	-42.244	-1.389
Turkey	0.144	0.224	0.277	87.376	-25.071	51.948
United Kingdom	0.403	0.143	0.457	30.136	-15.065	-0.560
United States	0.431	0.151	0.457	5.987	-15.221	-1.298
Viet Nam	0.058	0.221	0.488	18.045	-43.592	2.635
Unweighted mean	0.266	0.160	0.417	70.605	-32.896	10.777

Notes: Esh^{HS}, Esh^{Y}, and Esh^{F} denote employment shares of high-skilled, young, and female workers, respectively. For the calculation of the means of variables by country income group and year in Panel A, we first average these across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group and year without using country weights. For the calculation of the mean percentage changes of these variables by country income group in Panel A, we first average the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by country income group without using country weights. For the calculation of the means of variables by country and year in Panel B, we average these variables across industries by country and year using as weights the share of each industry's employment in economy-wide employment in 2000. For the calculation of the mean percentage changes of these variables by country in Panel B, we calculate the weighted averages of the percentage changes across industries by country using as weights the share of each industry's employment in economy-wide employment in 2000. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ILO Harmonized Microdata.

Table C.8: Employment shares by sector or by industry

Panel A: By sector

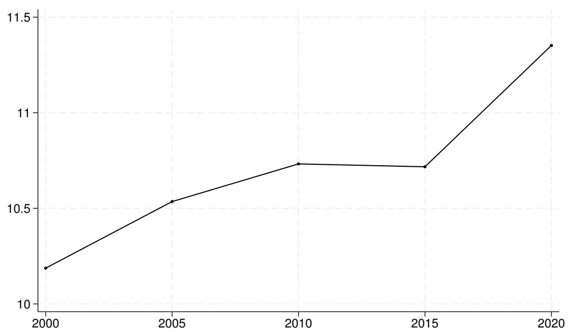
Sector	Mean level 2000			Mean % ch. 2000–2019		
	Esh^{HS}	Esh^{Y}	Esh^{F}	Esh^{HS}	Esh^{Y}	Esh^{F}
Primary	0.067	0.145	0.330	117.904	-30.099	-3.249
Manufacturing	0.179	0.181	0.363	64.402	-33.741	21.454
Utilities & Construction	0.154	0.159	0.105	91.709	-35.647	21.104
Market services	0.286	0.165	0.405	13.775	-29.419	14.324
Personal and professional services	0.509	0.125	0.544	48.559	-27.532	18.651

Panel B: By industry

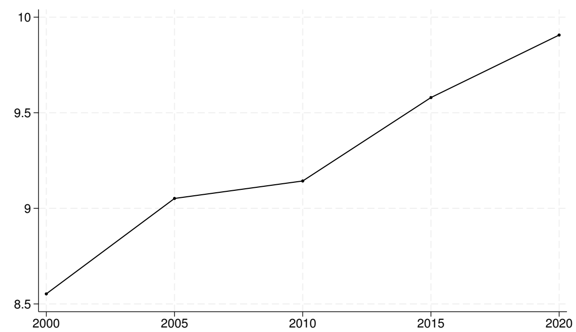
Industry	Mean level 2000			Mean % ch. 2000–2019		
	Esh^{HS}	Esh^{Y}	Esh^{F}	Esh^{HS}	Esh^{Y}	Esh^{F}
15t16	0.122	0.170	0.423	44.917	-28.128	2.094
17t18	0.108	0.183	0.679	65.360	-39.228	11.126
19	0.156	0.209	0.402	49.800	-36.478	58.921
20	0.085	0.170	0.195	68.648	-37.143	38.022
21t22	0.314	0.162	0.270	16.762	-30.643	78.404
23	0.393	0.118	0.217	61.305	-21.364	94.175
24	0.369	0.145	0.340	72.988	-28.674	47.755
25	0.174	0.190	0.300	49.581	-31.413	92.023
26	0.132	0.164	0.207	81.456	-34.597	32.375
27t28	0.135	0.167	0.160	69.124	-26.265	79.553
29	0.216	0.171	0.199	79.513	-25.511	110.851
30t33	0.332	0.209	0.362	58.408	-33.518	20.229
34t35	0.221	0.195	0.217	82.490	-31.671	116.829
36t37	0.141	0.186	0.235	83.899	-40.544	29.809
50	0.173	0.209	0.147	7.920	-34.888	44.490
51	0.405	0.143	0.339	30.815	-31.776	15.504
52	0.223	0.188	0.539	-5.411	-28.615	6.939
60	0.086	0.115	0.119	0.043	-33.927	10.958
61	0.337	0.130	0.153	22.941	-22.718	333.452
62	0.380	0.123	0.272	2.635	-16.473	313.545
63	0.195	0.159	0.250	5.531	-29.353	66.389
64	0.310	0.145	0.349	14.972	-23.572	13.129
70	0.504	0.114	0.427	38.562	-33.429	19.851
71t74	0.519	0.154	0.366	20.963	-34.616	17.918
AtB	0.057	0.144	0.340	116.411	-29.667	-5.141
C	0.182	0.145	0.158	122.926	-29.027	32.547
E	0.300	0.114	0.187	77.231	-23.812	48.217
F	0.134	0.167	0.089	85.295	-37.132	20.209
H	0.162	0.210	0.539	21.237	-17.263	3.473
J	0.453	0.138	0.501	97.280	-27.254	2.959
L	0.420	0.099	0.335	43.405	-28.619	26.545
M	0.760	0.101	0.622	5.938	-18.530	12.172
N	0.599	0.115	0.681	10.923	-24.517	9.315
O	0.319	0.172	0.478	28.989	-29.781	14.662
P	0.127	0.206	0.655	457.118	-52.814	93.754

Notes: Esh^{HS}, Esh^{Y}, and Esh^{F} denote employment shares of high-skilled, young, and female workers, respectively. For the calculation of the means of variables by sector and year in Panel A, we first average these across industries by country, sector and year using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector and year without using country weights. For the calculation of the mean percentage changes of these variables by sector in Panel A, we average the percentage changes across industries by country and sector using as weights the share of each industry's employment in economy-wide employment in 2000. Then, we average across countries by sector without using country weights. For the calculation of the means of variables by industry and year in Panel B, we average these across countries by industry and year without using country weights. For the calculation of the mean percentage changes of these variables by industry in Panel B, we average the percentage changes across countries by industry without using country weights. For the description of these calculations, see also Section B. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on ILO Harmonized Microdata.

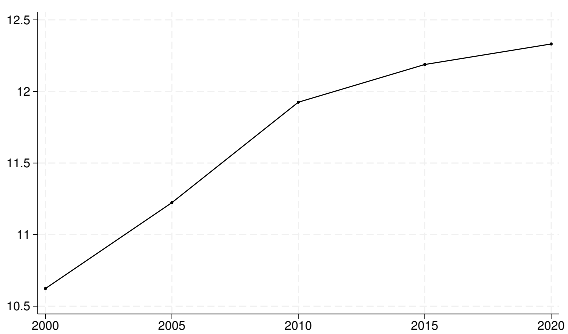
Figure C.2: Years of completed education of young and older individuals by country income group



