WORK PACKAGE 3

Recent and emerging impact of GVCs and MNEs on employment and inequalities

Acknowledgements

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Executive summary

This report, a part of the TWIN SEEDS project funded by Horizon Europe, examines the complex interactions between Global Value Chains (GVCs), multinational enterprises (MNEs), and the labor markets of European regions. Through an analysis of the restructuring of GVCs, the influence of global disruptions like the COVID-19 pandemic, and technological advancements the report provides key insights into how these factors are reshaping employment patterns and exacerbating socioeconomic disparities across Europe. The findings underscore the need for region-specific and nuanced policy approaches to mitigate the adverse impacts of GVCs while promoting sustainable economic growth and inclusive labor market outcomes.

1. Impact of GVC Restructuring on Employment and Skills

The restructuring of GVCs, driven by reshoring and expansionary strategies, has led to disparate effects across different European regions, highlighting the importance of regional economic structures and competitive capacities. Reshoring efforts have contributed to employment growth in traditionally industrial regions, such as those in Central and Eastern Europe, where manufacturing jobs have been revitalized. However, in emerging manufacturing regions, reshoring has mainly led to increases in value-added production without a corresponding rise in job opportunities. This distinction reveals that the EU's dual objectives of modern reindustrialization and manufacturing employment growth are challenging to achieve simultaneously in all regions. The findings indicate that place-based industrial policies are crucial for adapting to these different regional contexts, allowing for targeted interventions that align with local economic capacities.

Furthermore, the study reveals that in regions like Southern Italy, Spain, and parts of France, a singular focus on increasing skill intensity may not lead to the desired growth outcomes. In these regions, increasing education levels without corresponding structural economic adjustments can result in overskilling, where there is an excess of highly educated workers without suitable employment opportunities. Instead, the report advocates for functional specialization and structural reforms aimed at aligning regional economies with the demands of GVCs. For less competitive regions, policies should prioritize secondary education and vocational training to develop technical skills relevant to regional manufacturing industries, which could improve both regional competitiveness and employment prospects.

2. Effects of COVID-19 and Technological Changes on Employment

The COVID-19 pandemic has had profound impacts on labor markets, with long-term employment trends being significantly disrupted by the crisis. The report highlights that the pandemic accelerated trends such as work-from-home (WfH) and automation, both of which reshaped employment dynamics across sectors. The findings indicate that some occupational groups particularly those engaged in non-routine, manual labor benefitted

from these changes, while others, especially mid-skilled workers, faced job displacement due to automation and sectoral shifts.

The pandemic also exposed the vulnerabilities of global production networks, leading to significant changes in GVC configurations. Some sectors saw a shift toward nearshoring and reshoring as companies sought to reduce their dependency on distant suppliers and increase the resilience of their supply chains. The report concludes that these shifts are likely to result in lasting changes in employment patterns, with potential increases in job polarization as the demand for high- and low-skilled workers grows, while middle-skilled jobs continue to decline.

3. Job Polarization and Inequality

Participation in GVCs has exacerbated job polarization across Europe, particularly in regions where foreign enterprises play a dominant role in local economies. High-income regions have seen significant increases in both high-skilled, high-wage jobs and low-skilled, low-wage positions, while mid-level occupations have declined. The research also emphasizes that labor market inequalities are not uniform across Europe, with some regions experiencing sharper disparities than others. However, regions with strong Employment Protection Legislation (EPL) have been able to mitigate the negative effects of GVC participation on job polarization. This underscores the critical role of labor regulations in protecting workers from the more extreme effects of globalization and internationalization.

To address the increasing polarization, the report recommends that internationalization policies should be complemented by cohesion policies that aim to reduce both regional and intra-regional disparities. Encouraging the reconfiguration of production, such as reshoring or nearshoring, could help limit job polarization in sectors most affected by GVCs, particularly at the European level. In sectors where job polarization is unavoidable, the introduction of stronger labor protections and a focus on equitable growth will be essential to ensuring that the benefits of internationalization are shared more equally.

4. Gender Disparities in the Labor Market

Contrary to initial expectations, the study reveals that GVC participation did not significantly exacerbate gender wage disparities. Instead, other factors, such as educational attainment and working hours, were more decisive in shaping the gender pay gap. Regions with a higher share of women with tertiary education tend to have narrower pay gaps, while sectors where men work longer hours see wider wage gaps. Nonetheless, the research indicates that GVC participation has been associated with a rise in precarious employment, particularly for women. This trend is mitigated by higher education levels, with women who have attained higher education facing less precarious employment.

The study also notes that job insecurity remains a persistent issue in sectors with high GVC integration, affecting both men and women. However, the gender gap in job insecurity narrows as GVC participation increases, although overall job insecurity for women tends to rise. These findings suggest that while GVC participation has not significantly worsened gender inequalities, it has introduced new challenges, particularly in terms of job security and employment stability for women.

5. Working Conditions and Offshoring

The report highlights the detrimental effects of offshoring on working conditions across Europe. Increased offshoring is associated with higher levels of work intensity, lower worktime quality, a decline in the social environment, and reduced job security for workers in affected sectors. These negative impacts are particularly pronounced in regions experiencing offshoring to developing countries, where the deterioration of working conditions tends to be more severe. While some of these effects, such as lower worktime quality and reduced job prospects, are temporary, others, such as increased work intensity and poorer social environments, persist over the longer term, posing significant risks to worker well-being and productivity.

To address these challenges, the report advocates for government-imposed labor standards that ensure workers in offshoring sectors are protected from unfair labor practices and excessive work demands. Trade unions and worker representation organizations must also play a stronger role in negotiating better working conditions for employees in offshoring firms, ensuring that the negative effects of globalization do not disproportionately affect vulnerable workers.

6. Supporting Export Quality Upgrading and Innovation

The findings also highlight the potential for export quality upgrading to drive employment growth, particularly in high-income regions. Improving the quality of exports can enhance a firm's competitiveness in the global market, leading to higher employment levels. However, the research emphasizes that GVC integration is not a prerequisite for positive employment outcomes. Instead, countries can achieve similar benefits through domestic capacity-building initiatives that focus on research and development (R&D) and innovation. By supporting firms in improving their export quality, policymakers can create more high-quality jobs and boost regional economic growth.

Conclusion

The report underscores the need for a multifaceted, region-specific policy approach to address the challenges posed by GVCs. While GVC participation offers opportunities for growth and competitiveness, it also intensifies labor market inequalities and threatens job quality in certain regions and sectors. By adopting policies that balance the benefits of global integration with the need to protect vulnerable workers, enhance labor protections, and foster innovation, European policymakers can ensure that the benefits of GVCs are shared more equitably across the continent.

1. Introduction

Global value chains (GVCs) have played a crucial role in shaping international trade and production processes in this globalisation wave. However, recent developments suggest a potential slowdown or even a reversal in these integrative forces. While geopolitical shifts and technological transformations can be regarded as two core pillars shaping the remarkable rise and the prospective restructuring of GVC-based production structures, in present days, there is a broad consensus that the COVID-19 pandemic and the Russian invasion of Ukraine have amplified and accelerated these shifts that impact GVCs (Jankowska et al. 2023).

Yet, while the immediate socio-economic effects of these more recent changes are considered to be already evident, the long-term consequences on GVCs are complex, still unfolding and require further investigation. Indeed, the reorganisation of GVCs that followed the above-mentioned challenges has involved both the restructuring of activities and the re-allocation of tasks and functions across space, with important implications, especially for jobs and their quality, working conditions and inequalities.

There is a large evidence that a decreasing trend in international economic integration has characterised the last fifteen years. Different factors influenced this trend, such as the COVID-19 pandemic, the increasing geo-political instability together with the increasing citizens' demand for protectionism, especially in developed countries. The globally fragmented production system is thus confirmed to be extremely fragile and exposed to shocks of different kinds (Brenton et al., 2022) as demonstrated - after a first period of rapid expansion, which occurred approximately between 1990 and 2007 - by the COVID-19 pandemic, the war in Ukraine and the economic crisis that followed the pandemic period.

From 2008 until today, a new phase started, characterised by the slowing down, and in some cases by a reversing, of the intensification of trade and offshoring of production activities. After 2008, almost all advanced (i.e. offshoring) countries experienced a phase of constant (and still persistent) stagnation of GDP and productivity and, in parallel, a sharp increase in unemployment rates. Consequently, policymakers started casting doubts on the advantages of GVCs' participation and on the effects on both competitiveness and employment of alternative production models, more oriented towards onshoring rather than offshoring.

More specifically, in the EU, backshoring (bringing back to the area where goods were previously produced) is a strategy largely envisaged to put in place the reindustrialisation process (EC 2021) and, in particular, to favour a modern reindustrialisation and the dynamics of employment in manufacturing.

The unemployment dynamics in the EU pushed the "Manufacturing Imperative" launch to avoid the loss of long-term productivity growth and living standards (European Commission, 2014). More recently, the idea of Open Strategic Autonomy, meaning "cooperating multilaterally wherever we can, acting autonomously wherever we must", was launched by the EU (European Commission, 2021), witnessing the emergence of the EU to go towards self-sufficiency and independence in critical production processes (European Commission 2021) while staying open to global trade and cooperation. The COVID-19 pandemic relaunched both the reindustrialisation and the backshoring debates. On the one hand, the EU once stressed the political interest in strengthening the industrial capacity of Europe through the Open Strategic Autonomy (EC, 2022). On the other hand, the health crisis highlighted the fragility of the international production organisation, calling for backshoring processes.

As these trends evolve, employers face new challenges in managing their workforce, particularly in human capital investments and adapting to the pressures and opportunities of participating in global value chains (GVCs) (Van Zijl & Koster, 2024).

The COVID-19 pandemic accelerated changes in work organisation, particularly with the rise of remote work, which impacted industries differently based on their dependence on GVCs. Sectors with high levels of outsourcing were particularly vulnerable, revealing the need for more resilient supply chains (Guadagno et al., 2023). Meanwhile, technological advances like automation and robotisation are driving reshoring efforts, presenting both risks and opportunities for employment. While these technologies improve efficiency, they also displace certain jobs, with workers in roles complementing automation benefiting the most (Acemoglu & Autor, 2011).

High-income countries are countering competitive pressures from lower-wage economies by upgrading the quality of their exports. This strategy helps maintain market share and can lead to more stable employment outcomes (Schott, 2008; Khandelwal, 2010). However, shifts in GVCs and technology have also deepened inequalities, especially gender disparities in wages and job security, which have been exacerbated by the pandemic (Foucault & Galasso, 2020; Doorley et al., 2022).

Job polarisation, driven by technology and GVC restructuring, is another key trend. Middle-wage jobs are declining as both low-skill and high-skill jobs grow, creating a more divided labour market (Goos & Manning, 2007; Autor & Dorn, 2013). As GVCs continue to evolve, there is a pressing need for policies focused on skills development, equality, and job security to ensure that labour markets remain resilient and inclusive in the face of these challenges (Fernández-Macías et al., 2023).

With all these discussions gaining momentum, also within the policy debate, the assessment of the influences GVCs may exert on regional labour market scenarios and outcomes - i.e. the aims of this report - definitively becomes paramount.

The TWIN SEEDS project aims to provide robust empirical evidence on how GVCs have been affected by globalisation and most recent developments, as well as examine the trends in international trade, MNE behaviour, and production organisation in relation to the changing policy environment and new technologies (‘twin seeds’). This report – the third in a series of seven reports (see Figure 1) – is aimed to provide a detailed and comprehensive analysis of the different influences of GVCs on regional labour market scenarios and outcomes, including effects on employment, the composition of the labour force, wages, job quality and working conditions, by using national/regional data at industry- and employee-level at the highest possible level of disaggregation.

This has been done by structuring the analysis around two main tasks. The first deals with how changes in the organisation of GVCs have affected labour markets at the sectoral and regional level, while the second explores whether and to what extent GVCs have impacted working conditions and work quality and generated new or exacerbated existing inequalities.

Figure 1: Summary of the TWIN SEEDS project and its Work Packages

Work package 1 Trends and drivers of global value chains and the role of MNEs in the recent wave of globalisation	Work package 2 Emerging trends of GVCs and MNEs in the pandemic	Work package 3 Recent and emerging impact of GVCs and MNEs on employment and inequality	Work package 4 Recent and emerging trends of GVCs and MNEs: impacts on the environment
Work package 5 Recent and emerging trends of GVCs and MNEs on growth, productivity and competitiveness	Work package 6 New Normal Scenarios	Work package 7 Policy Recommendations Emerging from the project	

Source: Authors' elaboration.

The report is organised into six chapters: the introduction, three analytical chapters, a discussion of key findings and finally, policy implications stemming from the research.

In Chapter 2, we investigate how the reorganization of GVCs has affected employment in European regions. In doing so, some main aspects have been considered, i.e. the restructuring strategies adopted (expansionary vs. re-shoring) and the ongoing focus on re-industrialization. Winners and losers at the regional level have been identified, with respect to the position each region may assume within GVC and the potential gain it may reap from GVC participation in terms of competitiveness and growth.

Chapter 3 empirically investigates how and to what extent some of the factors that contributed to the re-organisation of GVCs in recent years have changed employment trends and structures in (some groups of) EU regions. They include, besides the COVID-19 pandemic, robotisation, employment strategies of EU organisations, export quality upgrading and anti-globalisation sentiments.

Chapter 4 follows with an in-depth analysis of changes in labour markets, including effects on wages (gender pay gaps), working conditions, and job quality, for which empirical evidence is still scarce. We also explore the inequality implications by analysing the potential impact of GVC participation on the composition of the labour force in terms of skills and un-skilled workers across EU regions. In so doing, we distinguish the effects of local companies' offshoring strategies from those related to the presence of foreign companies.

In the remainder of the report, Chapter 5 summarises the key findings, and Chapter 6 provides policy implications stemming from the findings thanks to the relevance of the quantification of all effects and their pervasiveness across sectors and over space. The policy guidelines will help policymakers at different levels of governance to find the most effective ways of taking advantage of GVC participation.

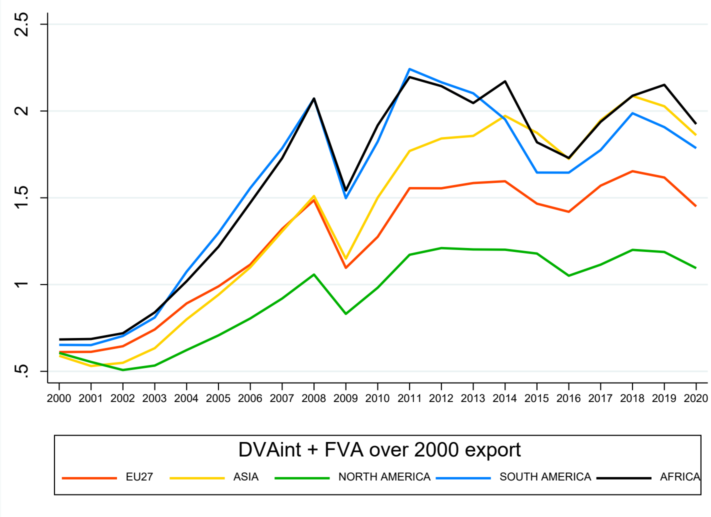
2. Reorganising GVCs: effects on regional employment, skill demand and re-industrialisation

Contextual background and research objectives

The theorised reorganisation of GVCs during crisis periods and the EU advocating for a relaunch of manufacturing activities in favour of job creation is the key foundation of all the analysis regarding the impact of GVC reconfiguration on employment and the dynamics in the labour market.