(a) Total, 15–24 – HI countries

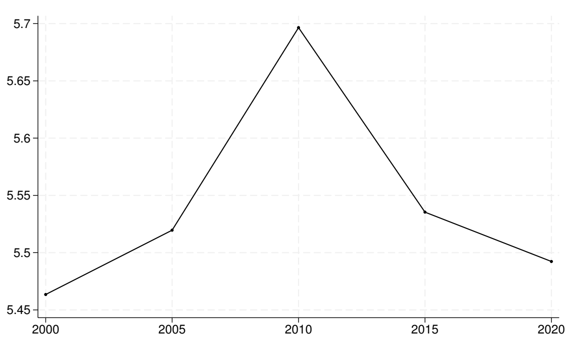


(b) Total, 15–24 – LMI countries

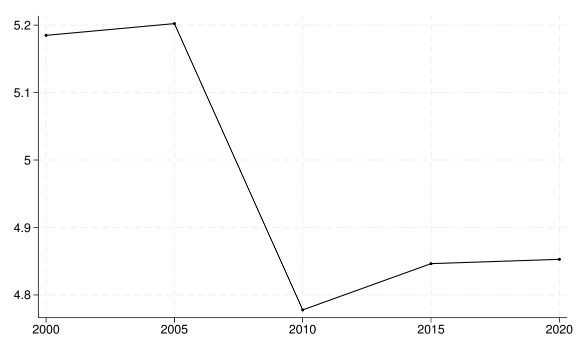


(c) Total, 25–64 – HI countries

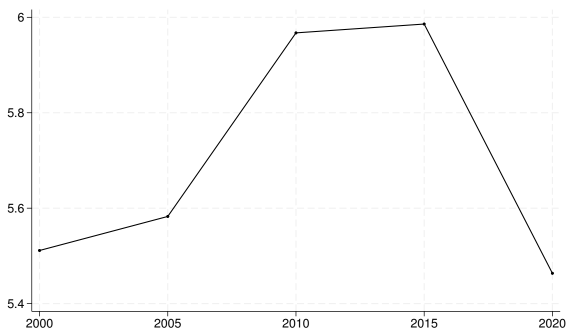
(d) Total, 25–64 – LMI countries



(e) Primary, 15–24 – HI countries

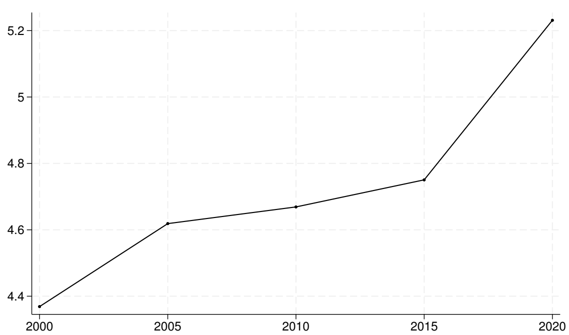


(f) Primary, 15–24 – LMI countries

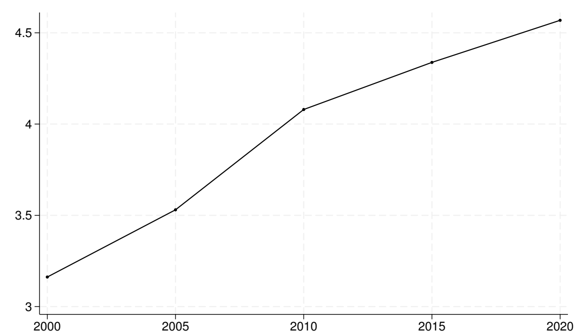


(g) Primary, 25–64 – HI countries

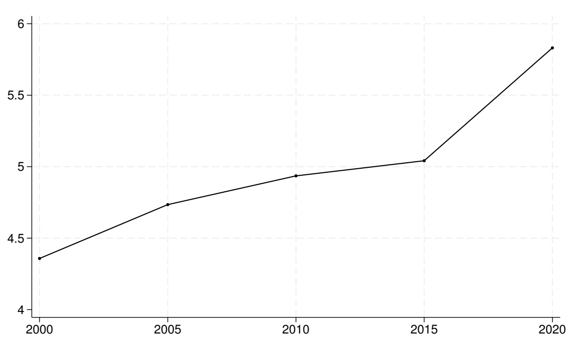
(h) Primary, 25–64 – LMI countries



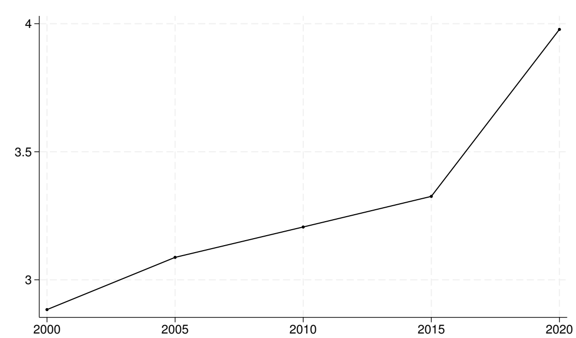
(i) Secondary, 15–24 – HI countries



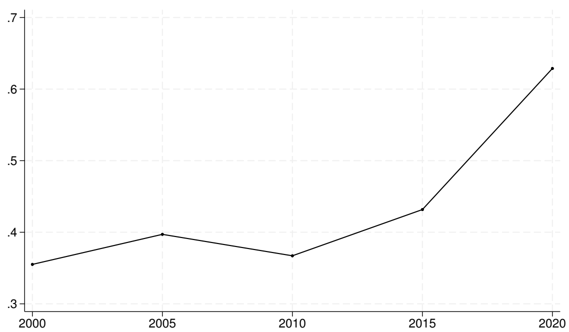
(j) Secondary, 15–24 – LMI countries



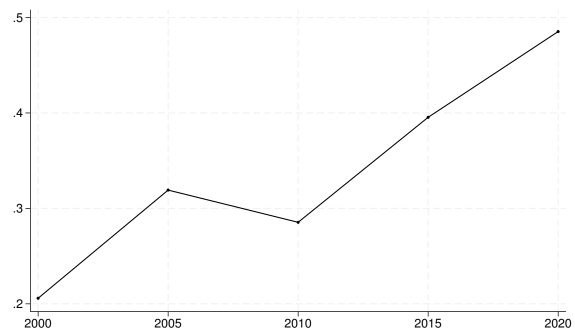
(k) Secondary, 25–64 – HI countries



(l) Secondary, 25–64 – LMI countries

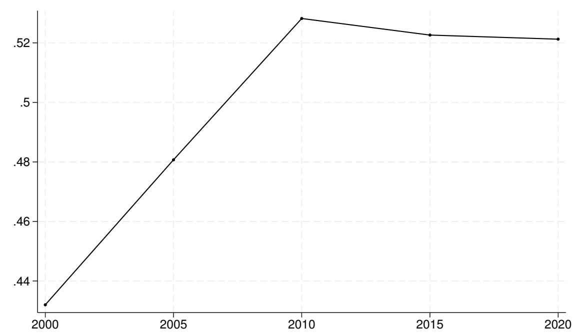


(m) Tertiary, 15–24 – HI countries



(n) Tertiary, 15–24 – LMI countries

(o) Tertiary, 25–64 – HI countries

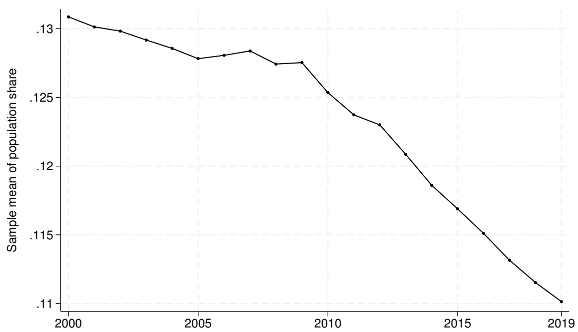


(p) Tertiary, 25–64 – LMI countries

Notes: Unweighted means of the years of completed primary, secondary, and tertiary education of individuals aged 15–24 (Panels (a)–(b), (e)–(f), and (m)–(n)) and individuals aged 25–64 (Panels (c)–(d), (g)–(h), (k)–(l), (o)–(p)) across countries by country income group and year. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.

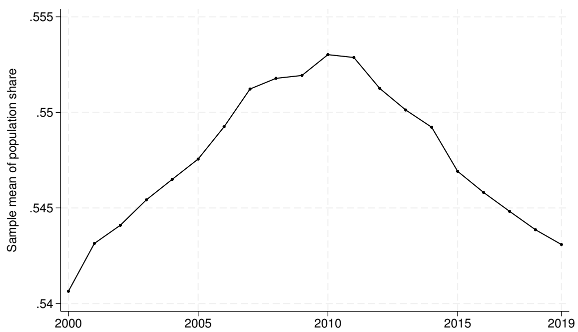
Source: Authors' calculations based on Barro and Lee (2013) and the World Bank's Historical Country Classification By Income.

Figure C.3: Share of young and older individuals in total population by country income group



(a) 15–24 – HI countries

(b) 15–24 – LMI countries

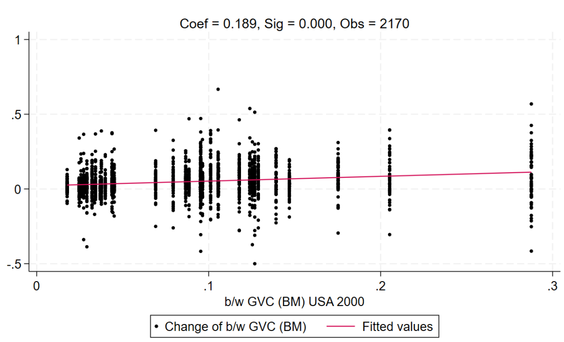


(c) 25–64 – HI countries

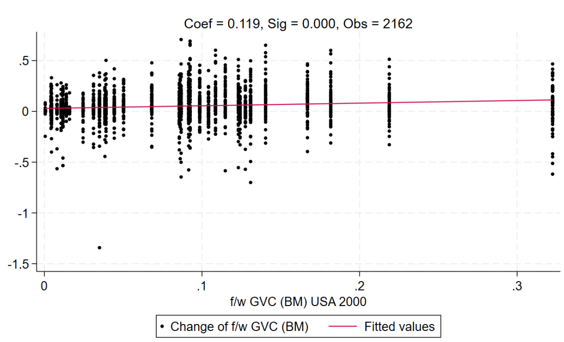
(d) 25–64 – LMI countries

Notes: Unweighted means of the shares of individuals aged 15–29 (Panels (a) and (b)) and 25–64 (Panels (c) and (d)) in total population across countries by country income group and year. Countries are classified as high-income (HI) or lower-income (LMI) according to the World Bank's Historical Country Classification By Income in 2000.
Source: Authors' calculations based on the OECD Demographics database and the World Bank's Historical Country Classification By Income.

Figure C.4: Correlations of IV–GVC–USA instruments with changes of respective key regressors



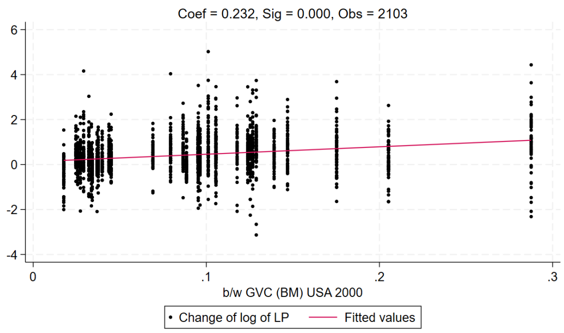
(a) ΔGVC_b – GVC$_b$ USA 2000



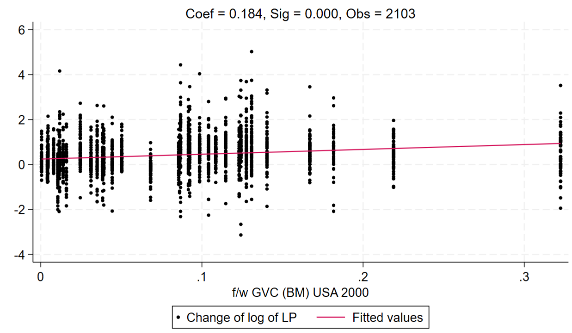
(b) ΔGVC_f – GVC$_f$ USA 2000

Notes: Raw correlations of the backward and forward GVC participation measures with the respective instruments according to IV–GVC–USA i.e., backward and forward GVC participation measures for the US in 2000.
Source: *Source*: Authors' calculations based on ADB MRIO Tables.

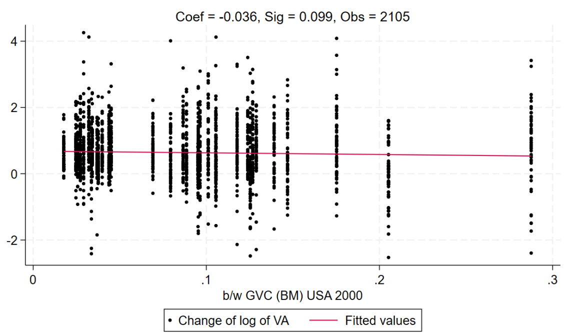
Figure C.5: Correlations of IV–GVC–USA instruments with changes of dependent variables