Many events –the COVID-19 pandemic and related economic crisis, the war in Ukraine and others – demonstrated that a globally fragmented production system is extremely fragile and exposed to shocks of different kinds (Brenton et al., 2022). Indeed, from 2008 until today, a new phase started, characterized by the slowing down, and in some cases by a reversing, of the intensification of trade and offshoring of production activities, as indicated by Figure 2. The evidence reported in the figure suggests that, after the drop of GVCs between 2008 and 2009, a recovery of the trade flows occurred in 2011, and remained stable up to the COVID period, when they registered again a decrease.

Figure 2: Change in the sum of DVA and FVA, over 2000 gross exports (source: OECD TiVa)



The relevance of the relaunch in industrialisation and jobs by the European Institutions originates from the 2008 economic crisis, when some unpleasant consequences of the deindustrialization trends in developed countries (loss of manufacturing jobs, slow-down in productivity dynamics) started to emerge (EC, 2010; EC, 2014; Ciffolilli and Muscio, 2018; Capello and Cerisola, 2023a). The situation was aggravated by emerging doubts about the efficiency of the international mode of production process (Baldwin 2009, Accetturo and Giunta 2016). The integrated, interdependent, and specialized trade structure was, in fact, interpreted as one of the main causes of the collapse of international trade by about 30 per cent between the first half of 2008 and the first half of 2009 (WTO, 2009).

Consequently, policymakers started casting doubts on the advantages of GVCs' participation and on the effects on both competitiveness and employment of alternative models of production, more oriented towards onshoring rather than offshoring. The COVID-19 pandemic relaunched both the reindustrialization and the backshoring debates as the health crisis highlighted the fragility of the international organisation of production, calling for backshoring processes and changes in the GVCs.

Indeed, despite backshoring being widely assumed to be performance-enhancing for the firm and beneficial for the country (Karatzas et al., 2022), the empirical investigation of the phenomenon, its trends (patterns) and its real effects are still quite limited.

Against this background, the objective of this chapter is to provide a framework for describing how the GVC organisation has evolved and what implications arise from the point of view of employment in the EU regions.

The analysis of the impact of GVCs reorganization on employment brings about the crucial question of whether a relaunch of manufacturing employment via a backshoring in Europe takes place with an intensity large enough to be captured by aggregate statistics or if this phenomenon is still to be treated in an anecdotal way, with macroeconomic effects on home countries still to come. With this respect, such an analysis requires an understanding of the overall entity of the phenomenon, and of its effects.

As per our knowledge, evidence of a backshoring trend at the regional (subnational) level does not exist and the territorial trends and impacts of backshoring in Europe are largely unknown. In particular, backshoring can take place in different ways in different types of regions due to the different regional specializations in production and trade. Backshoring can be an extensive or intensive margin reindustrialisation process, giving rise to different reindustrialisation patterns.

In addition, the studies aimed at analysing the effect on the employment dynamics of offshoring countries led to mixed and still inconclusive results. Some of them pointed to a positive effect of offshoring on employment growth also for low-skilled workers (Timmer et al., 2013), while some others suggested a contraction of jobs in labour-intensive occupations (Hijzen et al., 2005; Biscourp and Kramarz, 2007). The reasons for the still inconclusive results lie, among others, on:

- little conceptualization of the restructuring strategies, mostly interpreted in terms of changes in the participation in GVCs, overlooking the role that countries and regions play within GVCs;
- a focus mostly on countries, which hides the broad heterogeneity of GVC involvement at the subnational level. Some studies (although few due to limited data availability) pointed to the conceptual and empirical relevance of the analysis of the role of regions within GVCs (Autor et al., 2015; Capello et al., 2023).

Stemming from these considerations, there is the need for a clear understanding of the effects of alternative GVC restructuring strategies on jobs so as to orientate trade policies, also taking into account the specific characteristics of regions which exhibit significant economic disparities, with marked differences in GDP per capita, industrial specialization, and labour market conditions. Backshoring has been considered as a way to favour manufacturing employment dynamics in Europe, but this role cannot be simply assumed. In fact, it depends on the specific features of different regions.

This Chapter aims to fill such a knowledge gap by:

- measuring the effects at the macroeconomic (regional) level of reshoring on employment dynamics with the aim of understanding whether some normative ideas of the EU are feasible;
- assessing if strategies oriented towards reshoring are associated, more than others, with employment growth, and for which occupations (low-skilled vs high-skilled);
- assessing if other strategies (not intuitively associated with an expansion of jobs) lead to an increase in employment, and under which conditions;
- exploring the integration of EU NUTS2 regions into global, European and domestic value chains, examining the regional disparities, the impact of global value chains on regional economies, and the respective policy implications;
- analyse the skills demanded by the EU regions' foreign and domestic trade activities and compare them to the actual skill supply of the regions as an indication of potential skill mismatches in certain regions in order to prevent them from engaging in higher valued added trade activities.

Methods of analysis and data

To achieve the above-mentioned research objectives, we applied a combination of methodologies tailored to the different facets of global value chain (GVC) restructuring and its impact on employment.

In order to evaluate whether backshoring bringing production back to home countries can revitalize manufacturing employment in European regions, we categorized regions into two groups: traditionally manufacturing backshoring regions and emerging manufacturing backshoring regions, based on their levels of industrial specialization between 2000 and 2017. By analyzing employment patterns over this period, we sought to understand whether regions that increased their manufacturing focus through backshoring also saw improvements in local labour market outcomes.

To measure the impact of backshoring, we developed a quantitative indicator that captures a region's reduced dependence on GVCs and its reindustrialization efforts. This indicator was constructed by measuring changes in the value of manufacturing inputs imported into a region and embodied in its exports. Additionally, we created a reindustrialization index to compare shifts in the share of manufacturing value added before and after the 2008 financial crisis. These two indicators allowed us to track how much production was being relocated back to domestic regions and whether this translated into positive employment trends. To further explore these dynamics, we employed a pooled OLS (Ordinary Least Squares) model using data from European NUTS2 regions, which provided insights into the relationship between backshoring and manufacturing employment. The model also incorporated local labour market characteristics to account for how backshoring affects different types of jobs. Specifically, we distinguished between high-skilled and low-skilled occupations and analyzed how these were influenced by the backshoring process in different regions. This allowed us to uncover whether backshoring benefits certain types of workers more than others, particularly in regions with a strong manufacturing base. The interaction between regional characteristics and occupation types provided a clearer picture of which regions are better positioned to capitalize on backshoring to boost employment in specific job categories.

For the broader analysis of GVC restructuring strategies, we relied on trade in value-added data. Using a methodology developed by Capello et al. (2023), we measured how regions participate in GVCs by considering their economic power and level of integration in global trade networks. Our approach enabled us to overcome the common limitations of firm-level studies, which often miss the macroeconomic effects of GVC strategies. By applying this method at the regional level, we were able to assess the heterogeneous impacts of restructuring on employment dynamics for both high- and low-skilled workers.

These analyses have been carried out by using a multi-regional input-output matrix, provided by the JRC, which allowed us to estimate regional value-added trade flows generated by domestic, European, and global value chains. The method is based on similar methods applied at the country level for global input-output (I/O) tables. The I/O table covers the EU-NUTS-2 regions as well as the main global economies such as the US, China, Russia, India, and Brazil, as well as a summary of the Rest of the World category. Also, the I/O table covers 15 industries, which allows for a detailed analysis of value-added trade of the EU regions by specific sectors. By combining these trade data with information on skill intensities, such as the skill content of the jobs created by regional trade activities, we could link regional trade participation to labour market outcomes. This enabled us to evaluate the broader employment effects of GVC restructuring in different European regions and identify key factors driving economic growth and competiveness of EU regions according to their degree of participation to GVCs.

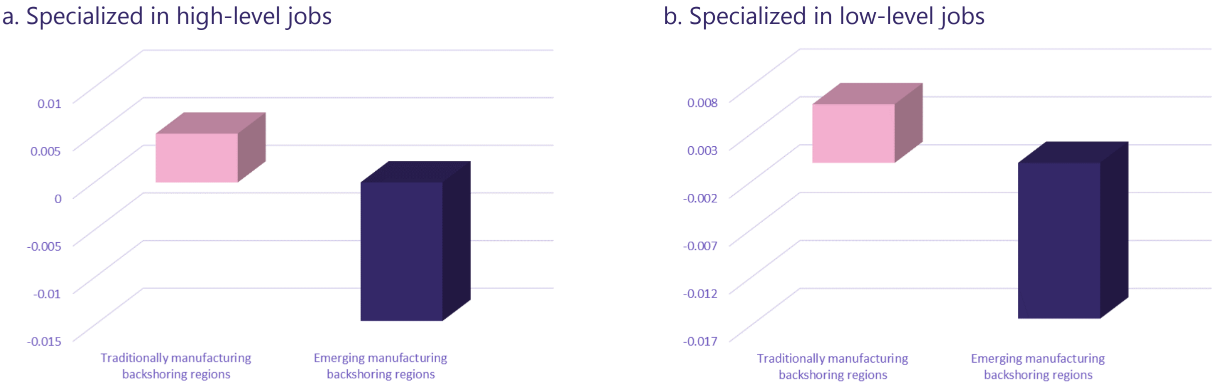
Unfortunately, these data are available only up to 2010. For this reason, the 2008 crisis is analysed as a proxy to gain insights on which potential restructuring patterns to expect in the waive of recent disruptions such as COVID-19. In fact, as pointed out by Baldwin and Weder di Mauro (2020), both crises share the characteristics of being severe, sudden, and synchronized, despite their different causes.

Findings and discussion

On the effect of backshoring favouring the manufacturing employment growth and revitalizing previously existing industrial vocations, interesting results emerge. However, at the aggregate level, the effects of job reinstatement through backshoring do not show up. Backshoring per se does not create employment dynamics in European regions.

While backshoring, in general, does not lead to an increase in employment growth, it produces positive effects in regions historically specialised in manufacturing, suggesting that this process helps in relaunching traditional industrial know-how and vocations in manufacturing regions in Europe that ultimately are associated with significantly higher manufacturing employment growth than elsewhere (expansionary production processes). Moreover, traditionally, manufacturing backshoring regions are associated with expansionary production processes, relaunching the industrial vocation through both high- and low-level occupations. A different story emerges for emerging manufacturing backshoring regions, which are associated with significantly lower manufacturing employment growth than in other regions (intensive production processes). Backshoring in emerging manufacturing regions is thus accompanied by a relaunch of an intensive production process, probably related to automation that displaces particularly blue-collar jobs (Figure 3). These different results suggest that strategies of modern reindustrialization and of relaunch of manufacturing employment have to be pursued in different regions taking into account their specific endogenous characteristics.

Figure 3: Effects of backshoring in different regions by functional specialisation



**Please note that the values come from different specifications. See technical appendix.*
The values displayed are those associated with the 75th percentile of the distribution in high/low-level functional specialization

The study also provides a quantitative assessment of the aggregate effects on regional labour markets, differentiating these effects on different occupational groups to derive policy implications for trade and industrial policy. Our results suggest that both expansionary GVCs and reshoring have an expansionary effect on employment, consistently with our expectation that an increase in control is assumed to generate a positive effect on jobs. However, this expansionary effect on employment varies between the two strategies since it operates on different occupational groups. In particular:

- *reshoring strategies* are associated with an expansion of low-skilled jobs, suggesting the occurrence of processes in which bringing back production phases previously allocated to third countries is able to boost domestic low-functional occupations. Keeping other things constant, the growth of total manufacturing employment in regions undertaking a reshoring strategy was 1.5 per cent higher than in the other regions (Figure 4a). The better performance of regions characterized by a reshoring strategy concerns the expansion of low-skilled jobs (Figure 4b), which was higher by about 1.6 per cent compared with the rest of the EU;
- *expansionary GVC strategies, instead, are associated with an increase in* high-skilled jobs (1.4 per cent higher than in the rest of the EU, Figure 4b). We interpret this result, which is partially consistent with our expectations, as supporting the idea that the regions' capability of improving their own terms of trade, still operating within GVCs and even reinforcing their embeddedness, mirrors an increase in the quality and innovativeness of the intermediate goods produced, and therefore an expansion of high-skilled employment, and not of low-skilled jobs.

Figure 4: The association between regional GVCs restructuring strategies and employment dynamics

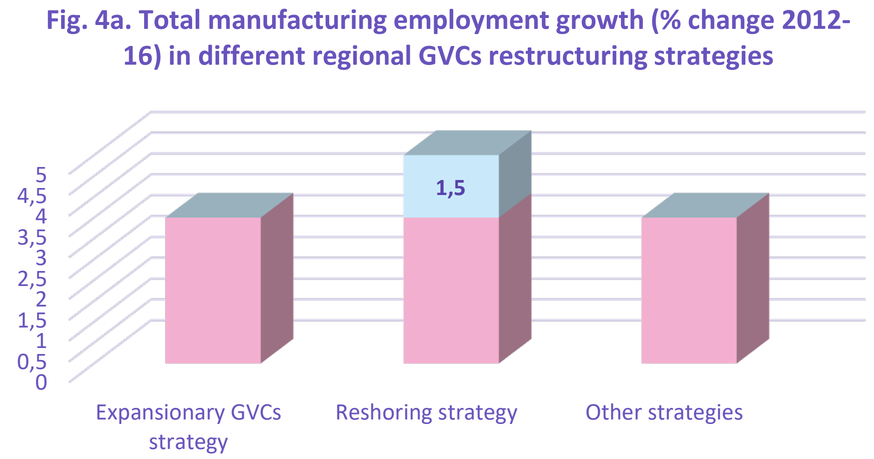


Fig. 4b. High-skilled manufacturing employment growth (% change 2012-16) in different regional GVCs restructuring strategies

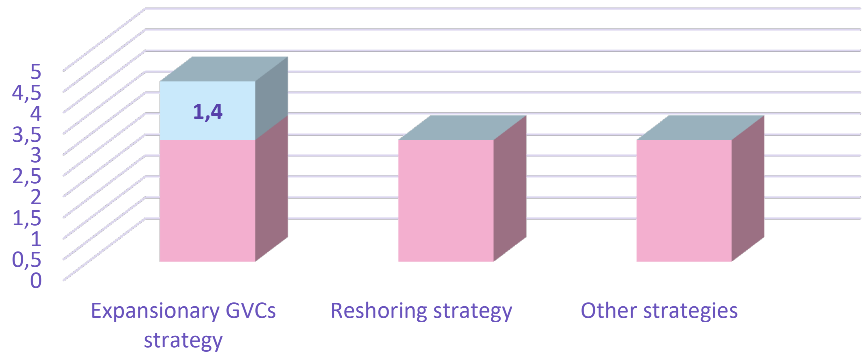
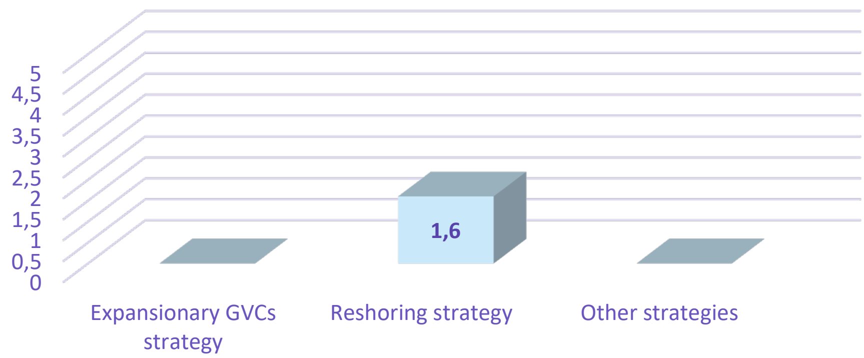


Fig. 4b. Low-skilled manufacturing employment growth (% change 2012-16) in different regional GVCs restructuring strategies



Overall, our findings suggest that the "pure" change in GVC participation is not necessarily associated with an increase in jobs. What matters is the gains an economic system can retain from participating in GVCs. Reshoring, when associated with an improvement of economic power, generates a relatively higher growth of low-skilled occupations, while the literature provides mixed evidence in this respect.

Lastly, our analysis has shown a high diversity of the EU regions in terms of their involvement in European and global value chains measured as the share of region value-added activity on total value-added traded with the EU and the Rest of the World (RoW). On the one hand, there are strong exporting regions, where the value-added exports contribute a significant proportion to their total value added, i.e. GDP. On the other hand, there are regions where value-added exports are of minor importance, and most of the value-added stays within a respective region or the country it is located in. At the same time, the analysis has shown that the higher the share of the regions' value-added exports, the more likely they are to have positive net value-added trade balances, mainly in high technology-intensive manufacturing or knowledge-intensive services. This indicates that differences in the regions' exporting activities are likely to be expressions of differences in the regions' competitiveness on EU and global markets. Regional differences in skill intensities accompany this.

To summarize these regional differences in trade competitiveness and skill intensities, we grouped the regions according to their respective characteristics into eight distinct categories that are indicative of the region's trade and growth model. To build this categories, regions have been grouped first into four categories according to their net trade balance. These groups are:

a) less competitive regions, i.e. regions with a negative value-added trade balance vis-à-vis the EU and the RoW;
b) partly competitive regions with a negative total value-added trade balance, i.e. regions with a negative total value-added trade balance, but a positive trade balance either vis-à-vis the EU or the RoW;
c) partly competitive regions with a positive total value-added trade balance, i.e. regions with a positive total value-added trade balance, and a positive trade balance either vis-à-vis the EU or the RoW;
d) globally competitive regions, i.e. regions with a positive value-added trade balance vis-à-vis both the EU and the RoW and hence a positive total value-added trade balance.

These four groups are then further split by their skill intensities, classifying each region with a trade skill intensity below the EU average as less skill intensive and the regions with an above the EU average skill intensity as more skill intensive. Thus, we end up with eight groups of regions (Figure 5 and Table 1). The resulting geographic distribution is highly instructive:

- regions with *low global competitiveness* are mainly located in the EU South, i.e. Greece, the South of Italy, Spain, and Portugal, but also include many regions in France and the UK. Thereby, the Greek, Italian and French regions tend to have a lower skill intensity in their trade, while the British and Spanish regions, as well as the French regions bordering Spain and the Bretagne are more skill intensive. As far as the EU South is concerned, in total it has only a few regions that are partly competitive on global markets, like Madrid, Paí-s Vasco or Andalucia in Spain or Lisbon, Centro and Norte in Portugal and even fewer regions that are highly competitive, i.e. Cataluña and Valencia, both in Spain;
- as far as the at least *partly competitive regions, though with an overall negative net value-added trade balance* are concerned, the low-skill intensive regions are located mostly in the EU East, i.e. in Poland, Slovakia, Hungary or Latvia. Many of these regions are specialised in manufacturing industries and typically show a trade deficit vis-à-vis the EU but a surplus in their value-added trade with the RoW. The same type of regions, yet with a high skill intensity, are predominantly located in Spain, Lithuania, Belgium and the UK;
- turning to the regions *partly competitive with a net positive value-added trade balance*, the less skill-intensive regions are mostly located in Austria, Germany,

Czechia, Slovenia and the Western parts of Hungary, Poland and Slovakia. These regions correspond to the strong industrial regions within Europe;
- by contrast, *global competitive regions* with a positive net value-added trade balance and high skill intensities are many times either capital cities or major urban agglomerations, such as London, Paris, Berlin, Munich, many regions in the Benelux, as well as capital cities in the EU East. All these regions specialised in high-skill-intensive exports, predominantly in the services area.

This descriptive analysis suggests that there is a correlation between the extent to which regions are engaged in value-added trade and the size of the benefits, i.e. the net value-added trade balance they gain from it. A rigorous econometric analysis investigated whether value-added exports to the EU or the RoW are important for regional economic growth. The analysis returns a very variegated picture; indeed, economic growth in the EU Northern regions is driven by innovation, skills and capital accumulation, while in EU Eastern regions, development is driven more by manufacturing industries with strong value chain linkages to the EU North and especially German regions. In the EU South, instead, growth and value-added exports tend to be more services-driven, except for a few strong industrial regions like Paí-s Vasco, Navarra, Aragón or Cataluña in Spain. Lastly, capital city regions and large urban centres, like Munich, Hamburg, Inner London, Budapest or Bratislava, to mention a few, are highly competitive in value-added trade, being specialised in highly skill-intensive exports, mostly in the services sector. This hints towards differences across regions with respect to their functional specialisation and different positions within the European and global value chains.

Overall, the econometric analysis also suggests that a high skill intensity provides regions with a competitive advantage in trade. Despite that, there are many regions being highly competitive in EU and global markets with a rather low skill intensity of their exports. In many cases, this is because of differences in the regions' pattern of specialisation, as those regions being specialised and competitive in manufacturing industries tend to be less high-skill intensive but rather rely on highly trained employees with completed secondary education, like in the case of Austria, Germany or Czechia.

Figure 5: Regional types of regions by trade competitiveness and skill intensities

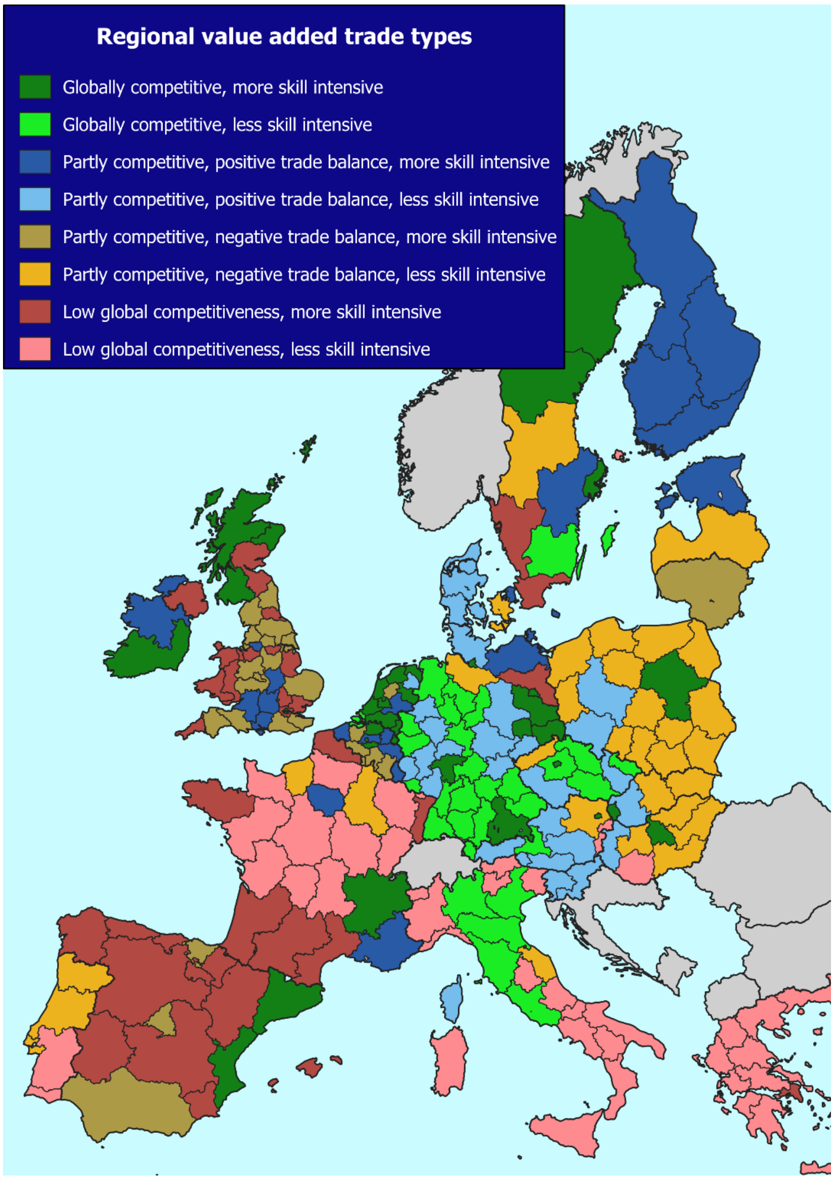


Table 1: Summary statistics for the eight group of regions

	Number of regions	Global value-added exports	Net value-added exports	High skill intensity
Low global competitiveness, less skill intensive	42	16.5	-10.3	19.2
Low global competitiveness, more skill intensive	36	18.5	-16.3	34.2
Partly competitive, negative trade balance, less skill intensive	32	29.7	-4.6	19.1
Partly competitive, negative trade balance, more skill intensive	25	26.3	-3.7	35.8
Partly competitive, positive trade balance, less skill intensive	28	32.4	4.0	20.2
Partly competitive, positive trade balance, more skill intensive	22	33.1	4.5	36.5
Globally competitive, less skill intensive	31	31.4	8.4	19.7
Globally competitive, more skill intensive	34	33.5	12.0	36.1
EU	250	26.9	-1.5	27.0

3. Transforming GVCs: COVID, robotisation, employment strategies, export quality and anti-global sentiments

Contextual background and research objectives

The previous Chapter has highlighted a scenario of apparent ambiguity regarding the effects of the post-pandemic reorganisation of GVCs on employment because of the complexity inherent to its study, namely the heterogeneity of workers' skills, the levels of development of the economies, the characteristics of the GVCs, and the reorganisation strategies implemented at country or regional level. This scenario acquires additional complexity because of the difficulty of isolating the net effects of GVCs from those exerted by other phenomena directly or indirectly via GVCs (Carneiro et al., 2024).

Among such phenomena, one can envisage the pandemic shock and the potential changes it induced on employment trends and on employment strategies of firms participating in GVCs, rapid robotisation and export quality, the perception of costs and benefits of GVCs by different groups of emplyees. All these phenomena are part of Task 3.1 and empirically expored in Work Package 3. In particular, the following questions are addressed: i) how the pandemic shock has changed employment trends at occupation and sector levels; ii) opportunities offered by rapid robotisation and export quality upgrading; iii) potential changes induced by the pandemic on employment strategies of firms participating in GVCs; iv) the perception of costs and benefits of GVCs by different groups of employees.

The COVID-19 pandemic disrupted global value chains as international trade declined due to lockdowns, restrictions, and firm closures. Initially, articles written during the pandemic highlighted the sudden and severe nature of the crisis but were largely speculative about its long-term effects on organizational structures, labor markets, and firms (George et al., 2020; Venkatesh, 2020; Verbeke, 2020). As the world shifted towards a post-COVID phase and more data became available, it became possible to assess the true impact of the pandemic and explore how disruptive it was for global value chains and labor markets. This analysis also provides insights into whether the pandemic has had lasting consequences on organizational practices and employment, offering valuable lessons for policymakers about potential measures to mitigate future shocks.

Concerns about the negative labor market implications of globalization and technological innovation have influenced policymakers to consider reshoring previously offshored production and reducing dependency on foreign inputs (e.g., the EU's "strategic autonomy" and the U.S. "Made in America" initiatives). In this context, technologies like automation and artificial intelligence are seen as both opportunities and risks. While they offer potential solutions to shorten supply chains and reduce reliance on foreign labor, they also pose challenges to domestic job markets. Many studies have examined the impact of automation, particularly robots, on employment. For instance, Acemoglu and Restrepo (2020) found negative employment impacts in U.S. regions heavily exposed to robots, while Dauth et al. (2021) did not observe such effects in Germany. The mixed findings suggest significant variation across countries, sectors, and occupations, highlighting the need for further research into the heterogeneous impacts of automation.

High-income countries often face competitive pressure from lower-wage nations, a dynamic vividly illustrated by the "China shock" following China's entry into the World Trade Organization. This shock led to significant manufacturing declines in the U.S. and Europe (Autor et al., 2013). In response, export quality upgrading has emerged as a key strategy to maintain competitiveness. Firms that successfully improve the quality of their exports are expected to experience better employment outcomes, though empirical evidence linking quality upgrading to positive labor market effects remains limited. It also remains unclear how participation in GVCs influences the relationship between export quality improvements and employment dynamics.

While there is a well-established body of literature examining the relationship between GVC participation and employment, more recent research has begun to explore the strategic decisions firms make regarding human resources in the context of GVCs. These strategies are crucial for sustaining productivity, especially through investments in human capital, such as training programs and the use of permanent or temporary contracts (Dekker & Koster, 2017). Previous analyses, particularly those from Work Package 2, demonstrated that many organizations were resilient in their employment strategies in response to the challenges posed by COVID-19 (Jankowska et al., 2023). However, it remains to be seen how GVC participation influences long-term skill upgrading and innovation within firms.

The COVID-19 pandemic, coupled with rising geopolitical instability, has contributed to a slowdown in globalization and a surge in protectionist sentiments, particularly in developed nations. Anti-trade attitudes were already emerging before 2020, as evidenced by events like Brexit and the election of Donald Trump, both of which reflected growing skepticism about international integration. Although protectionist policies, such as trade restrictions, have been shown to have negative economic effects (Oberhofer & Pfaffermayr, 2021; Schimmelfennig, 2021), they remain politically popular in certain regions. In the U.S., for instance, voters in areas exposed to tariffs were more likely to support Trump in the 2020 election (Lake & Nie, 2023). This trend poses a significant challenge for Europe, where rising protectionism threatens both economic and political integration. Understanding the root causes of anti-trade sentiments is crucial for designing policies that highlight the benefits of economic integration and counteract the negative perceptions associated with globalization.