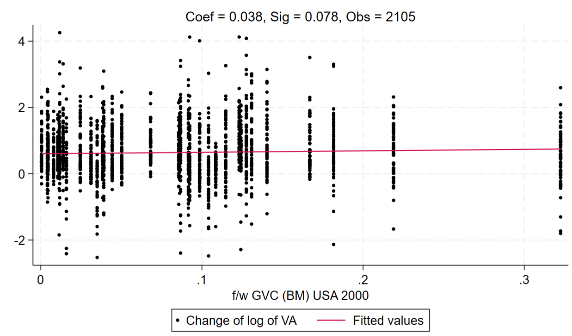
(a) $\Delta Log(LP)$ – GVC$_b$ USA 2000



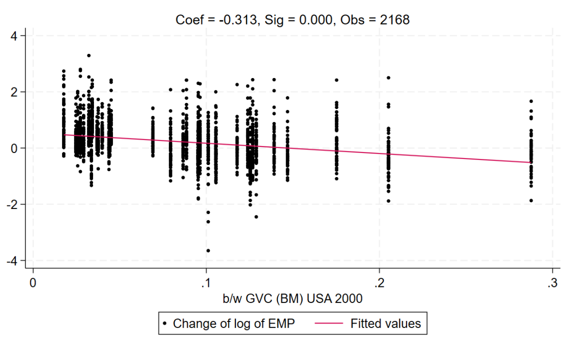
(b) $\Delta Log(LP)$ – GVC$_f$ USA 2000



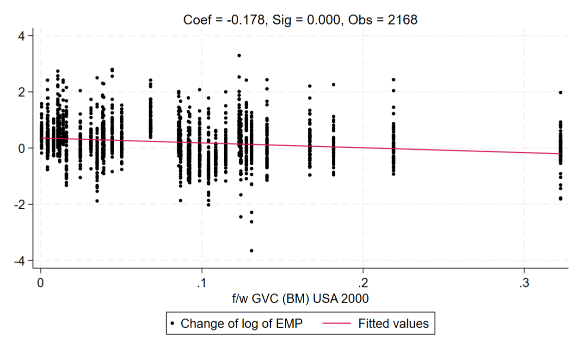
(c) $\Delta Log(VA)$ – GVC$_b$ USA 2000



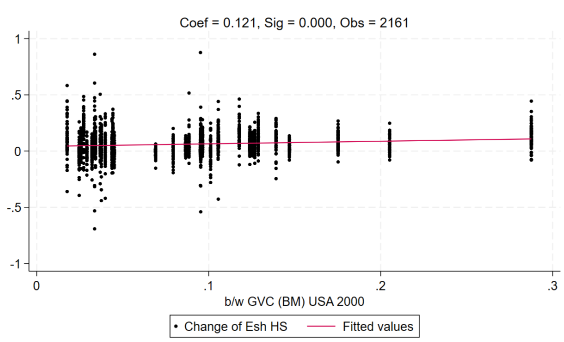
(d) $\Delta Log(VA)$ – GVC$_f$ USA 2000



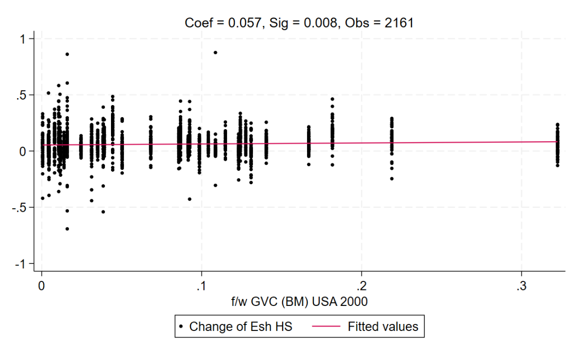
(e) $\Delta Log(E)$ – GVC$_b$ USA 2000



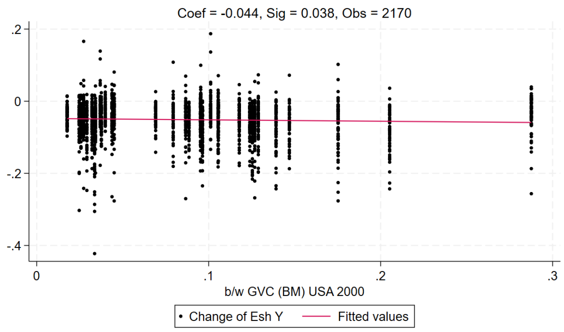
(f) $\Delta Log(E)$ – GVC$_f$ USA 2000



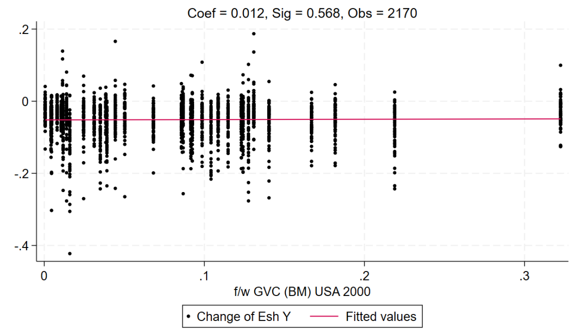
(g) ΔEsh^{HS} – GVC$_b$ USA 2000



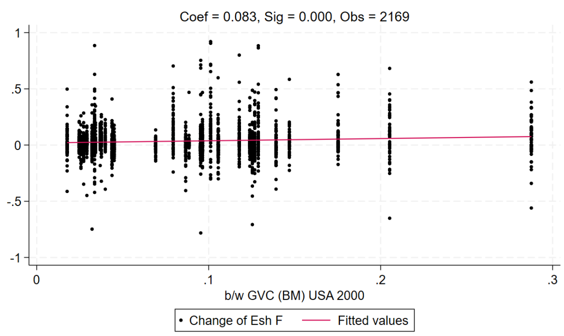
(h) ΔEsh^{HS} – GVC$_f$ USA 2000



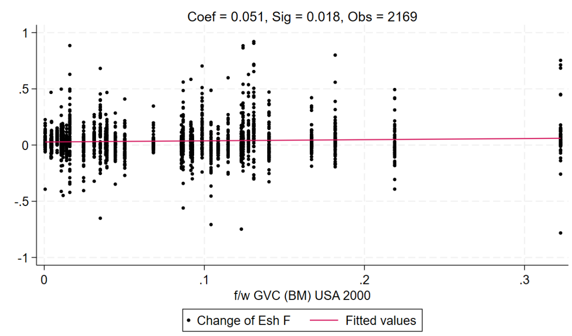
(i) ΔEsh^{Y} – GVC$_b$ USA 2000



(j) ΔEsh^{Y} – GVC$_f$ USA 2000



(k) ΔEsh^{F} – GVC$_b$ USA 2000



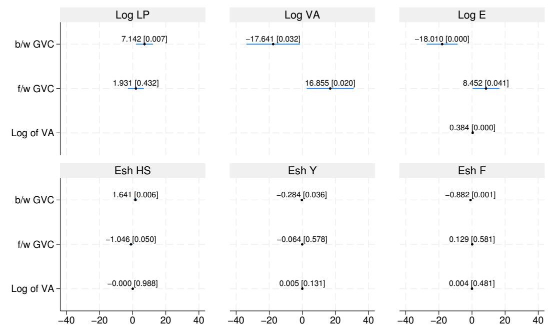
(l) ΔEsh^{F} – GVC$_f$ USA 2000

Notes: Raw correlations of the backward and forward GVC participation measures with the log of labour productivity (Panels (a) and (b)), log of value added (Panels (c) and (d)), log of total employment (Panels (e) and (f)), and the employment shares of high-skilled (Panels (g) and (h)), young (Panels (i) and (j)), and female (Panels (k) and (l)) workers.

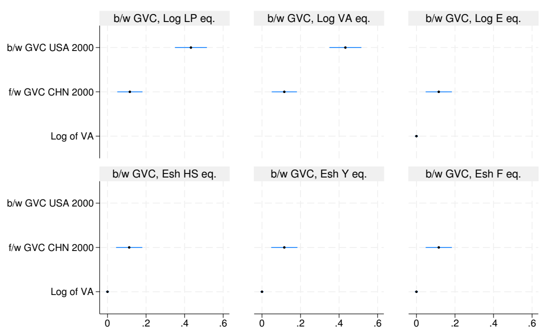
Source: *Source*: Authors' calculations based on ADB MRIO Tables and ILO Harmonized Microdata.

D Additional econometric results

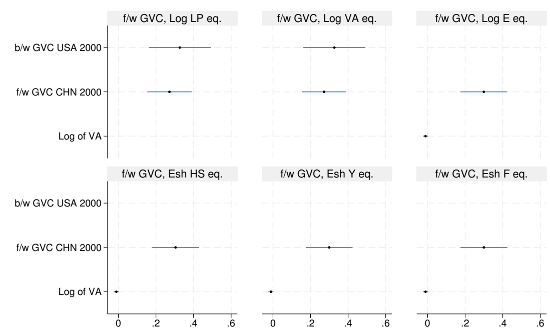
Figure D.1: GVC participation and labour productivity and demand, additional IV strategies



(a) GVC_b: IV–GVC–USA; GVC_f: IV–GVC–CHN



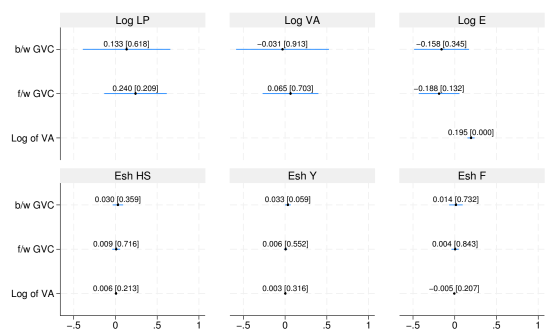
(b) GVC_b, first stage



(c) GVC_f, first stage

Notes: 2SLS estimations with robust standard errors in Panel (a) and respective first-stage results in Panels (b) and (c). The equations in Panel (a) include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

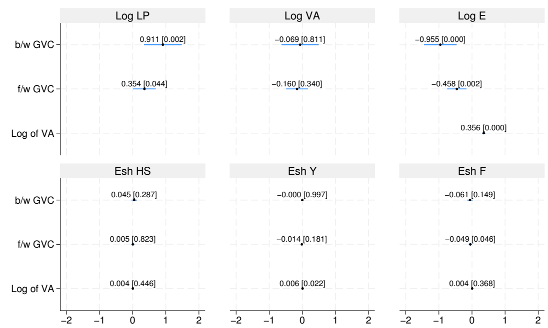
Figure D.2: GVC participation and labour productivity and demand, industry fixed effects controlled for



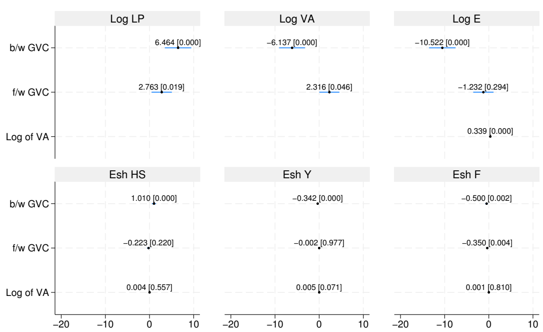
(a) OLS

Notes: OLS estimations with robust standard errors. The equations include country fixed effects and industry fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

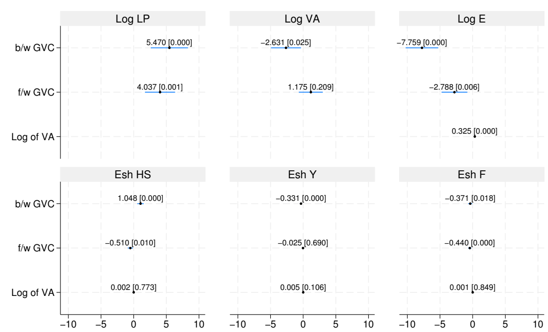
Figure D.3: GVC participation and labour productivity and demand, clustered s.e. by country and by industry



(a) OLS



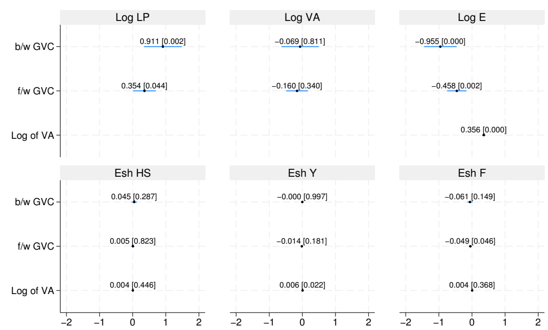
(b) IV–GVC–USA



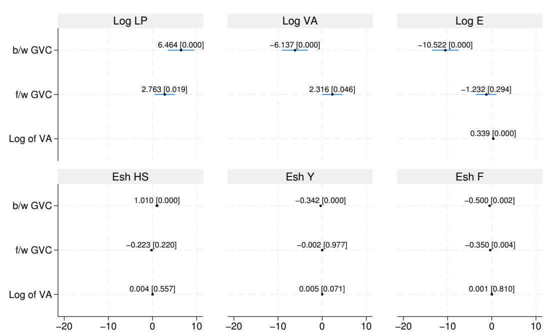
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with two-way clustered standard errors by country and industry in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

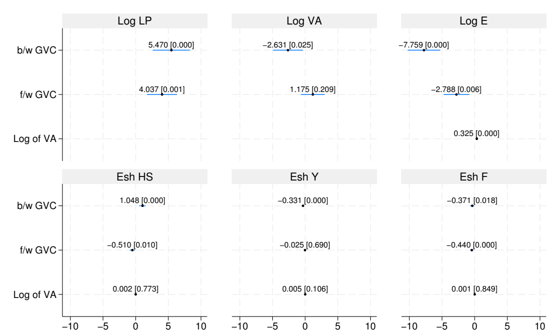
Figure D.4: GVC participation and labour productivity and demand, clustered s.e. by industry