Chapter 3 of this report tackles research questions related to the abovementioned issues. The main research questions can be grouped according to the different socio-economic facts that may interact with GVCs in affecting employment trends at both the country and regional levels. In detail:

- *Pandemic shock and employment trends*: Working from home and outsourcing as mediator factors. How did the pandemic shock affect employment patterns in the EU? In which way are shifts in employment patterns connected to (i) the speeding up of work from home, which affected different occupations and sectors, and (ii) the dependency of different sectors on outsourcing, hence on the impact of GVC reconfiguration? Are these impacts homogenous across sectors?

- *Robot, (re-)shoring, and employment*. Does robotisation in Europe lead to reshoring production steps? If so, what are the employment consequences? Are these consequences homogenous across different groups of labourers?

- *Export quality upgrading, employment and GVCs*. Does quality export upgrading generate more employment? How does participation in GVC affect the relationship between quality export upgrading and employment?

- *Covid, GVCs and employment strategies*. How are GVCs and employment strategies linked? Is there any difference in this relationship during and after the pandemic shock?

- *Citizens' perception of costs and benefits of GVCs*. How do individuals develop their own perceptions of trade? How do individual (i.e. occupational) and contextual (i.e. regional GVC exposure and functional specialisation) factors empirically interact to determine trade preferences? Do trade perceptions significantly differ in a period of crisis?

Methods of analysis and data

Given the variegated nature of the topic tackled in this chapter, data at different levels of disaggregation have been analysed with the help of different methodological approaches applied to different geographical scales and sectoral partitions.

To address the issue of the impact of the pandemic shock on employment trends, we first applied a decomposition analysis to test to which extent shifts in employment patterns were due to (i) across-sector differences in overall employment growth or (ii) intra-sectoral changes in occupational composition. The first effect is the so-called extensive margin: as industries expand, more workers are needed, and the overall number of workers will grow. The second one, instead, is the intensive margin: industries may need more workers for a specific occupation and less for another, which will change the employment structure within industries and across occupations. This information is relevant for policymakers to implement policies to assist affected workers or, conversely, to prepare for potential skill shortages due to an over-proportional increase in the demand for a certain profession. We then applied econometrics techniques (pooled OLS with industry and country fixed effects and clustered standard errors) to investigate the relations between the pandemic and employment changes across different sectors and the mediating role of working from home and participation in GVC. The data for this part of the analysis come from two different sources, i.e. the EU Labour Force Survey (EU-LFS), a large household sample survey that provides quarterly data on labour participation of persons aged +15 as well as of persons outside the labour force We use two different types of EU-LFS data: the dependent variable stems from Eurostat's online database while information on working from home (WFH) is calculated from EU-LFS microdata that are available to researchers for scientific purposes (SUF-files). The countries in our sample refer to all EU member states (as of 2020) except for Germany due to the break in the data. The data in the analysis refer to persons aged 15+ who were employed during the reference week. Second, trade-related data is taken from the Full International and Global Accounts for Research in input-Output analysis (FIGARO), which provides information on international linkages of production processes and structures of trade in final goods across 64 industries (NACE Rev. 2, A64) and 64 commodities, covering all 27 EU member states, the United Kingdom, the United States and 16 main EU partners, plus a rest of the work aggregate. It is available from 2010 to 2021. We use information for both domestic and imported inputs at the one-digit industry level to construct the different offshoring measures described above.

Econometric techniques were also used to explore the relationship between robotisation-induced GVC reorganisation and employment. In particular, various industry-level data sets have been linked and a regression analysis for long-run employment changes for 15 manufacturing industries across 35 countries has been performed. The estimation approach is consistent with de Vries et al. (2020). To measure reshoring and production relocation, the OECD ICIOTs (inter-country input-output tables) have been used, following the approach suggested by Krenz et al. (2021) and Krenz and Strulik (2021). We use an update of de Vries et al. (2020) for employment, as provided by Kruse et al. (2023). Robot data comes from the International Federation of Robotics.

To investigate the relationship between export quality upgrading, in the context of GVC, and employment, several Dutch firm-level datasets from Statistics Netherlands have been exploited. In line with the extant literature, we estimated export quality from information on product prices and foreign demand characteristics (Khandelwal et al., 2013). Labour market outcomes, such as employment, wages, and inequality, are then regressed on quality upgrading. We, therefore, rely on a first-difference regression model that accounts for unobserved heterogeneity across firms (and sectors). We compare 3-year changes over the (average) 2013-2015 to the (average) 2016-2019 period. This approach is intuitive for our research question: it shows us how medium-term employment changes are associated with firms' export quality changes.

The issues related to the effects of the pandemic shock on employment strategies, always in the context of GVCs, have been investigated using the World Bank Enterprise Survey (WBES). The first research question was answered with the standard WBES questionnaire gathered between 2019 and 2024. The second research question is assessed with a specific Covid-module that was gathered between 2019 and 2022. While the empirical work overlaps with respect to the timeframe, the data do not. The standard WBES enables the investigation of almost 68,945 companies from 70 countries, while the Covid-module only includes 17,175 companies in 12 countries. What is more, the items differ in these two data sources. While both have information on investments in training, the Covid-module also has information about changes in the composition of the workforce. Therefore, the datasets are analysed separately to answer the two research questions. Four types of GVC participation are distinguished, ranging from a minimal definition (being a two-way trader) to a very strict definition (Dovis & Zaki, 2020; Elsharaawy & Ezzat, 2022). The measures are explained in the Technical Appendix. The data are analysed using two different approaches. The dichotomous variable training programs are assessed with a logistic multilevel regression analysis, and the variables measuring changes in the workforce are assessed with a multinomial regression analysis using country dummies.

The last topic, i.e. the drivers of anti-globalisation sentiments, has been analysed by exploring individual (cross-sectional) statements from two Eurobarometer (EB) surveys (covering all EU27+UK countries), conducted in 2010 and 2019. EB surveys disclose information on a number of characteristics of the respondent, including their region of residence. This allows the study of anti-trade sentiment as a function of the occupational profile of the individual (high vs. low-skilled) and regional GVCs exposure/functional specialisation.

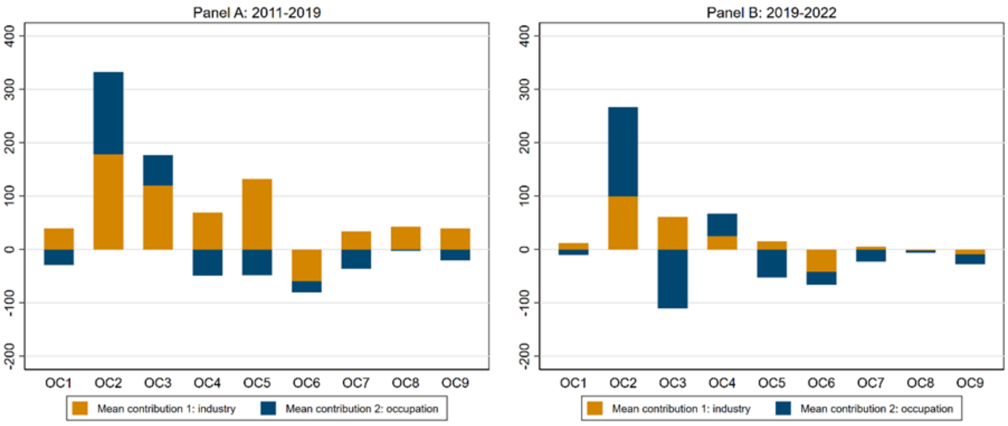
Findings and discussion

Pandemic shock and employment trends: working from home and outsourcing as mediator factors.

Our analysis suggests that a shock like the pandemic might have both short- and long-run impacts on employment patterns, thus exerting differential impacts on different industries and professions/occupations within each specific industry across different groups of EU countries. Despite that, on average, Europe managed the employment impact of the COVID-19 pandemic relatively well, partly because of the implementation of job retention schemes. Developments in labour force participation do not suggest major negative effects. Manufacturing, transport, craft and trades-related workers and plant and machine operators experienced considerable stress during the pandemic. Structural change continued, but perhaps less rapidly than one could have expected - the 'green transition' of our economies and less open global markets will certainly pose further challenges. This is more relevant for the Central Eastern and Southern European countries. A comparison of employment trends in Western Europe with and without Germany suggests that there is a serious challenge for Germany.

The analyses also suggest that there are also winners, both in industries and occupations. They include information and communication technology, professionals, scientific and technical activities and, to a lesser extent, health and human services, education, and public administration. These trends are not homogenous across different groups of EU countries. For example, Northern and Western Europe not only have higher shares in these industries but also their growth rates are mostly higher - no convergence between the regions. There might be a shift from technicians and associated professionals to professionals – that could be interpreted as a welcome upgrade, but it also poses the risk of some medium-skilled workers being left behind. Employment of clerical workers continued to grow at a relatively high rate across the EU except in the North, which could be a signal that something is changing here as well, not to speak of the potential impacts of recent technological developments. It is also worth noting that women professionals and clerical workers did better than men also in the South.

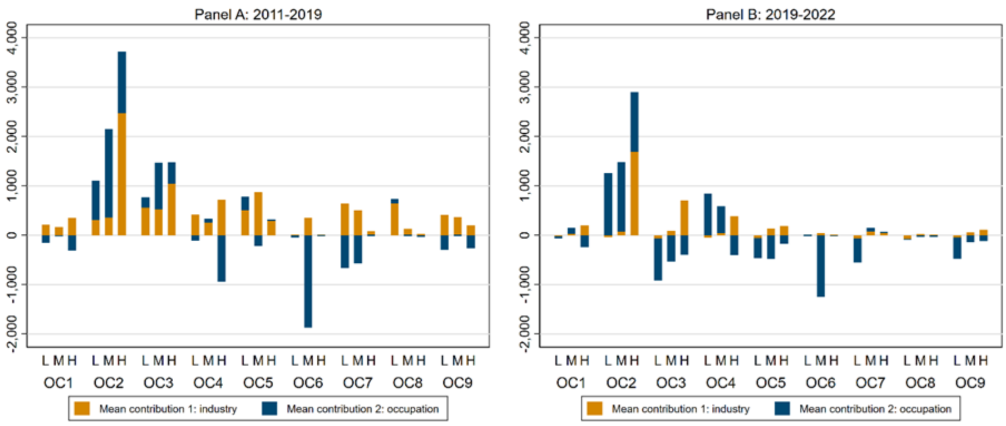
Figure 6: Decomposition analysis: EU as a whole



Note: OC1 refers to ‘Managers’, OC2 to ‘Professionals’, OC3 to ‘Technicians and associate professionals’, OC4 to ‘Clerical support workers’, OC5 to ‘Service and sales workers’, OC6 to ‘Skilled agricultural, forestry and fishery workers’, OC7 to ‘Craft and related trades workers’, OC8 to ‘Plant and machine operators and assemblers’, and OC9 to ‘Elementary occupations’. OC0 (Armed forces occupations) is excluded.

Source: EU-LFS, own calculations.

Figure 7: Employment changes in EU by occupations (in 1.000 persons), 2011-2019 and 2019-2022; differentiated by ‘work from home’ intensity



Note: L refers to low work-from-home intensity/share, M to medium work-from-home intensity/share, and H to high work-from-home intensity/share. OC1 refers to ‘Managers’, OC2 to ‘Professionals’, OC3 to ‘Technicians and associate professionals’, OC4 to ‘Clerical support workers’, OC5 to ‘Service and sales workers’, OC6 to ‘Skilled agricultural, forestry and fishery workers’, OC7 to ‘Craft and related trades workers’, OC8 to ‘Plant and machine operators and assemblers’, and OC9 to ‘Elementary occupations’. OC0 (Armed forces occupations) is excluded.

Source: EU-LFS, own calculations.

The analysis of factors driving employment changes, underlines the importance of professionals for future employment trends as it is the only occupation which grows in numbers due to their presence in growing industries and due to a growing share within the industry in both periods. Unsurprisingly, services display the highest capacity to work from home, except for health, human support and social services. Professionals, technicians and associated professionals, and clerical workers seem to benefit most from it. In industries with a high capacity to work from home clerical workers do less well as their share in the respective industry declines (Figure 7).

Regarding outsourcing and global and regional value chains, an issue particularly relevant for the TWIN SEEDS project, we found a differential impact across sectors and occupations within sectors driven by international specialisation and the offshoring of tasks (see Technical Appendix D, Table D.1 and D.2). The insights obtained from this type of analysis are important to tailor labour market and educational/training policies to adjust to longer-term trends in employment patterns in different EU economies, to hysteretic impacts of the Covid crisis and to longer-term effects of Working from home possibilities (differentiated by occupations and sectors) and to any reorganisation of GVCs (Europe/non-Europe; with developing and advanced economies).

Robot, (re-)shoring, and employment.

Overall, our analysis highlights three striking facts. First, employment is quite strongly and positively correlated with robot adoption, once certain sector characteristics are accounted for. This is particularly to the benefit of labourers performing non-routine analytical tasks.

Secondly, there is no clear sign of robot-induced reshoring: robotising sectors generate more domestic value added but this increasing value added is not significantly higher than an associated increase in foreign input use. Overall, sectors that are faster robot adopters provide relatively fewer inputs to domestic sectors, which is at odds with robotisation being associated with reshoring patterns. Only when focusing on sectors that are actually reshoring, reshoring intensity is positively correlated with robotization.

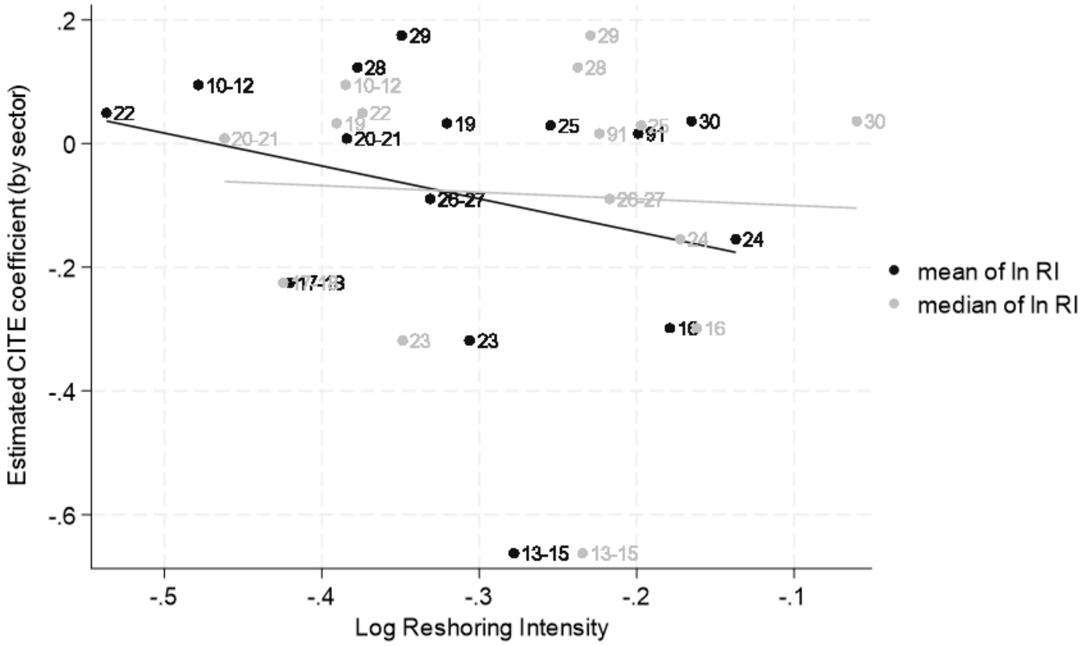
Lastly, reshoring is not significantly associated with favourable employment trends, and neither is the association between robots and employment more favourable in sectors that increasingly reshore. Particularly, we find that reshoring is negatively correlated with employment shares of workers who perform routine and manual tasks.

The interplay between robotisation, employment and (re-)shoring intensity is depicted in Figure 8. In particular, it shows the relationship between robotization and employment for each manufacturing sector covered in the study (vertical axis). It plots this relationship against reshoring intensity (horizontal axis). Two patterns stand out:

1. For many sectors, the relationship between robotization and employment is positive (above 0 on the vertical axis, e.g. sectors 22, 10-12, 28, 29 etc.).

2. On average, the relationship between robots and employment becomes increasingly negative the more reshoring a sector experiences (rightward move on the horizontal axis).

Figure 8: The relationship between robotisation and employment by reshoring intensity



Export quality upgrading, employment and GVCs

As for the relationship between firms' export quality upgrading and labour market outcomes in the context of GVCs, our analysis highlights several interesting facts that contribute to improving the existing debate on the issue:

- Firms that upgrade their export quality enjoy more favourable employment developments. This is a very robust finding. A one-standard-deviation improvement in export quality is associated with 2.2 percentage points higher employment growth (over three years) compared to a firm that does not improve its export quality.
- Wage increases are uncorrelated with export quality upgrading. We don't find any evidence that firms' changes in export quality significantly correlate with their changes in average wages.
- Firm's export quality upgrading is not associated with higher wage inequality within firms.
- Participation in GVCs does not seem to matter much in this context. We neither find that any of the above-mentioned results are clearly contingent on firms' participation in GVCs. We find some evidence that GVC participation is positively associated with improvements in export quality, but the economic magnitude of this association is negligible. Thus, we can conclude that firms' participation in GVCs does not boost export quality.

Overall, our results allow us to gauge the relevance of export quality upgrading for employment dynamics. However, changes in export quality explain only a small fraction of firms' employment developments.

Covid, GVCs and employment strategies

GVC participation explains an important part of the use of training programs. This holds for all four types of international trading companies. Nevertheless, the analyses also show that two-way trading companies are more likely to have a training program. However, the companies that are two-way traders, have an international certificate, and foreign-owned are the most likely to have them. With regard to the COVID period, the analyses show that there are only a few differences between organisations that operate internationally and those that are oriented at the national market. It turns out that there are some two-way trading organisations that saw an increase in permanent workers, accompanied by a reduction in temporary workers. These results only hold for the two-way traders and those with an international quality certificate. The other types of GVC participation do not deviate from the other organisations.

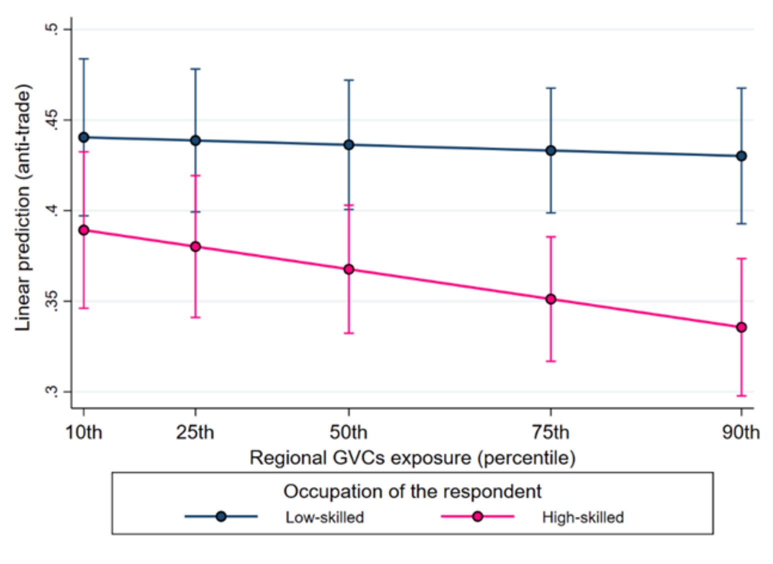
The contribution of our results to the existing debate on the issue is manifold. First, we uncovered that GVC participation is positively related to the use of training programs, which aligns with research about upgrading and upskilling. This is surprising and new, in particular in light of the first wave of COVID-19 papers that emphasised the uncertainties and struggles of organisations during the beginning of the pandemic. While there has been a short-term disruption, it seems that organisations soon started to catch up and invest in their personnel. This result corroborates the idea of the hysteretic effects of the pandemic, as discussed at the beginning of this section. Secondly, organisations in EU countries rely more on training programs and their GVC participation is higher compared to non-EU countries. This is basically in line with results from national-level research. However, as far as we know, this has not been investigated with internationally comparative organizational-level data to date. Third, the results do not suggest that the COVID-19 period led to a particularly strong reduction in the workforce among organisations that participate in GVCs. This is again surprising given the supposed disruptive nature of COVID-19, but that reinforces previous results (see, Covid and employment patterns). Finally, there are sectoral differences, i.e. organizations in the service sector use training more often than their counterparts in other sectors.

Citizens' perception of costs and benefits of GVCs.

Special attention deserves the results concerning the determinants of EU citizens' perception of the regional costs and benefits of participation to GVCs for their potential policy implications. Our main results are the following ones (a table with full estimates is reported in the technical annex H):

- Consistently with standard trade theory, taking medium-skilled workers as a reference, the probability of being anti-trade is 3.6% higher (4.1% lower) for low- (high-) skilled workers. Therefore, low-skilled workers perceive international trade as less beneficial than high-skilled ones.
- On average, regional GVC exposure does not significantly affect the probability of being anti-trade. On the other hand, a one-standard-deviation increase in high-skill regional specialisation decreases the probability of being against international free trade by 1.2%. Again, this is consistent with the assumption that in developed countries, international trade favours regions specialized in high-skilled jobs.
- In regions with low exposure to GVCs (Figure 9), high- and low-skilled workers do not significantly differ in terms of anti-trade sentiment. Increasing the regional GVCs exposure lowers the probability of high-skilled workers being anti-trade, and larger differences in how the two categories perceive trade are observed. Indeed, as trade increases, high-skilled workers increase their utility, and this is mirrored in their improving perception of the benefits of international trade. It is worth noting that, on the other hand, perceptions of low-skilled workers do not significantly change at different levels of regional GVC exposure.

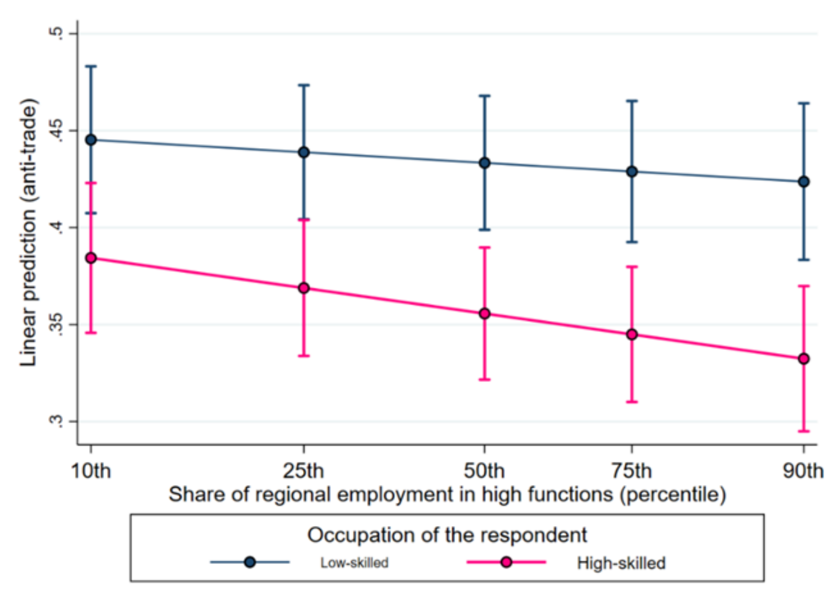
Figure 9: Predicted anti-trade sentiment (0-1) at different levels of regional GVCs exposure



- In regions specialized in low-skilled jobs (Figure 10), high- and low-skilled workers do not significantly differ in terms of anti-trade sentiment. Increasing the specialisation in high functions reduces the probability of high-skilled workers of being anti-trade, and larger differences in how the two categories perceive trade are observed. Indeed, in regions specialised in low-skilled jobs, the more intense negative effects generated by trade (unemployment, etc.) reduce the high-skilled workers' increase in their utility, and this is mirrored by their perception of trade, not significantly different from the one of the low-skilled workers.

- In a period of crisis (like 2010), individuals are between 1.1 and 1.3 per cent more likely to be anti-trade than in a period of higher macroeconomic stability (like 2019). In this respect, it is worth noting how the regional dynamics of employment growth (not directly and exclusively related to trade) are likely to affect individuals' perceptions of trade.

Figure 10: Predicted anti-trade sentiment (0-1) at different levels of regional specialization in high-skilled



Overall, the empirical analysis suggests that individuals' perceptions are significantly affected by the characteristics, in terms of GVCs exposure and functional specialisation, of their community of residence. The highest levels of anti-trade perceptions characterise regions less exposed to trade. This finding is interesting and somehow surprising since it suggests that trade, per se, does not directly promote an anti-integration sentiment. Instead, it is in those regions excluded from a globally fragmented division of labour that anti-trade sentiment finds a more fertile ground.

4. GVC reconfiguration and inequality

Contextual background and research objectives

As Chapters 2 and 3 of this report have highlighted, the globalisation of production through Global Value Chains (GVCs) has profoundly reshaped labour markets worldwide, particularly in Europe. Over the past decade, inevitably, GVC integration, characterized by the international division of labour and offshoring of tasks, has also contributed to rising labour market inequalities, which will be the focus of this last chapter of the WP3 report.

The restructuring of GVCs, spurred by technological changes, trade liberalization, and global disruptions such as the COVID-19 pandemic, has further intensified labour market inequalities (Task 3.2). The pandemic accelerated shifts in global production networks, introducing new pressures on firms to adapt their international strategies, reshaping workforce management practices, and exacerbating inequalities (Guadagno et al., 2023). One of the key outcomes has been job polarization, where high-skill/high-wage and low-skill/low-wage jobs have expanded at the expense of middle-skill jobs. (Goos & Manning, 2007; Autor, Levy & Murnane, 2003).

The rise in job polarization is closely linked to the ongoing restructuring of global production. The decline of routine-based middle-skill jobs, driven by automation and task offshoring, has been accompanied by an increase in demand for both highly skilled professionals and low-wage service workers (Autor & Dorn, 2013). Firms participating in GVCs, particularly those adopting efficiency-seeking and market-seeking strategies, have further contributed to this polarization by outsourcing tasks to regions with lower labour costs, thereby reshaping employment structures both in Europe and beyond (Cortes et al., 2017; Goos et al., 2014).

However, the nature and intensity of job polarization vary across regions depending on the specific strategies of firms, the sectors involved, and the characteristics of local labour markets (Verdugo and Allegrè, 2020). Technological change and GVC participation are thus creating a labour market where middle-skill jobs are increasingly disappearing, and the workforce is bifurcating into low-wage and high-wage segments.

As GVCs reorganize, the consequences for workers are unevenly distributed, leading also to increased job insecurity, wage inequality, and disparities in working conditions across different sectors and regions (Rodrik, 2013). Indeed, while GVC participation can boost competitiveness and drive economic growth, it poses significant challenges to job quality and working conditions. The competitive pressures firms face in GVCs often lead to cost-cutting measures, which can result in a "race to the bottom" in labour standards, particularly in regions where labour rights enforcement is weak (Manning, 2004; Baldwin & Okubo, 2014). In contrast, some firms engage in technological upgrading in response to GVC participation, which may improve working conditions for a subset of workers, particularly in high-skill positions. However, these improvements are not evenly distributed, and many workers face precarious employment and worsening job conditions due to the competitive dynamics of global production (Feenstra & Hanson, 2003; Reijnders & de Vries, 2018).

Understanding the relationship between GVC integration and job quality is crucial, especially as GVCs increasingly determine the structure of labor markets. These changing conditions heavily influence workers' health, productivity, and job satisfaction, and the effects vary significantly across regions and types of employment.

The restructuring of GVCs has also deepened gender inequalities in the labour market. Existing research indicates that GVC participation has a complex relationship with gender pay gaps, with outcomes that can be both positive and negative. While technological upgrading associated with GVCs can lead to skill upgrading and wage gains, these benefits often accrue disproportionately to men, exacerbating gender disparities in pay and job security (Bamber & Staritz, 2016). Men are sometimes better positioned to benefit from new opportunities created by GVC participation. At the same time, women are more likely to be employed in precarious, low-wage jobs within the same sectors (Nikulin & Wolszczak-Derlacz, 2022).

The COVID-19 pandemic further intensified these gender disparities, as many sectors with high female employment, such as retail, hospitality, and manufacturing, were severely disrupted by GVC restructuring (Doorley et al., 2022). These sectors experienced a decline in job security, and women, in particular, faced increased precariousness in employment. Additionally, the growing adoption of automation and digital technologies has raised new concerns about the gendered impacts of GVC participation, as men and women are unequally affected by these trends in various industries.

Workpackage 3 investigates also the broader implications of GVC restructuring for labour market inequality, focusing on job polarization, job quality, and gender gaps, as promised by Task 3.2. Specifically, the research aims are threefold. First, the impact of GVC participation on job polarization will be analyzed, focusing on how internationalization strategies - such as offshoring and foreign direct investment - contribute to the bifurcation of labour markets into high-wage and low-wage jobs. Secondly, the relationship between GVC integration and job quality will be studied, exploring how competitive pressures and technological upgrading affect working conditions, job security, and overall job satisfaction. The research will assess how these effects differ across regions, sectors, and types of employment. Finally, we will investigate the gendered impacts of GVC restructuring, analyzing how GVC participation influences gender pay gaps, job insecurity, and precarious employment, particularly in light of the changes accelerated by the COVID-19 pandemic.