(a) OLS



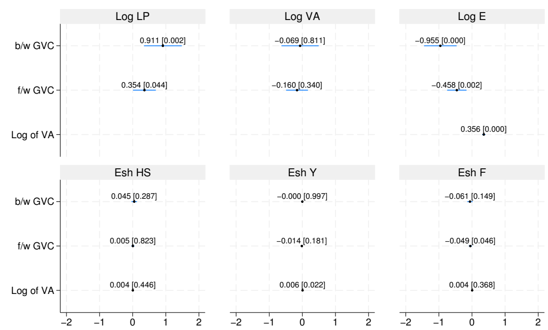
(b) IV–GVC–USA



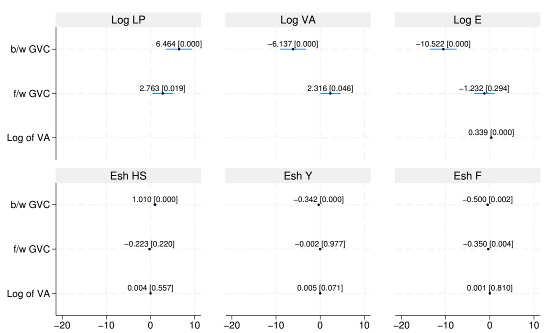
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with clustered standard errors by industry in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

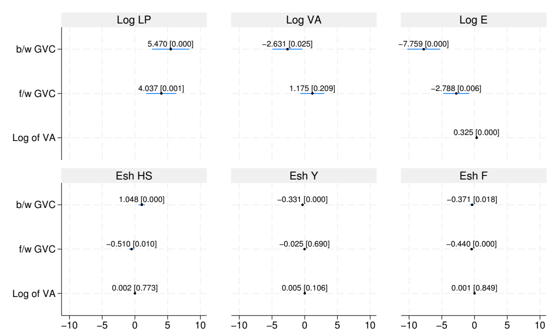
Figure D.5: GVC participation and labour productivity and demand, clustered s.e. by country



(a) OLS



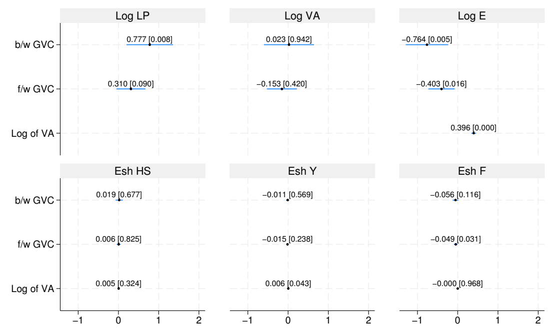
(b) IV–GVC–USA



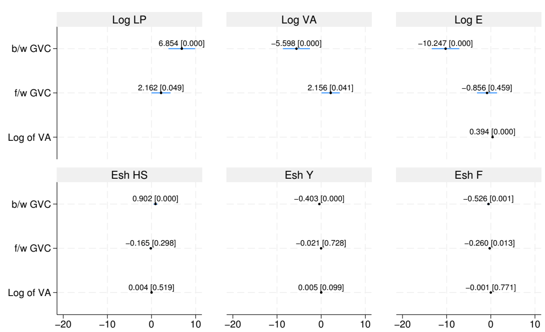
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with clustered standard errors by country in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

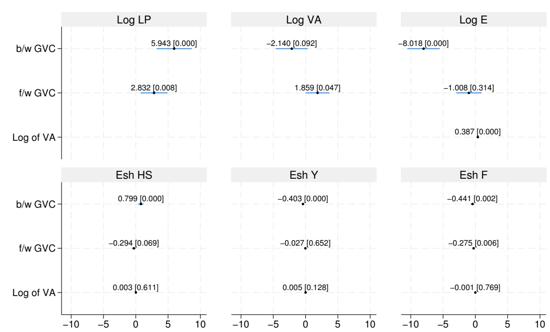
Figure D.6: GVC participation and labour productivity and demand, alternative specification weights



(a) OLS



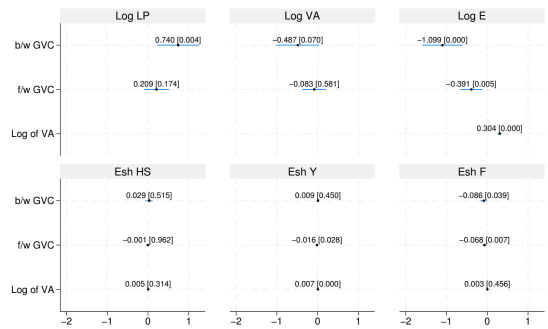
(b) IV–GVC–USA



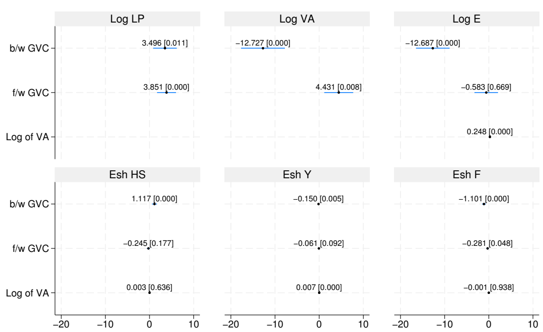
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust standard errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the cross-year average of the share of each industry's employment in economy-wide employment in 2000–2019.

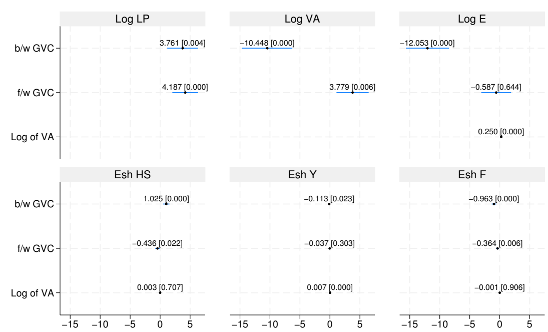
Figure D.7: GVC participation and labour productivity and demand, mean reversion controlled for



(a) OLS



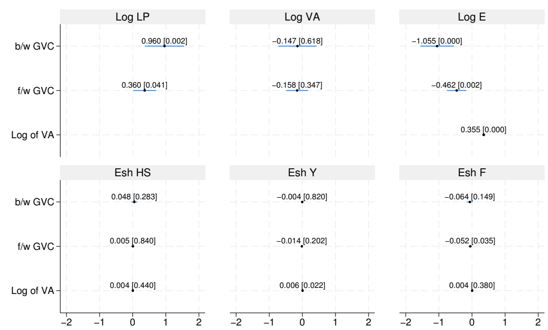
(b) IV–GVC–USA



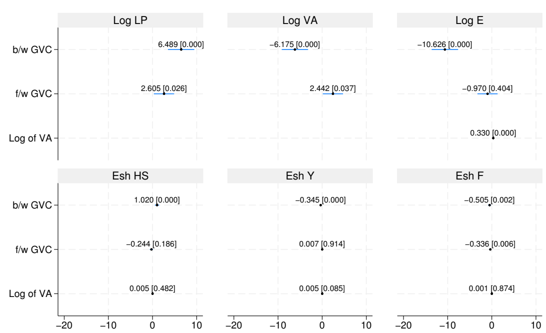
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. The equations also include the corresponding outcome variables in 2000, but their coefficient estimates are not disclosed for the sake of exposition.

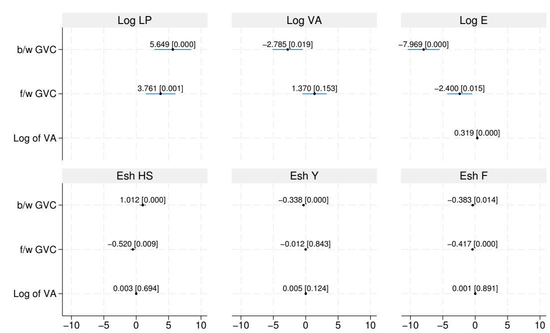
Figure D.8: GVC participation and labour productivity and demand, WWZ measures



(a) OLS



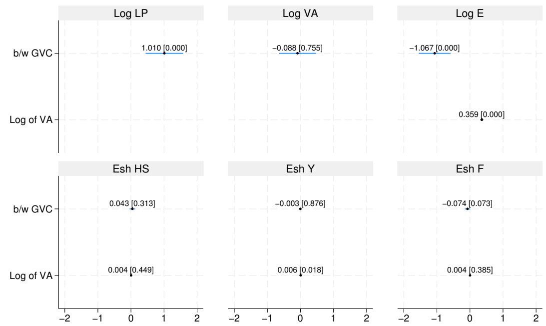
(b) IV–GVC–USA



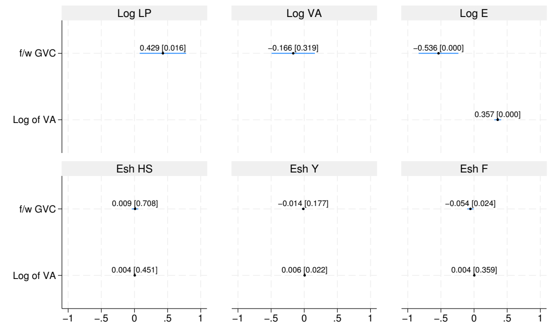
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

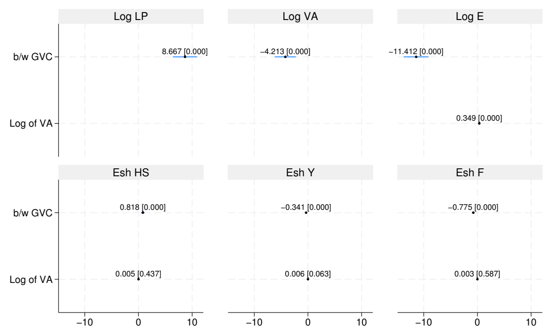
Figure D.9: Backward or forward GVC participation and labour productivity and demand



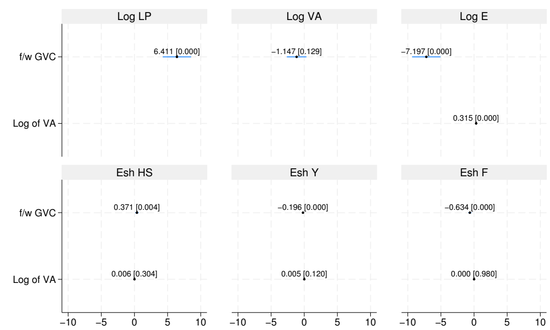
(a) GVC_b, OLS



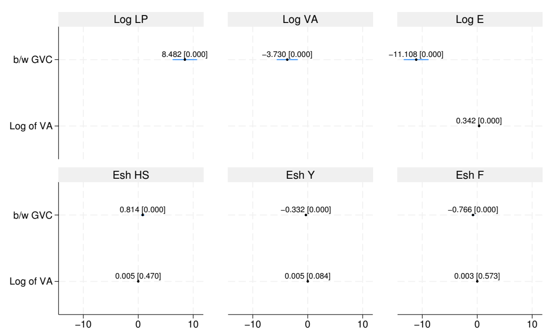
(b) GVC_f, OLS



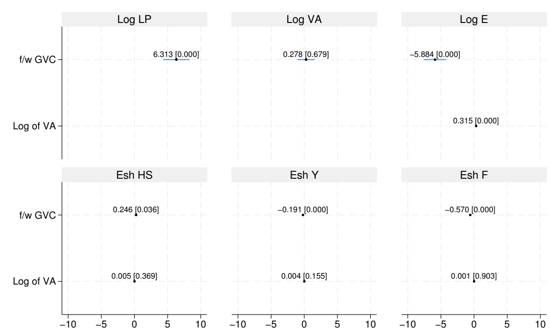
(c) GVC_b, IV–GVC–USA



(d) GVC_f, IV–GVC–USA



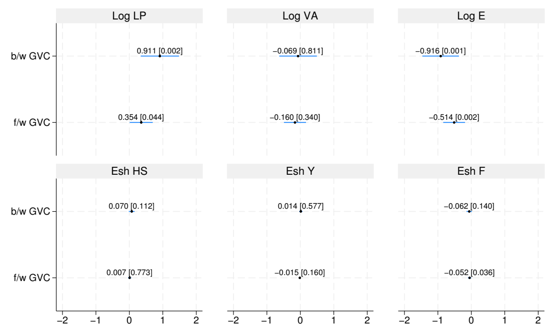
(e) GVC_b, IV–GVC–USA–CHN



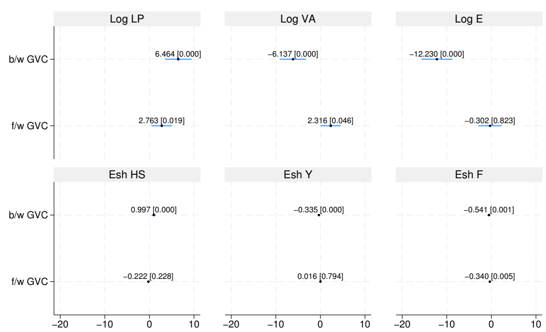
(f) GVC_f, IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panels (a)–(b) and Panels (c)–(f), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