By addressing these objectives, this part of WP3 aims to contribute to a deeper understanding of how GVC restructuring influences labour market inequalities and offers insights for policymakers seeking to balance the benefits of globalization with the need to protect vulnerable workers and ensure more equitable labour market outcomes.

Methods of analysis and data

This section outlines the data sources and analytical methods used to investigate the impact of Global Value Chain (GVC) restructuring on labour market inequality, including job polarization, job quality, and gender disparities. The analysis draws on several European datasets at both the individual and sectoral levels, combined with various econometric techniques designed to address the multi-dimensional nature of labour market changes in the context of GVCs.

Data

The data used for the analyses are aggregated at different levels to capture individual worker characteristics and broader economic trends at the sectoral and regional levels.

Measures of GVC participation

In studying the effects of GVCs on job polarization in the local labour market, regional participation in GVC is proxied by data about the Global Production Networks derived from the Amadeus/Orbis Database. This provides detailed information on firm internationalization activities, including the number of Global Ultimate Owners (GUOs) headquartered in each NUTS2 region and their foreign subsidiaries, as well as the presence of foreign MNEs. These indicators allow the study to assess the impact of both outward internationalization and the attraction of foreign firms on regional job polarization.

To study the effect of GVCs on working conditions, Trade-related data are sourced from the World Input-Output Database (WIOD), which tracks the international linkages of production processes and trade in final goods across 38 industries and 51 countries. This dataset allows us to analyzes industry-level offshoring and its effects on working conditions and job quality.

Finally, the intensity of participation in GVCs at the country and sectoral levels is retrieved from the Trade in Value Added (TiVA) Database and merged with the Eurostat and EWCS datasets to capture GVC participation at the sectoral level in each country and year. This indicator measures the extent of a sector’s participation in global production, using the log-transformed share of imported intermediate inputs in gross output, which reflects both forward and backward GVC linkages. These data are then used to study how changes in the organization of GVCs have affected gender differences in the labour markets at the sectoral and individual levels.

Outcome variables: inequalities in the labour markets

The outcome variables are measured either at the regional, sectoral, or individual level. Specifically, to study the heterogeneous effects of GVCs on different labour market outcomes and working conditions we consider the following indicators:

- *Job polarization*: Polarization was measured with an overall index defined in each NUTS2 region in each year as the ratio between employment in low (ISCO 9) and high (ISCO 1-2-3) occupations over employment in medium skill occupations (ISCO 4- 8). This data spans the period 2007 to 2022.
- *Gender disparities in the labour market*: three different indicators were used. The *gender pay gap* (in unadjusted form) is the difference between the average gross hourly earnings of men and women expressed as a percentage of the average gross hourly earnings of men at the sector-by-country level. The variable *percentage of women in precarious employment* is the percentage of female employees with a short-term contract of up to 3 months in each sector-country. Finally, the variable *perceived job insecurity* is measured at the individual level, using the response to the question "I might lose my job in the next 6 months".
- *Job quality*: Six key indicators are constructed to measure job quality: physical environment, work intensity, worktime quality, social environment, skills and discretion, and future prospects, using the dedicated questions in the EWCS and adopting a factor analysis to aggregate different question on the same construct.

We use fixed-effects estimators on longitudinal datasets at both the regional and sectoral levels to estimate the impact of regional participation in GVC on job polarization, as well as the effect of sectoral GVC participation on the gender wage gap and the share of women in precarious employment. These models control for unobserved heterogeneity across regions and years and include a range of control variables, such as employment structure, economic development indicators, and country/sector trends. This approach helps to capture the long-term effects of GVC participation and internationalization strategies on the labour market.

To analyze job quality and gender inequalities, we employ multilevel mixed-effects regression models. This three-level model accounts for individual workers (level 1), industries (level 2), and countries (level 3), incorporating both worker-level data from the European Working Conditions Survey (EWCS) and industry-level measures of GVC and ICT. Interaction terms are added to explore how GVC participation and technological change affect workers across different occupations (e.g., managers, clerks, manual workers) and regions (e.g., advanced Europe, developing Europe, non-European regions).

In addition, ***interaction terms** and* differencing techniques are used to assess how the effects of GVC participation and technological change evolve over time. By applying differencing over time periods ranging from 1 to 4 years, we compare the short- and long-term impacts of the participation to GVCs on working conditions. These interaction terms also help to determine whether these effects differ by occupation, region, or the source of offshoring (e.g., advanced vs. developing economies).

Findings and discussion

In this part of WP3, our findings reveal that participation in GVCs worsens labor market inequalities across Europe. Job polarization intensifies, gender disparities are amplified, and working conditions deteriorate. In the following section, we will outline the key results related to these three dimensions of inequality.

Both outward internationalization of domestic firms and inward attraction of foreign enterprises contribute positively to regional job polarization. However, the effects are notably uneven across regions. In high-income regions, the presence of foreign firms is strongly associated with increased polarization, while in lower-income regions, this relationship is not significant. This indicates that the economic characteristics of a region play a crucial role in determining the impact of foreign firm presence on the local labor market.

For outward internationalization, the results are similarly nuanced. The study finds that the positive effects on polarization are primarily driven by two specific internationalization strategies: market-seeking and efficiency-seeking. Companies adopting these strategies tend to create a more polarized labor market, increasing the demand for both high-skilled, high-wage jobs and low-skilled, low-wage positions. In contrast, the other two strategies - diversification and strategic-seeking - show no significant direct effect on job polarization. This differentiation underscores the importance of recognizing the diverse motivations behind internationalization and their varying implications for regional labor markets.

A key finding of the study is the moderating role of labor market legislation. Regions with stronger Employment Protections Legislations (EPL) exhibit a reduced impact of both internationalization and inward attraction on job polarization. This suggests that labor regulations can mitigate the adverse effects of globalization on inequality by providing a buffer against the more extreme forms of job polarization that typically accompany internationalization.

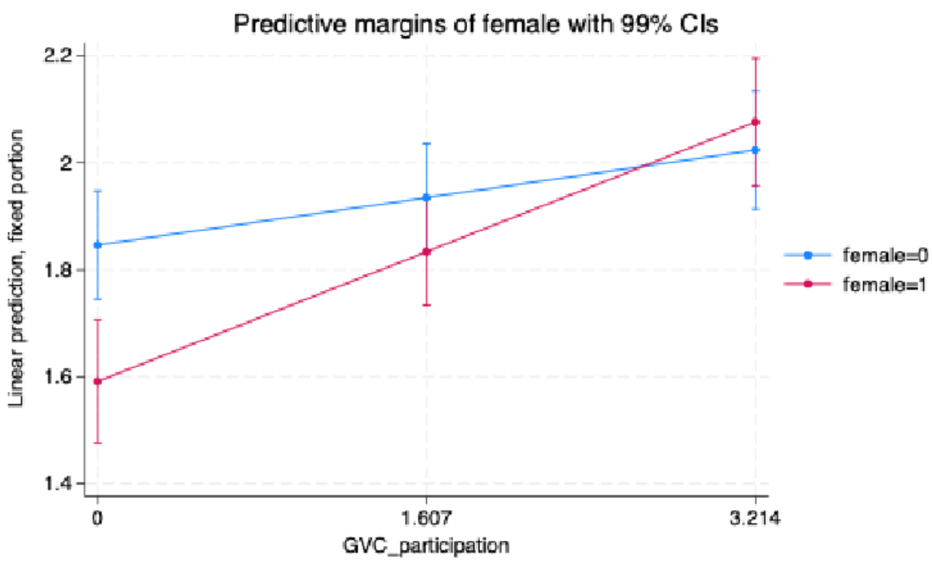
The novelty of this study lies in its dual focus on disentangling the effects of GPNs, distinguishing between the outward internationalization of domestic firms and the inward attraction of foreign enterprises. Furthermore, it introduces a nuanced understanding of internationalization by measuring the impact of four distinct strategies and their differential effects on polarization. For the first time, the mediating role of labor legislation in these processes has been empirically evaluated, offering new insights into how policy can shape labor market outcomes in the face of globalization.

In terms of gender disparities, the analysis provides some surprising insights. Despite the ongoing discussions about the role of GVCs in exacerbating gender inequalities, the research reveals that GVC participation does not significantly influence the gender pay gap. Instead, other factors such as educational attainment and working hours are more decisive in shaping gender wage disparities. A larger share of women with tertiary education is associated with a narrower gender pay gap, while men's working hours are positively correlated with a wider gap.

Additionally, the research finds a positive relationship between GVC participation and precarious employment, particularly for women. Sectors with higher GVC integration tend to have a larger percentage of women in precarious employment. However, this relationship is mitigated by higher education levels: as women's education level increases, the percentage of precarious employment decreases. Conversely, sectors where men work longer hours tend to show an increase in precarious employment for women.

GVC participation at the sectoral level affects also perceived job security (Figure 11). The results indicate that GVC participation is associated with higher levels of job insecurity for both men and women, though the differences between the two genders are not statistically significant. The interaction effect shows that the gap in job insecurity between men and women is largest in sectors with low GVC participation. As GVC participation increases, the gender gap in job insecurity narrows, but the overall insecurity for women increases, particularly in sectors with high GVC integration.

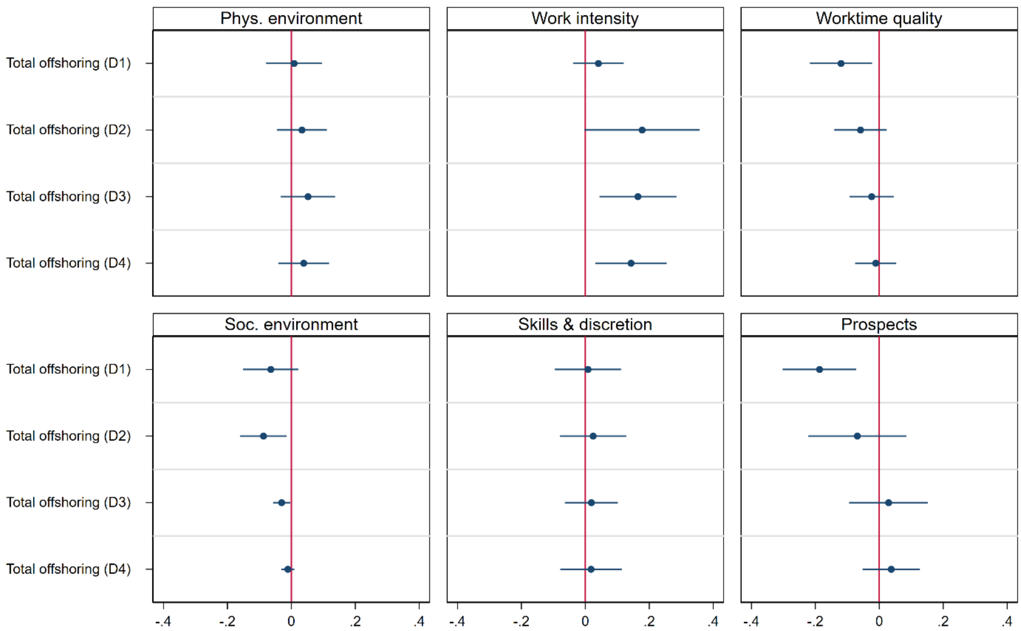
Figure 11: The interaction between GVC participation and gender on job insecurity



GVC integration, particularly offshoring, has a negative impact on workers' working conditions, manifesting as higher work intensity, lower worktime quality, a poorer social environment, and reduced prospects for career progression and job security. While the effects on worktime quality and job prospects are short-term, the impacts on work intensity and social environment persist over the longer term. These results highlight the broad and persistent challenges that GVC integration can impose on the workforce, varying across different dimensions of job quality.

The study also uncovers heterogeneous effects across different types of workers. Manual workers, for example, benefit from an improved social environment in both the short and long term, while low-skilled white-collar workers, such as clerks, gain in terms of better skills and discretion but suffer from worse worktime quality. In contrast, high-skilled professionals, including managers and craft workers, experience increased work intensity and a decline in their working environment. These findings indicate that offshoring creates both winners and losers, with more vulnerable groups of workers, such as clerks and manual workers, sometimes experiencing gains, while highly skilled workers bear the brunt of negative outcomes Figure 12).

Figure 12: Working Conditions – Total Offshoring

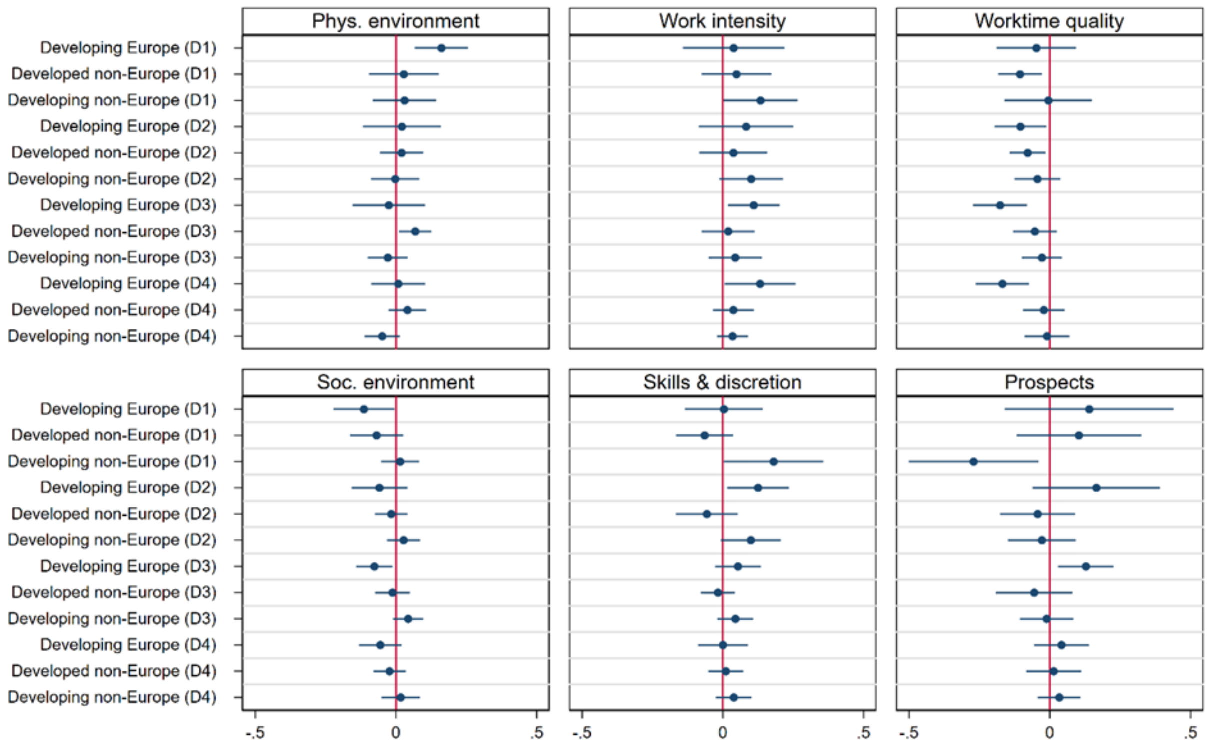


Source: Multilevel regressions using data from the 5th and 6th European Working Conditions Survey. Dots represent coefficient estimates, and lines show 95% confidence intervals.

A particularly novel aspect of the study is the discovery that the source region of offshoring matters (Figure 13). Increased offshoring to developing Europe, compared to developed Europe, is linked to deteriorating working conditions, including higher work intensity, lower worktime quality, and a poorer social environment. However, offshoring to developing Europe also results in better skills and discretion for workers, making jobs cognitively more demanding and providing greater decision-making latitude. Similarly, offshoring to developed non-Europe improves the physical work environment but reduces worktime quality, while offshoring to developing non-Europe increases work intensity and reduces job prospects but enhances workers' skills and discretion.

The effects of offshoring also differ by worker type and source region. Managers and professionals, for example, are negatively affected by offshoring to developing Europe in terms of lower worktime quality and a poorer social environment but benefit from better prospects when offshoring is directed to developed non-Europe. Clerks experience improved worktime quality and social environment from offshoring to developing Europe but are adversely affected by offshoring to developing non-Europe. Craft workers see improvements in skills and discretion from offshoring to developing Europe and better physical environments from offshoring to developed non-Europe but experience lower prospects from offshoring to non-Europe. Manual workers benefit in terms of better prospects from offshoring to developing Europe but suffer from poorer physical environments and lower prospects when offshoring is directed to non-European regions.

Figure 13: Working Conditions – Offshoring by Source Region



Source: Multilevel regressions using data from the 5th and 6th European Working Conditions Survey. Dots represent coefficient estimates, and lines show 95% confidence intervals.

5. Summary of key findings

The key findings of this report can be summarised as follows:

1. Our analysis has shown a high diversity of the EU regions in terms of their involvement in European and global value chains and the extent to which they benefit from this economically. These differences in regions' exporting activities will likely be expressions of differences in the regions' competitiveness on EU and global markets. This is accompanied by regional differences in skill intensities that often evolve along country lines.

2. Against this background, changes in the "pure" participation in GVCs are not necessarily associated with increased jobs. What matters is the increase in the gains an economic system can retain from participating in GVCs.

   - Reshoring (when associated with improved economic power) is associated with a relatively (compared with other regions) higher growth of low-skilled occupations and overall employment.
   - An expansionary GVC strategy can also increase employment, although only for high-skilled jobs.

3. Backshoring, strongly envisaged by the EU to implement its reindustrialisation process per se, does not favour manufacturing jobs. The effects on job growth depend on the characteristics of the regional context:

   - backshoring in traditional manufacturing regions stimulates growth in both high- and low-level manufacturing jobs;
   - backshoring in emerging manufacturing regions penalises it, being associated with intensive production processes, probably related to automation that displaces particularly blue-collar jobs.

4. GVC restructuring may be induced, besides the recent pandemic, by other socio-economic factors affecting employment trends. Workpackage 3 has analysed a number of these factors, i.e. the Covid pandemic, the opportunities offered by robotisation and export quality upgrading, potential changes in organisation employment strategies induced by the pandemic, as well as EU citizens' perception of regional benefits and costs of GVCs, measured at macro-level. To this respect, key findings indicate that:

   - the Covid pandemic had short- and long-run effects on employment patterns, affecting different occupations within and between industries differently. Working from home and outsourcing are crucial to understanding the heterogeneous impact the pandemic shock had on different occupations and industries.

- The relationship between robotisation, employment and (re-)shoring intensity is positive for many sectors. However, it becomes increasingly negative the more reshoring a sector experiences.
- Firms that upgrade their export quality observe more favourable employment development.
- GVC participation is related to the use of training programs. EU organisations rely more on training programs and their GVC participation is higher than non-EU organisations. Organisations participating in GVCs did not experiment a strong reduction in employment because of the Covid.
- Regions less involved in GVCs and specialised in low-skilled jobs show the highest anti-trade sentiments. However, as regional integration in GVCs and high-skilled regional specialisation increase, high-skilled workers increasingly favour international trade. In contrast, perceptions of low-skilled workers do not change. Anti-trade sentiments increase in periods of crisis.

5. As for inequalities, the findings from this study reveal that participation in Global Value Chains (GVCs) exacerbates labor market inequalities in Europe. These inequalities manifest as intensified job polarization, worsened gender disparities, and deteriorating working conditions. The key results related to these dimensions of inequality are:

    - GVC participation, particularly through both outward internationalization of domestic firms and inward foreign enterprises, intensifies job polarization. High-income regions are more affected, with foreign firm presence linked to increased labor market disparities, while lower-income regions show no significant impact.
    - Market-seeking and efficiency-seeking strategies drive the effects of internationalization on job polarization. In contrast, diversification and strategic-seeking strategies do not directly impact labor market polarization.
    - Labour market institutions, particularly Employment Protection Legislation (EPL), moderate the negative effects of GVCs on job polarization. Stronger EPLs help reduce the extent of job polarization by providing a buffer against the adverse impacts of globalization.
    - Although GVC participation does not significantly affect the gender pay gap, it is linked to higher precarious employment for women. This trend is mitigated when women attain higher education levels.
    - GVC participation increases job insecurity for both men and women, with the overall insecurity being higher for women in sectors with high GVC integration. Interestingly, the gender gap in job insecurity is larger in sectors with low GVC participation but narrows as GVC participation increases.

- GVC integration, especially offshoring, negatively affects working conditions, including increased work intensity and reduced worktime quality. These effects vary by worker type, with manual and lower-skilled workers sometimes benefiting while higher-skilled professionals face more challenges.

6. Policy implications

Our analysis has shown a high diversity of the EU regions in terms of their involvement in European and global value chains and the extent to which they benefit from this economically. Also, the reorganization of GVCs has been uneven across regions, as has been its impact on labour market outcomes, working conditions and inequalities.

In particular, WP3 demonstrated that in order to stimulate employment, restructuring strategies should consider the role (in terms of economic power) of the local economic system within the value chain since they impact different occupations.

This implies that, in order to stimulate employment creation, **trade policies** have to be accompanied by **place-based local policies**, reinforcing their (globally scarce) assets, their innovative capacity and the qualities of their produced goods. In this way, regions, intended as actors within GVCs, are able to reinforce their capacity to impose a division of labour and consequent remunerations to other places that are trade partners, where the mutual advantage and the emerging surplus are unequally shared in favour of the strong and controlling regions. Thanks to their favourable terms of trade, they turn out at the end to be able to grow through both a productive and a distributive mechanism.

Moreover, we demonstrated that reshoring only produces employment growth opportunities in traditionally manufacturing regions, where industrial vocations are relaunched. In emerging manufacturing regions, instead, it relaunches value added through modern reindustrialisation rather than expansion of jobs.

This implies that the two main policy objectives of the EU, i.e. **modern reindustrialization** and **relaunch of manufacturing employment**, seem to be potentially hard to achieve together. Although they are both widely acceptable, it is particularly important to consider that they do not fit all regions similarly. Modern reindustrialization strategies can be pursued in some emerging manufacturing areas, while a relaunch of manufacturing employment strategy seems to be more effective in traditional manufacturing regions. Once again, this calls for **place-based industrial policies**.

Turning to the factors at the base of the reorganization of GVC, the insights obtained from our detailed analyses – across industries and occupations within and across industries – are important to tailor **labour market and education/training policies** to adjust to longer-term trends in employment patterns in different EU economies, to hysteretic effects of the Covid pandemic and to longer-term effects of working from home possibilities – differentiated by occupations and sectors – and to any reorganisation of GVCs within or outside Europe.

We find no evidence that robot adoption will affect manufacturing employment outcomes. We neither find evidence that reshoring, possibly in connection with robot adoption, will lead to favorable manufacturing employment outcomes. Policies that aim at **slow robot adoption** or **increased reshoring** are hence unlikely to lead to strong manufacturing employment responses.

For both, robotization and reshoring, non-routine and manual laborers seem to benefit over-proportionally. **Policies supporting this structural transformation** (e.g., through **appropriate training and education**) hence seem most promising to lead to favourable employment trends in the context of automation and associated production relocation.

Helping firms improve their export quality can support higher employment in high-income countries. However, more research will be needed to substantiate what policies can promote such export quality upgrading, but **education and training** appear, once again, as natural candidates. Likewise, policies that typically support firms' innovation capacity.

Our results further suggest that integration into GVCs is not necessary to reap positive employment effects of export quality upgrading. Rather, those innovative capacities have to be acquired domestically.

The variegated way in which different categories of workers perceive the benefits and costs of trade and participation in GCVs suggest that **redistributive policies** (from high- to low-skilled workers) are needed to counterbalance potential negative effects. These policies, however, should also consider the asymmetric territorial distribution of trade perceptions. It is, indeed, in the less advanced, lagging behind regions excluded from GVCs and trade integration that the highest levels of anti-globalisation sentiments persist.

This implies that imposing **trade restrictions** may lead to a double undesired effect. First, this would impose an aggregate social cost to the whole society. Second, it could further fuel anti-globalisation sentiments in regions becoming increasingly marginalized in the global production chains.

GVCs seem to contribute to the spread of job insecurities, to worsen working conditions and to increase regional labour market polarization. While **employment protection policies** may moderate the negative effect of participation in GVCs on polarisation, specific policy interventions are needed to prevent a permanent deterioration of working conditions and protect workers. Interventions could take the form of higher government-imposed **labour standards.** However, since the impact of GVCs on working conditions is heterogeneous across occupations and industries, e.g. managers/professionals, craft workers and workers in industries with increased offshoring to developing Europe, special attention has to be paid to these specific groups. Trade unions and other worker interest representations may be crucial to identify interventions tailored to the specific needs of these groups of workers.

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8. Technical appendices

Appendix A: Method

(1) $\text{emp man growth}_{r(t,\,t+3)} = \alpha + \beta_1\text{backshoring}_r + \beta_2\text{time} + \beta_3\text{backshoring}_r\text{*time} + \beta_4\text{high-level functions}_{rt} + \beta_5\text{low-level functions}_{rt} + \beta_6\text{human capital}_{rt} + \beta_7\text{gdp pc}_{rt} + \beta_8\text{va man}_{rt} + \beta_9\text{metro}_r + \varepsilon_{rt}$

where emp man $\text{growth}_{r(t,\,t+3)}$ is the dependent variable and is computed as the regional (r) compound growth rate of the employment in manufacturing in two periods: 2013-2016 and 2016-2019. The control variables enter the model in their value at the beginning of the growth period (t), with the only exception of backshoring_r, which is time invariant. This is our main variable of interest, and it is a dummy equal to one if the region backshores. Time is a dummy variable equal to one in the first period; it is included to control for time fixed effects, and it is interacted with backshoring to be able to interpret its marginal effects in the two different periods considered. high-level functions_{rt} is the share of ISCO1 employees in the region, and it is meant as a measure of high-level functional specialization, while low-level functions_{rt} is the share of ISCO8 employees, and it is meant as a measure of production-level functional specialization. Human capital_r is computed as the share of tertiary educated population, gdp pc_{rt} (GDP per capita) controls for the initial level of wealth, va man_{rt} is a measure of specialization in manufacturing and it is calculated as the share of manufacturing value added at the beginning of the growth period. Finally, metro is a dummy variable equal to one if the region includes at least one metropolitan region, as identified by the European Commission. Regional (NUTS1) fixed effects are also included, and robust standard errors are clustered by NUTS1 region.

Equation (1) is then slightly modified to assess if there is in fact a relaunching of traditional industrial know-how and vocations in manufacturing regions in Europe. Therefore, the empirical investigation focuses on traditionally manufacturing backshoring regions (equation (2)) and on emerging manufacturing backshoring regions (equation (3)), respectively, in this way:

(2) $\textit{emp man growth}_{r(t,\,t+3)} = \alpha + \beta_1\textit{backshoring in traditionally manufacturing regions}_r + \beta_2\textit{time} + \beta_3\textit{backshoring in traditionally manufacturing regions}_{r\,r}\textit{*time} + \beta_4\textit{high-level functions}_{rt} + \beta_5\textit{low-level functions}_{rt} + \beta_6\textit{human capital}_{rt} + \beta_7\textit{gdp pc}_{rt} + \beta_8\textit{va man}_{rt} + \beta_9\textit{metro}_r + \varepsilon_{rt}$

(3) $\textit{emp man growth}_{r(t,\,t+3)} = \alpha + \beta_1\textit{backshoring in emerging manufacturing regions}_r + \beta_2\textit{time} + \beta_3\textit{backshoring in emerging manufacturing regions}_r\textit{*time} + \beta_4\textit{high-level functions}_{rt} + \beta_5\textit{low-level functions}_{rt} + \beta_6\textit{human capital}_{rt} + \beta_7\textit{gdp pc}_{rt} + \beta_8\textit{va man}_{rt} + \beta_9\textit{metro}_r + \varepsilon_{rt}$

Finally, in the last step of the analysis, the specifications above are altered to accommodate the interactions between (different types of) backshoring regions and high-level/production functions, to shed some light on the type of occupations that are favoured by the backshoring of high- or low-level activities.