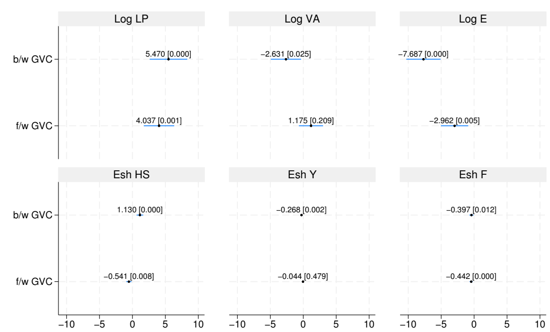
Figure D.10: GVC participation and labour productivity and demand, log of value added not controlled for



(a) OLS



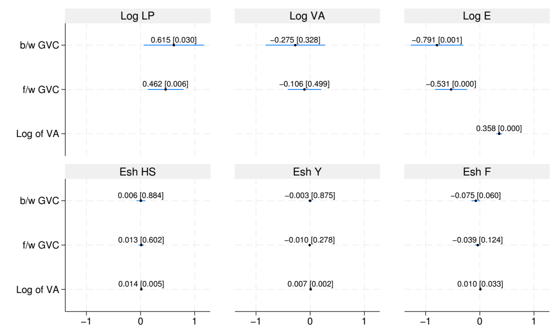
(b) IV–GVC–USA



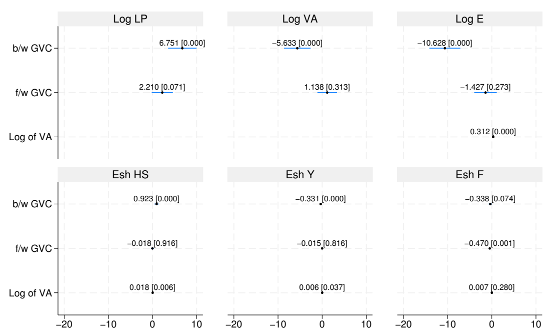
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

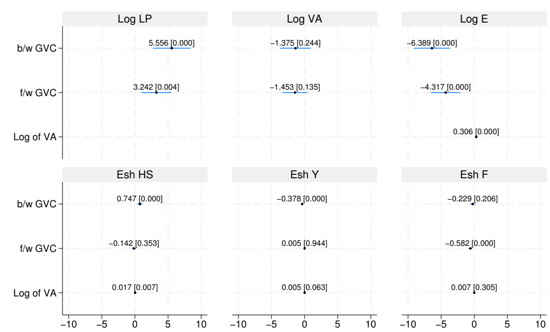
Figure D.11: GVC participation and labour productivity and demand, 2000–2020



(a) OLS



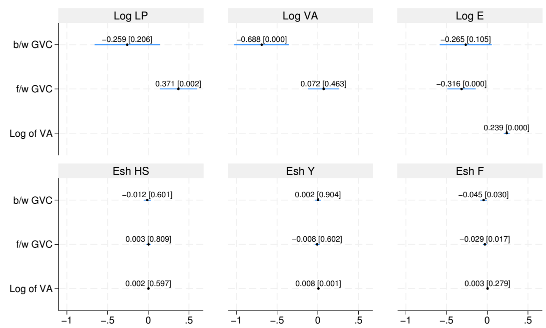
(b) IV–GVC–USA



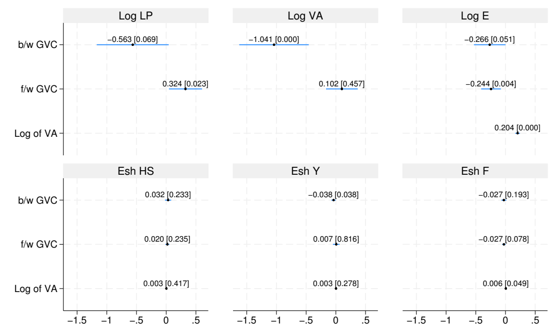
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. Long differences in these specifications imply that values of all variables for 2020 are subtracted from their respective values for 2000.

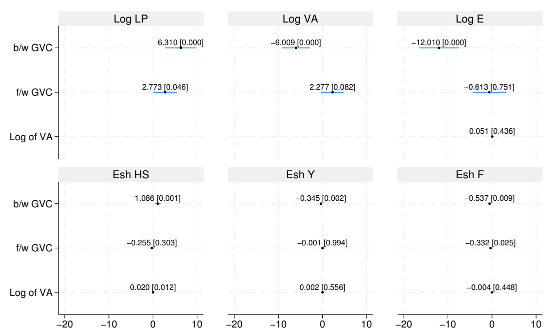
Figure D.12: GVC participation and labour productivity and demand, stacked differences



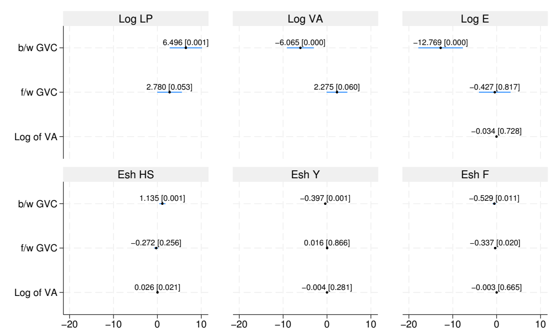
(a) Stacked diff., 2000–2010 & 2010–2019, OLS



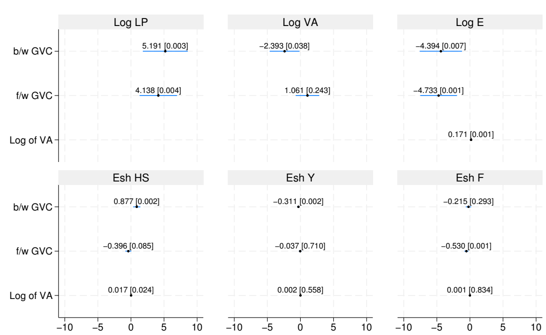
(b) Stacked diff., 2000–2007 & 2007–2019, OLS



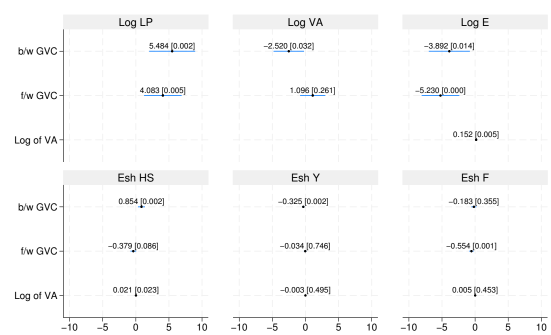
(c) Stacked diff., 2000–2010 & 2010–2019, IV–GVC–USA



(d) Stacked diff., 2000–2007 & 2007–2019, IV–GVC–USA



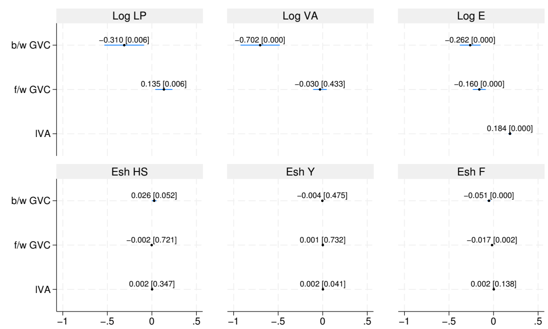
(e) Stacked diff., 2000–2010 & 2010–2019, IV–GVC–USA–CHN



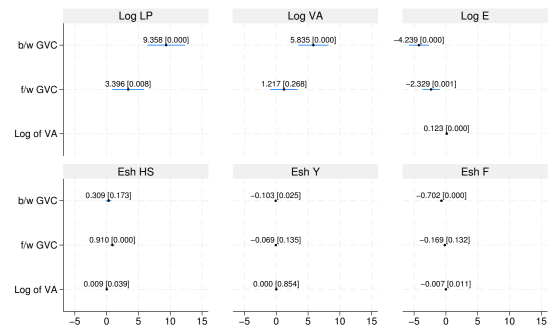
(f) Stacked diff., 2000–2007 & 2007–2019, IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panels (a)–(b) and Panels (c)–(f), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. The equations in Panels (a), (c), and (e) are in stacked differences for the sub-periods 2000–2010 and 2010–2019, while the equations in Panels (b), (d), and (f) are in stacked differences for the sub-periods 2000–2007 and 2007–2019.

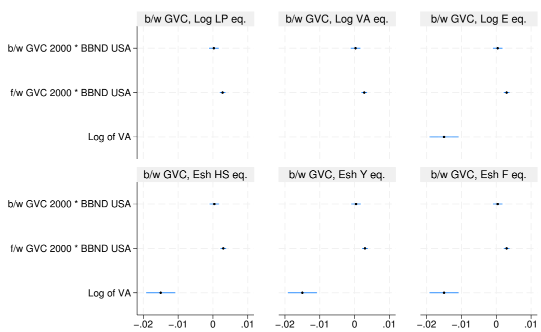
Figure D.13: GVC participation and labour productivity and demand, annual data



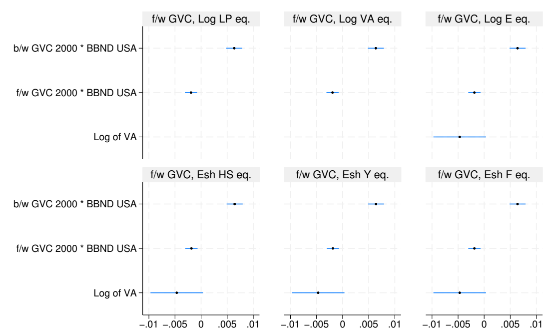
(a) OLS



(b) IV–GVC–BBND–USA



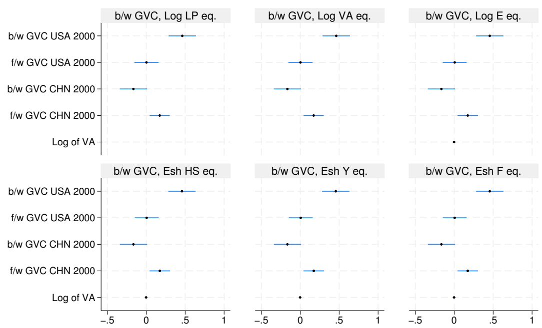
(c) IV–GVC–BBND–USA, first-stage



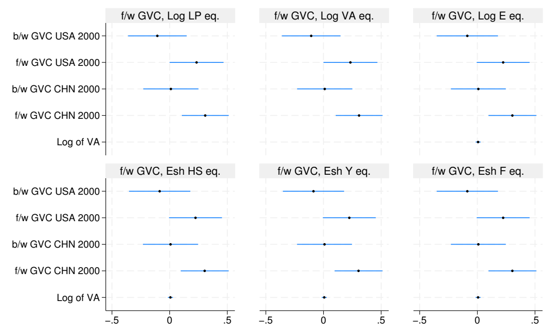
(d) IV–GVC–BBND–USA, first-stage

Notes: OLS and 2SLS estimations with robust errors on annual data in 2000–2019 in Panel (a) and Panel (b), respectively. First-stage results of 2SLS estimations of Panel (b) in Panels (c) and (d). The equations in Panels (a) and (b) include country-industry and country-year fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

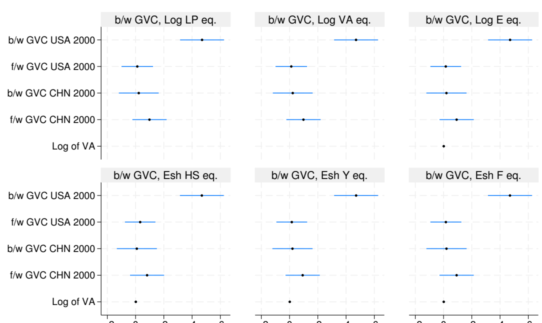
Figure D.14: First stages of 2SLS estimations in Figure 3



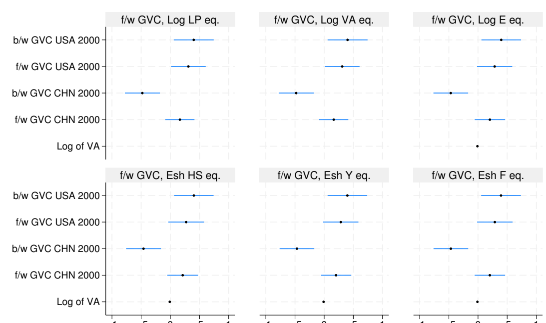
(a) GVC_b, HI countries



(b) GVC_f, HI countries



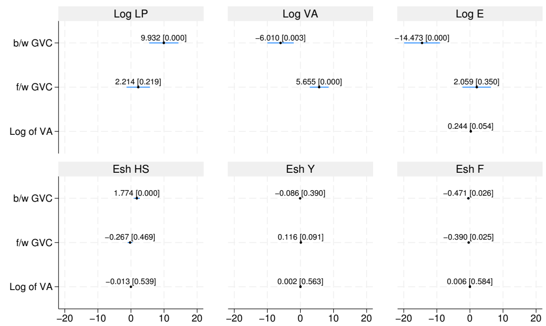
(c) GVC_b, LMI countries



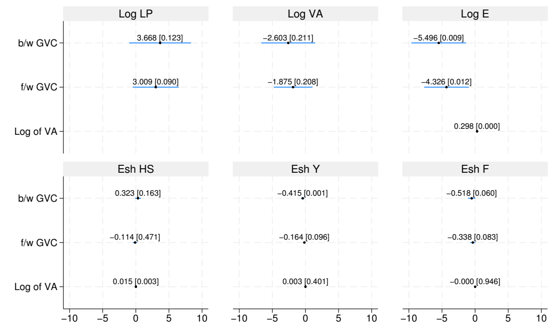
(d) GVC_f, LMI countries

Notes: Panels (a)–(b) and (c)–(d) display first-stage results of 2SLS estimations in Panels (c) and (d), respectively, of Figure 3.

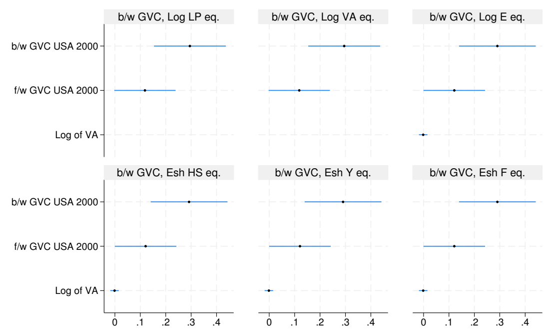
Figure D.15: GVC participation and labour productivity and demand by country income group, IV–GVC–USA



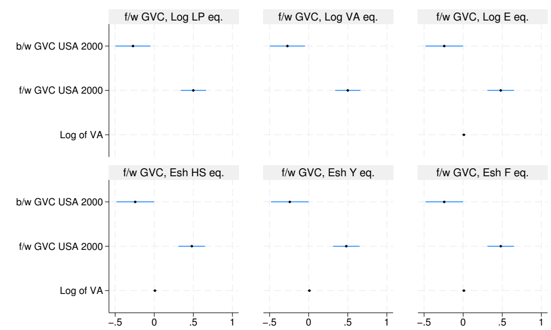
(a) HI countries



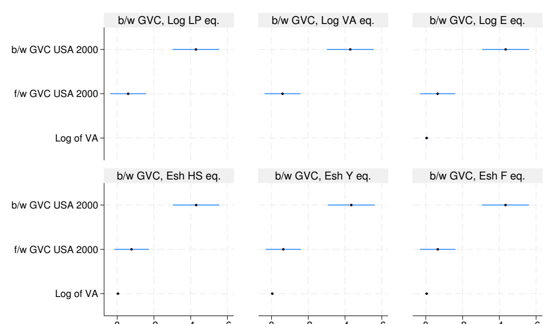
(b) LMI countries



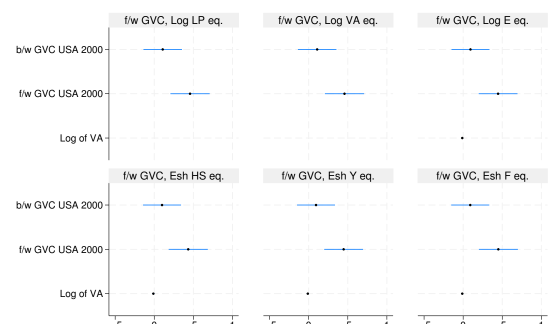
(c) HI countries, first-stage



(d) HI countries, first-stage



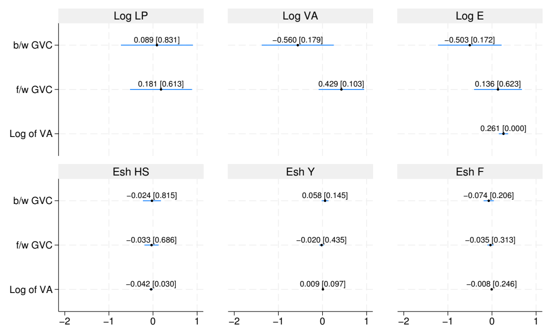
(e) LMI countries, first-stage



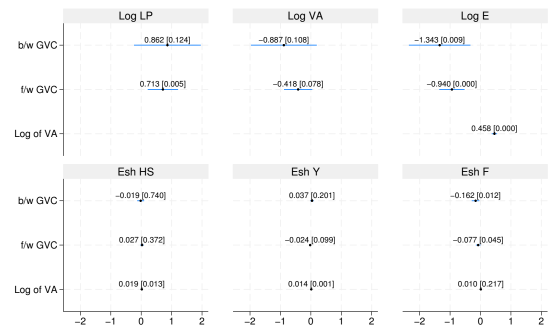
(f) LMI countries, first-stage

Notes: 2SLS estimations with robust errors in Panel (a) and (b) and respective first-stage results in Panels (c)–(d) and (e)–(f). The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. The estimating samples in Panels (a) and (b) comprise high-income (HI) and lower-income (LMI) countries, respectively, according to the World Bank's Historical Country Classification By Income in 2000.

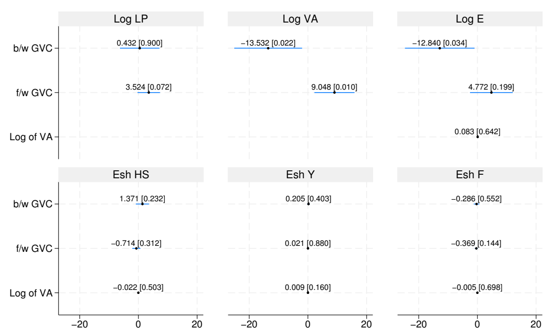
Figure D.16: GVC participation and labour productivity and demand, non-manufacturing industries



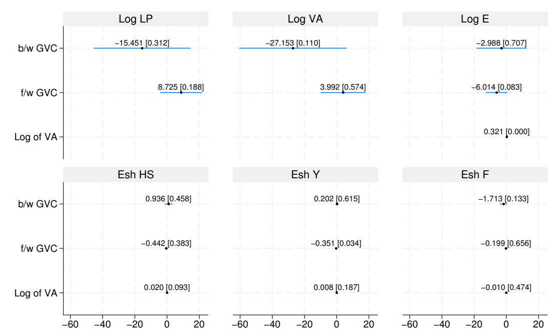
(a) HI countries, OLS



(b) LMI countries, OLS



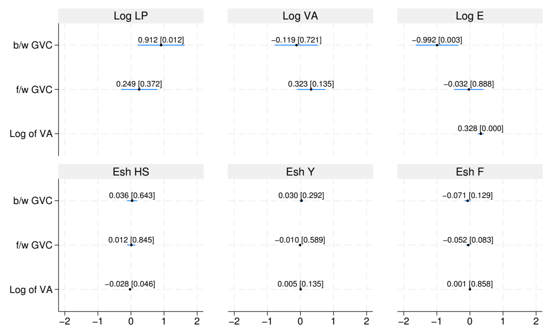
(c) HI countries, IV–GVC–USA



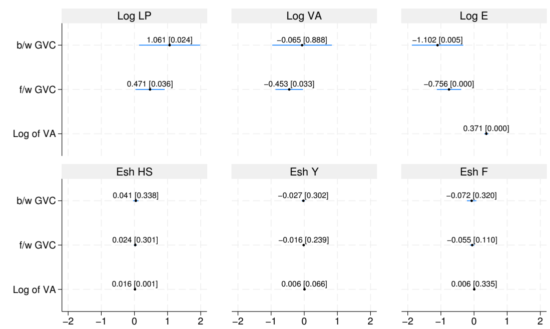
(d) LMI countries, IV–GVC–USA

Notes: OLS and 2SLS estimations with robust standard errors in Panels (a)–(b) and (c)–(d), respectively. The estimating samples in all panels comprise all industries except for those in the manufacturing sector (ISIC Rev. 3.1: 15–39). The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of employment of all manufacturing industries in 2000.

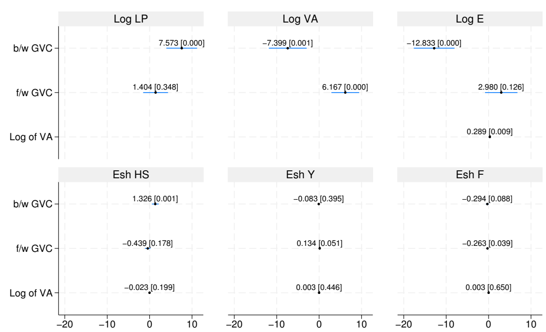
Figure D.17: GVC participation and labour productivity and demand, IT-using industries



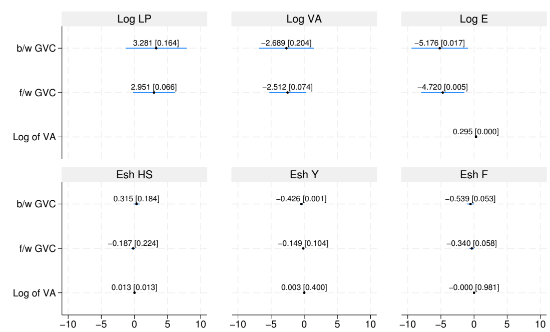
(a) HI countries, OLS



(b) LMI countries, OLS



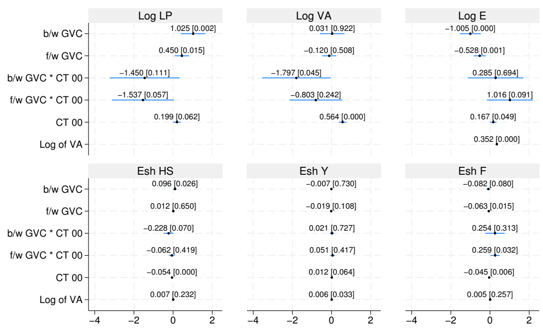
(c) HI countries, IV–GVC–USA



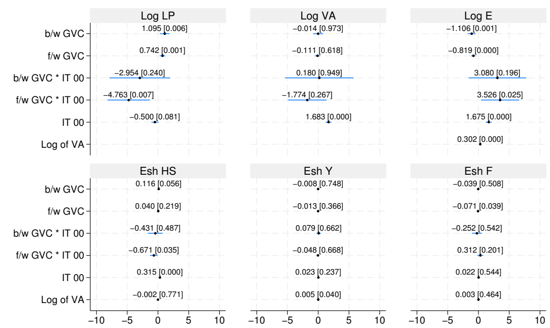
(d) LMI countries, IV–GVC–USA

Notes: OLS and 2SLS estimations with robust standard errors in Panels (a)–(b) and (c)–(d), respectively. The estimating samples in all panels comprise all industries except for IT-producing industries (ISIC Rev. 3.1: 29 and 30–33). The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of employment of IT-producing industries in 2000.

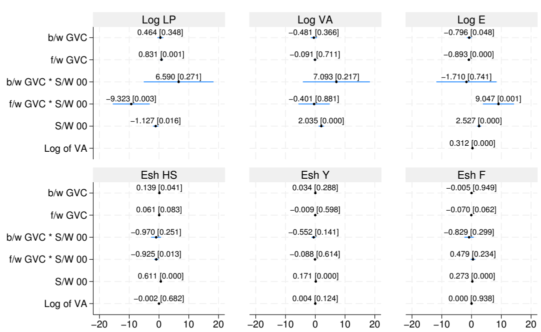
Figure D.18: Interplay between GVC participation and technology and labour productivity and demand, all countries



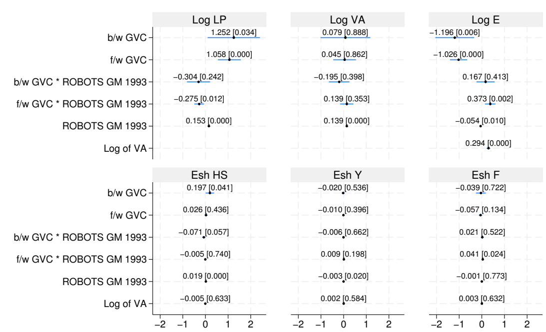
(a) CT



(b) IT



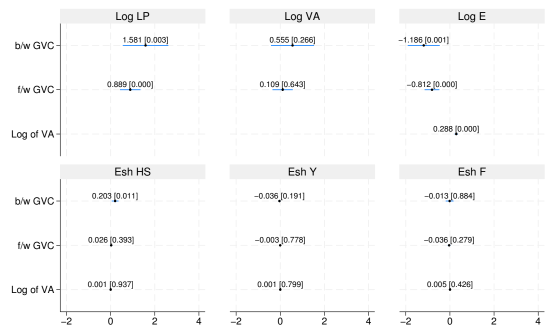
(c) S/W



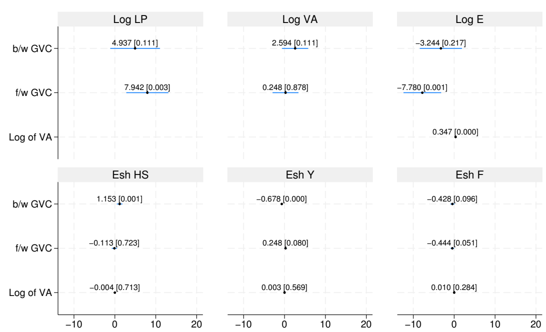
(d) ROBOTS

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with CT, IT, or S/W capital intensity for the US in 2000 (Panels (a), (b), (c)), or with the unweighted cross-country average of robot intensity (robot stock in units per million hours worked) by industry in 1993 (Panel (d)). The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

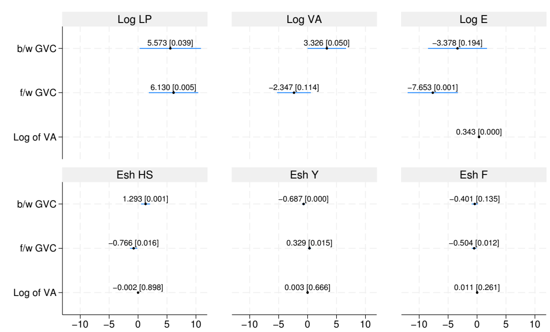
Figure D.19: GVC participation and labour productivity and demand, IFR sample



(a) OLS



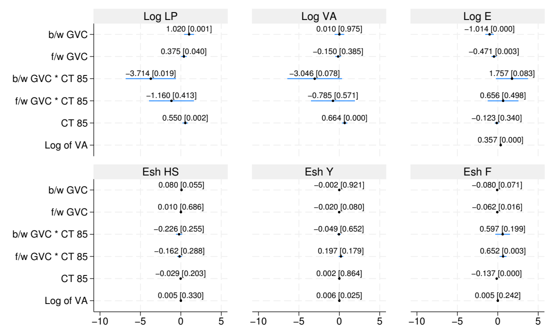
(b) IV–GVC–USA



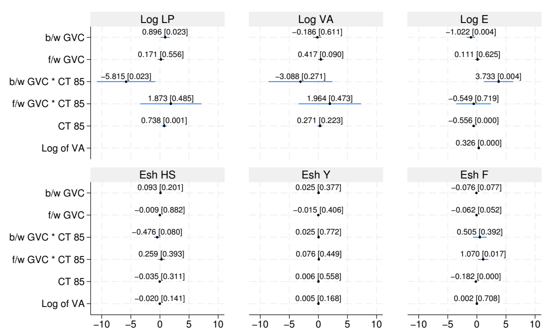
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in total employment of IFR industries in 2000. The estimating samples comprise only the industries that are available in the International Federation of Robotics (IFR) database (ISIC Rev. 3.1: AtB, C, 15t16, 17t18, 20, 21t22, 24, 26, 27t28, 30t33, 34t35, F, and M.)

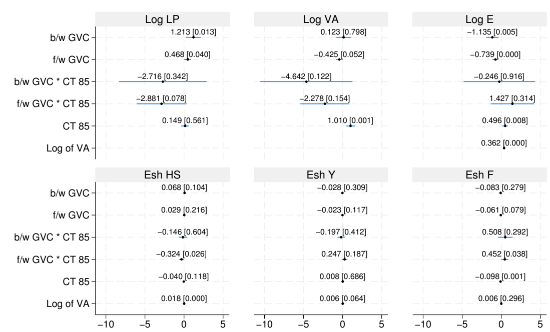
Figure D.20: Interplay between GVC participation and technology and labour productivity and demand, CT capital intensity in 1985



(a) All countries



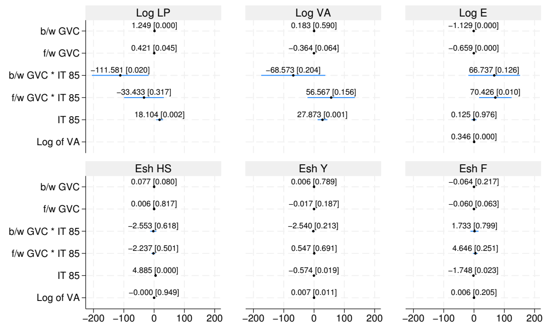
(b) HI countries



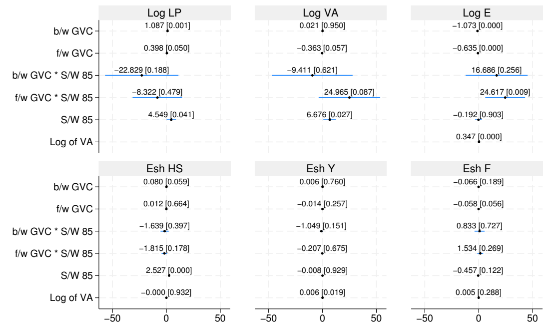
(c) LMI countries

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with CT capital intensity for the US in 1985. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000.

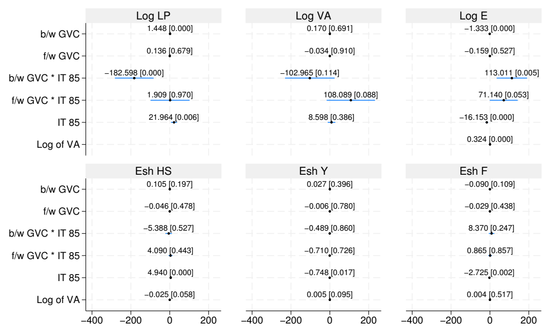
Figure D.21: Interplay between GVC participation and technology and labour productivity and demand, IT or S/W capital intensity in 1985



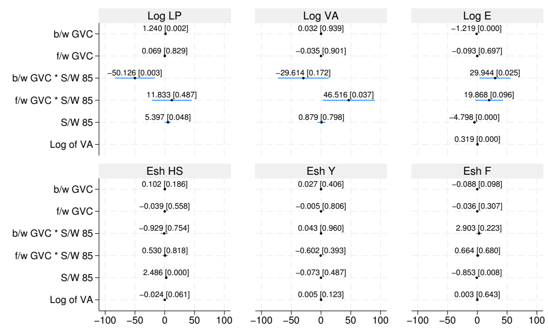
(a) IT – All countries



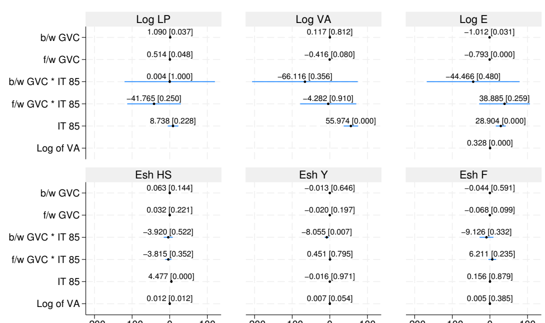
(b) S/W – All countries



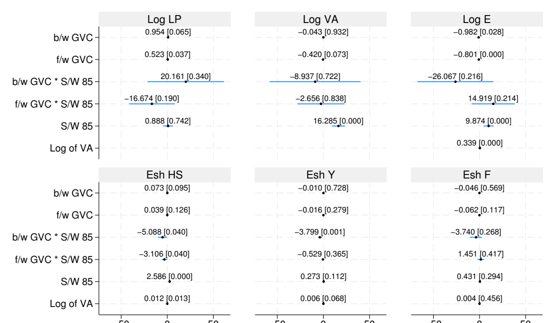
(c) IT – HI countries



(d) S/W – HI countries



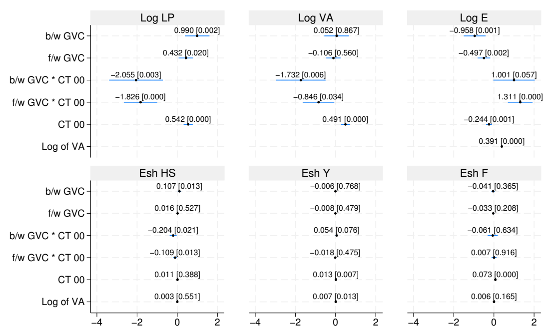
(e) IT – LMI countries



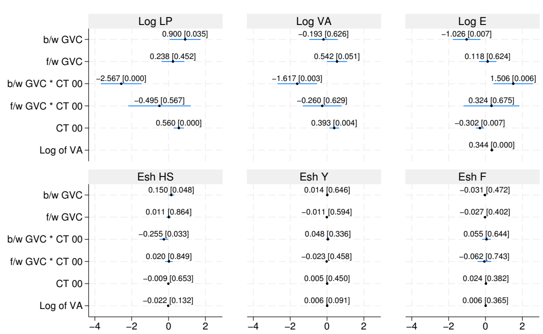
(f) S/W – LMI countries

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with IT (Panels (a), (c) and (e)) or S/W (Panels (b), (d) and (f)) capital intensity for the US in 1985. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment in 2000. The estimating samples in Panels (a) and (b) comprise all countries, while the estimating samples in Panels (c) and (d) and Panels (e) and (f) comprise high-income (HI) and lower-income (LMI) countries, respectively, according to the World Bank's Historical Country Classification By Income in 2000.

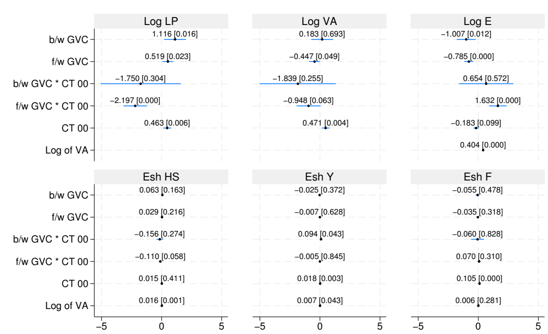
Figure D.22: Interplay between GVC participation and technology and labour productivity and demand, CT capital intensity in 2000 based on EU KLEMS February 2023 release



(a) All countries



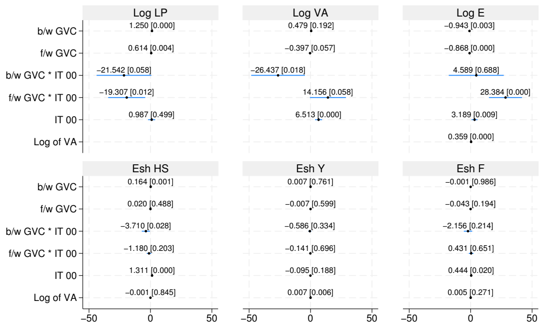
(b) HI countries



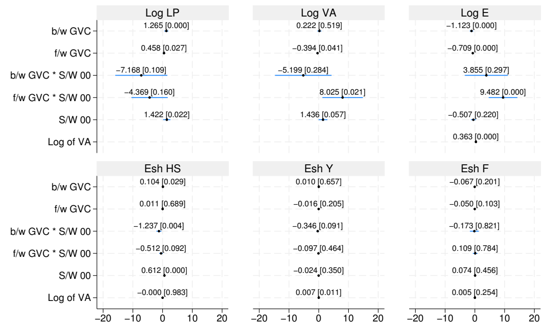
(c) LMI countries

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with CT capital intensity for the US in 2000. Information on the real CT capital stock is retrieved from the February 2023 release of the EU KLEMS database. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of the employment of industries with ISIC Rev. 3.1 codes 24, 50, 64, and L in 2000. The estimating samples comprise only the industries that are available in the February 2023 release of the EU KLEMS database (i.e., all 35 industries except for those with ISIC Rev. 3.1 codes 24, 50, 64, and L).

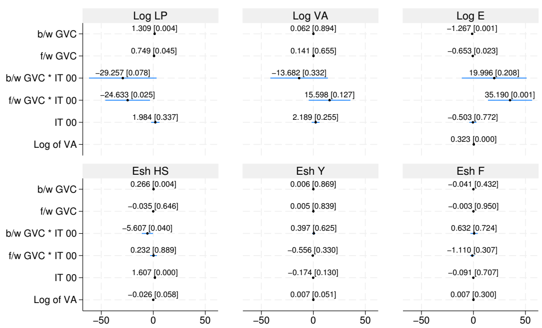
Figure D.23: Interplay between GVC participation and technology and labour productivity and demand, IT or S/W capital intensity in 2000 based on EU KLEMS February 2023 release



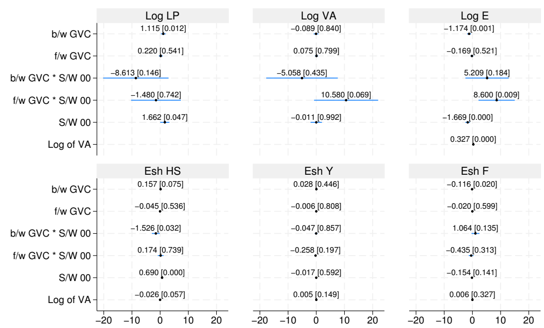
(a) IT – All countries



(b) S/W – All countries

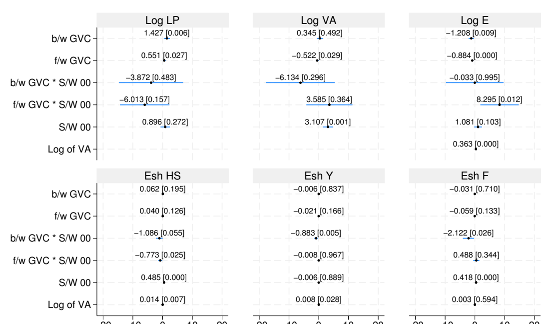


(c) IT – HI countries



(d) S/W – HI countries

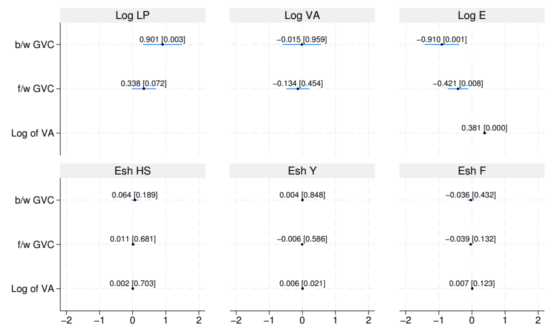
(e) IT – LMI countries



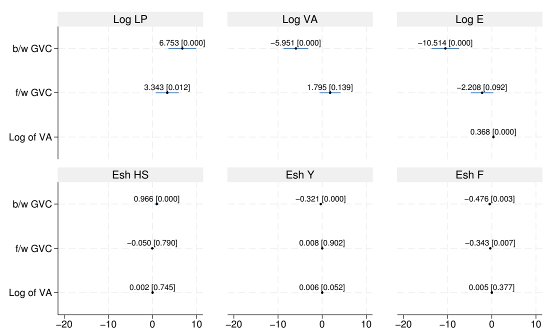
(f) S/W – LMI countries

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with IT (Panels (a), (c) and (e)) or S/W (Panels (b), (d) and (f)) capital intensity for the US in 2000. Information on the real IT or S/W capital stock is retrieved from the February 2023 release of the EU KLEMS database. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of the employment of industries with ISIC Rev. 3.1 codes 24, 50, 64, and L in 2000. The estimating samples in all panels comprise only the industries that are available in the February 2023 release of the EU KLEMS database (i.e., all 35 industries except for those with ISIC Rev. 3.1 codes 24, 50, 64, and L). The estimating samples in Panels (a) and (b) comprise all countries, while the estimating samples in Panels (c) and (d) and Panels (e) and (f) comprise high-income (HI) and lower-income (LMI) countries, respectively, according to the World Bank's Historical Country Classification By Income in 2000.

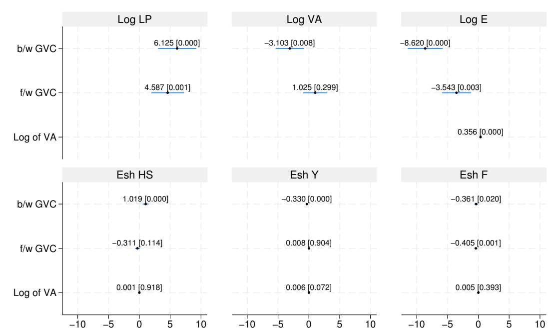
Figure D.24: GVC participation and labour productivity and demand, EU KLEMS February 2023 sample



(a) OLS



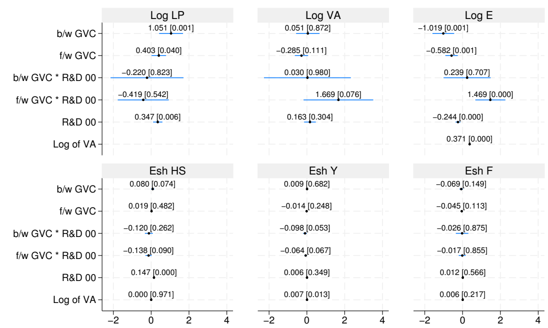
(b) IV–GVC–USA



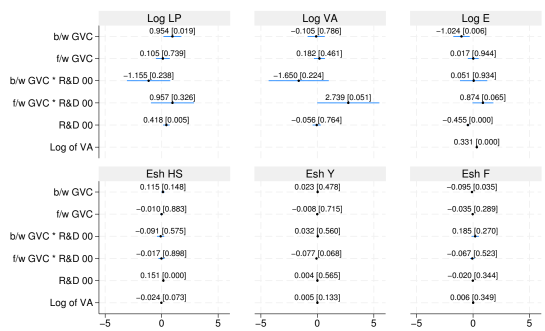
(c) IV–GVC–USA–CHN

Notes: OLS and 2SLS estimations with robust errors in Panel (a) and Panels (b)–(c), respectively. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of the employment of industries with ISIC Rev. 3.1 codes 24, 50, 64, and L in 2000. The estimating samples comprise only the industries that are available in the February 2023 release of the EU KLEMS database (i.e., all 35 industries except for those with ISIC Rev. 3.1 codes 24, 50, 64, and L).

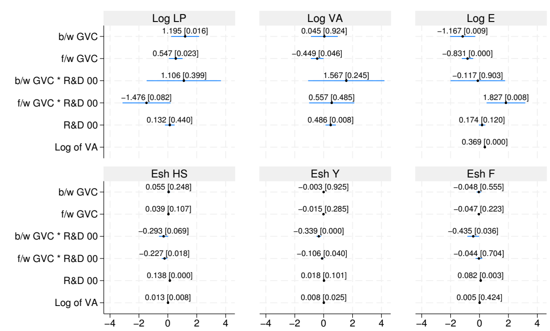
Figure D.25: Interplay between GVC participation and technology and labour productivity and demand, R&D intensity in 2000 based on EU KLEMS February 2023 release



(a) All countries



(b) HI countries



(c) LMI countries

Notes: OLS estimations with robust errors in all panels. The equations include interactions of the backward and forward GVC participation measures with R&D capital intensity for the US in 2000. Information on the real R&D capital stock is retrieved from the February 2023 release of the EU KLEMS database. The equations include country fixed effects and are weighted by the share of each industry's employment in economy-wide employment net of the employment of industries with ISIC Rev. 3.1 codes 24, 50, 64, and L in 2000. The estimating samples comprise only the industries that are available in the February 2023 release of the EU KLEMS database (i.e., all 35 industries except for those with ISIC Rev. 3.1 codes 24, 50, 64, and L).