Table A.1: Backshoring and manufacturing employment growth

	(1)	(2)	(3)
backshoring	0.00315		
	(0.00259)		
backshoring in traditionally manufacturing regions		0.00761**	
		(0.00318)	
backshoring in emerging manufacturing regions			-0.0204**
			(0.00792)
time	-0.00481	-0.00569**	-0.00701***
	(0.00315)	(0.00247)	(0.00247)
backshoring*time	-0.00413		
	(0.00409)		
backshoring in traditionally manufacturing regions*time		-0.00658	
		(0.00442)	
backshoring in emerging manufacturing regions*time			0.00977
			(0.00809)
high-level functions	-0.155	-0.145	-0.135
	(0.133)	(0.131)	(0.129)
low-level functions	-0.166	-0.159	-0.143
	(0.208)	(0.205)	(0.183)
human capital	-0.0633	-0.0638	-0.0571
	(0.0531)	(0.0538)	(0.0479)
gdp pc	0.738***	0.737***	0.741***
	(0.210)	(0.210)	(0.196)
va man	0.00483	-0.00470	0.000666
	(0.0252)	(0.0264)	(0.0240)
metro	-0.00549	-0.00552	-0.00635
	(0.00458)	(0.00454)	(0.00460)
Constant	0.00557	0.00710	0.00520
	(0.0223)	(0.0224)	(0.0199)
Observations	512	512	512
R-squared	0.455	0.458	0.465
NUTS1 FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Dep. var.: manufacturing employment growth.
Robust standard errors clustered by NUTS1 in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Backshoring marginal effects on manufacturing employment growth by period

	Overall	Period 1	Period 2
Backshoring	0.0010838	-0.0009826	0.0031501
Backshoring in traditionally manufacturing regions	0.004322*	0.0010326	0.0076114**
Backshoring in emerging manufacturing regions	-0.015527*	-0.0106414	-0.0204126**

*** p<0.01, ** p<0.05, * p<0.1

Figure A.1: Marginal effects of backshoring by increasing values of high/low-level functions (90% CIs)

a – High-level functions | *b – Low-level functions*

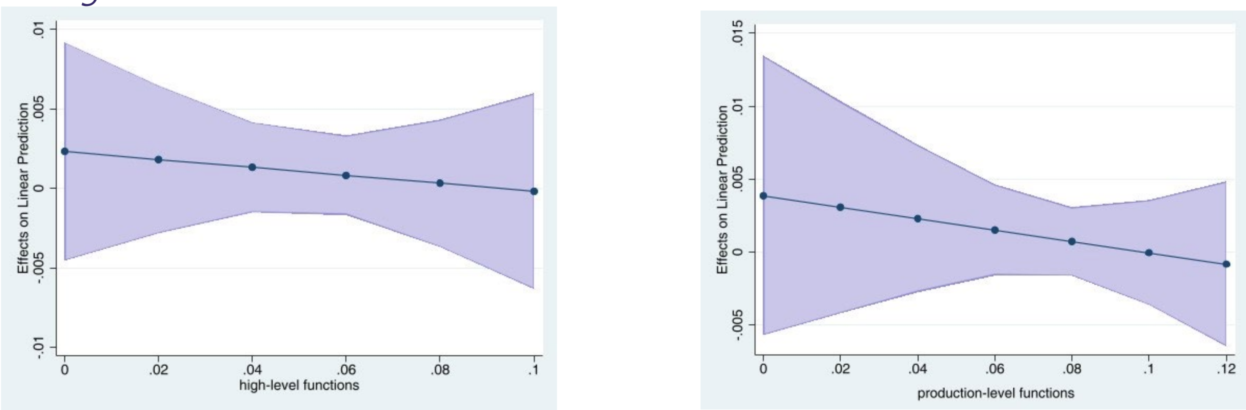


Figure A.2: Marginal effects of backshoring by increasing values of high/low-level functions in traditionally manufacturing regions (90% CIs)

a – High-level functions | *b – Low-level functions*

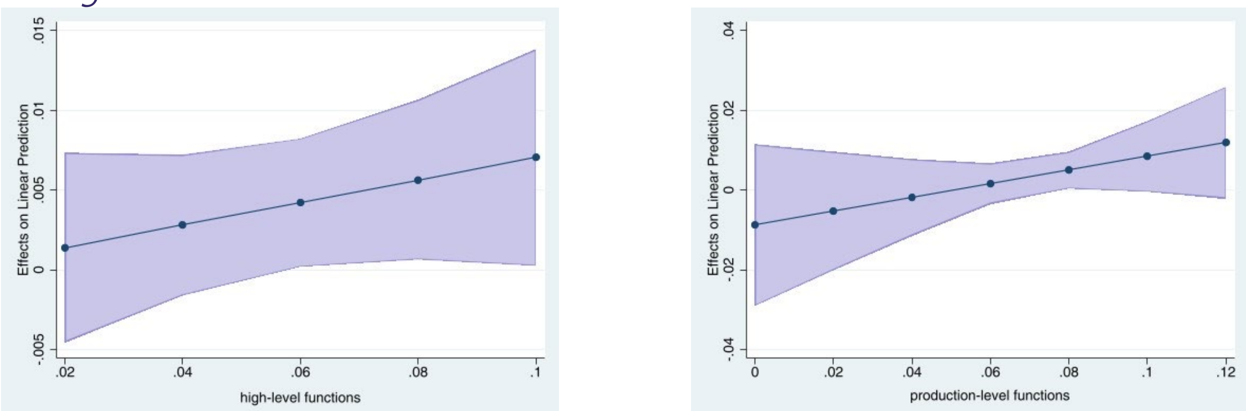
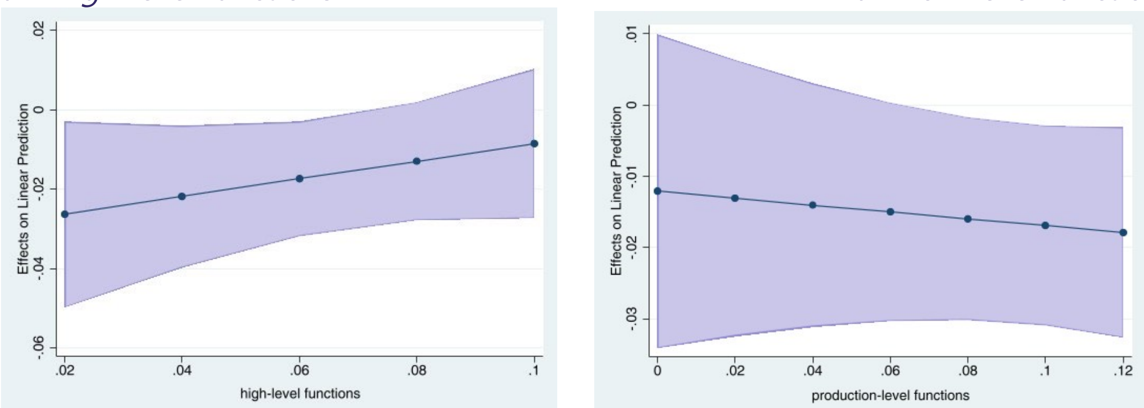


Figure A.3: Marginal effects of backshoring by increasing values of high/low-level functions in emerging manufacturing regions (90% CIs)

a – High-level functions | *b – Low-level functions*



Appendix B: Operationalization, functional specialization and methodology

B.1. The operationalization of regional restructuring strategies

In order to measure the effects of GVCs restructuring on employment dynamics it is fundamental to empirically measure the alternative GVCs restructuring strategies. Following the approach by Capello et al. (2023), we measure the change in the terms of trade of a region the ratio between domestic value added embedded in exports over foreign value added generated by trade of intermediate goods:

$$\Delta\, terms\ of\ trade\ in\ GVC_{r,i} = \Delta \frac{DVA_{r,i}^{INT}}{FVA_{r,i}} \qquad [1]$$

where r represents the region and i the economic sector. The numerator is the sum of the Domestic Value Added in intermediates (DVA^{INT}), capturing the value of the intermediate goods domestically produced and then exported[1], and the Foreign Value Added (*FVA*) embedded in regional exports, measuring the value of the inputs produced abroad that are first imported, domestically processed and then re-exported. A positive change of this indicator suggests that the region was able to increase, for each euro of imported intermediate goods (*FVA*), the amount of domestic value added (DVA^{INT}). This reflects an improvement of the terms of trade with which domestic intermediate goods are exchanged against foreign inputs along the GVC.

The level of GVCs embeddedness is instead captured by an indicator of participation broadly used in the literature, defined as the extent to which the overall exports are made up by value added in intermediate goods, either produced inside or outside the region (Hummels et al., 2001):

$$\Delta\, participation\ to\ GVC_{r,i} = \Delta \frac{DVA_{r,i}^{INT} + FVA_{r,i}}{Exports_{r,i}} \qquad [2]$$

when associated with a positive change in the terms of trade (i.e. equation [1]), the change in the participation in GVCs can indicate a restructuring strategy of:

- expansionary GVCs strategy: if both DVA^{INT} and *FVA* increase, but the former more than the latter to guarantee the condition of increasing terms of trade;
- reshoring strategy: if increases DVA^{INT} and *FVA* decreases.[2]

[1] Within the literature on GVCs, the interest is mostly on the domestic value-added content of intermediate goods that are furtherly transformed by third region to produce products along the chain (Wang et al., 2017).

[2] Notice that in this case we could have either a situation of increasing participation (if the increase in DVA^{INT} more than compensates the decrease in FVA) or a decreasing participation (if the growth in DVA^{INT} is lower – in absolute terms – than the reduction of FVA). The distinction of these two cases is not particularly relevant, as they both indicate a situation in which the country/region is substituting inputs from abroad with inputs domestically produced. There is a third possible situation in which a regions improves its economic control within the chain: it is the one where both DVA^{INT} and FVA decrease, but the former less than the latter. However, this would happen in a scenario in which the value of domestically produced inputs is decreasing in absolute terms, and therefore cannot be linked to an increase in economic power and competitiveness within GVCs.

The repositioning strategies of regions within GVCs are calculated using data from the interregional trade in value added I-O tables provided by the EUREGIO database (Thissen et al., 2018). This database merges world trade data among countries (sourced from the World Input-Output Database, WIOD) with regional economic accounts and estimates of interregional trade flows (Thissen et al., 2013). This leads to I-O matrices for all years between 2000 and 2010, providing data on the trade between the major global economies and EU27+UK NUTS2 regions. Importantly, data are available for 14 industries (NACE Rev. 1). This study focuses exclusively on the manufacturing sector, due to its primary involvement in the offshoring strategies of European firms in the last three decades (Sapir, 2022), and since it is at the core of the current debate on the implications of reshoring for Europe (Raza et al., 2021).

GVCs restructuring strategies are calculated for the period 2007-2010, i.e. the one characterized by the most intense contraction of trade. Our sample includes all NUTS2 regions in EU27+UK, with the exclusion of Romania and Bulgaria, for which data are available only at the country level, and have been as a consequence excluded from the analysis. The scope of the paper is to study the association between these repositioning strategies and the change of regional employment. The next section presents the data on jobs and occupations used in the analysis.

B.2. The functional specialization of regional labour markets

We assume that regional repositioning strategies have a heterogeneous effect on different occupations. In particular, expansionary GVCs strategies are expected to impact on all categories of workers, while reshoring strategies are assumed to lead to low-skilled jobs, related to the relaunch of local production. The testing of these assumptions implies the need for employment data decomposed between different occupational categories.

Unfortunately, official statistical institutes do not provide this information at the NUTS2 level for the manufacturing sector. Eurostat, however, discloses data on the overall number of employed people in NUTS2 regions for every ISCO-08 category, irrespectively of the economic sector of employment. In order to estimate the regional employment in the manufacturing sector in each ISCO-08 function ($Emp_{r,ISCO,man}$), we apply the following formula:

$$Emp_{r,ISCO,man} = Emp_{r,ISCO} * \left(\frac{Emp_{c,ISCO,man}}{Emp_{c,ISCO}}\right) * \left(\frac{Emp_{r,man}}{Emp_r}\right) \qquad [3]$$

where $ISCO$ denotes the occupation category, c the country to which the region pertains and *man* the manufacturing sector. $Emp_{r,ISCO}$ represents the total number of workers employed in each ISCO-08 category in a NUTS2 region. This number is assigned to the manufacturing sector according to two weights (multiplied and then rescaled to 100): the share of manufacturing employment in the region, and the weight of each function within the manufacturing sector, an information available only at the country level. This second weight corrects for the different mix of functions in each sector.

The values are estimated in time series from 2008 to 2017[3]. The percentage change in the period 2012-2016 for low- (ISCO-08 categories 08 and 09) and high-skilled (ISCO-08 categories 01, 02 and 03) workers represents our dependent variables.

B.3. Method

The empirical analysis studies the relationship between the regional restructuring strategies of the NUTS2 regions included in our sample and their change of employment (in total and in low/high-skilled occupations). Methodologically, we have a cross sectional data set, where the analysis is complemented by other controls able to capture regional heterogeneous characteristics that might affect employment dynamics:

$$\Delta Employment_{r,ISCO} = \alpha + \beta repositioning\ strategies_{r,s} + \gamma X_r + \delta_c \qquad [4]$$

where the dependent variables are represented alternatively by the regional change between 2012 and 2016 of overall, low-skilled and high-skilled employment. The main independent variable of interest is represented by the different regional GVCs restructuring strategies (indicated by the subscript s in equation [4]). The association between the two strategies defined in section 3, i.e. respectively the expansionary GVCs and reshoring strategy, and employment is evaluated relatively to the all the other possible kinds of restructuring (i.e. GVCs shrinking and increasing dependency strategies, Fig. 1), undertaken by the rest of regions. Other variables defined at the regional level (in equation [4]) control for some characteristics that may affect the change of employment. These characteristics include both the specialization and the labour productivity of the region in the manufacturing sector. The presence of a large city (dummy equal to one if the NUTS2 region hosts the country's capital) and the average land rent control for the occurrence of urbanization effects on employment, while the location of the region in a New Member State account for the different role of western and eastern EU countries in GVCs. Country fixed effects (δ_c) control for national unobserved characteristics. All continuous variables are mean-standardized, so to facilitate the interpretation of the results. Equation [3] is estimated by the means of OLS, where error terms are clustered at the regional level, in order to consider the potential within-country correlation of the residuals. A complete list of variables with some descriptive statistics is reported in Table B.1.

[3] Country data used in equation [3] are available from 2008 on, due to a revision of the ISCO classification.

Table B.1: List of variables and descriptive statistics

Name	Description	Source	Mean	Std. dev.
Dependent variables				
Δ in total employment	Change in total regional manufacturing employment, between 2012 and 2016	Authors' elaboration on Labour Force Survey and Eurostat data	0.025	0.073
Δ in high-skilled employment	Change in high-skilled (ISCO01-02-03) regional manufacturing employment, between 2012 and 2016	Authors' elaboration on Labour Force Survey and Eurostat data	0.016	0.038
Δ in low-skilled employment	Change in low-skilled (ISCO08-09) regional manufacturing employment, between 2012 and 2016	Authors' elaboration on Labour Force Survey and Eurostat data	0.005	0.041
Independent variables				
Expansionary GVCs strategy	Dummy equal to one if both regional and FVA increase between 2007 and 2010, but the former more than the latter to guarantee the condition of increasing terms of trade, and equal to zero otherwise	EUREGIO (Thissen et al., 2018)		
Reshoring strategy	Dummy equal to one if regional increases and FVA decreases between 2007 and 2010, and equal to zero otherwise	EUREGIO (Thissen et al., 2018)		
Labour productivity in manufacturing	Ratio between the value added and the number of workers employed in the regional manufacturing sector in 2012	EUKLEMS	59.400	27.191
Specialization in manufacturing	Ratio between the number of workers employed in the regional manufacturing sector and in all sectors in 2012	EUKLEMS	0.144	0.065
Capital city	Dummy equal to one if the region hosts the capital city and equal to zero otherwise	Eurostat		
Land rent	Average land rent of the region (thousand euros)	Eurostat	5.515	9.738
Eastern EU	Dummy equal to one if the region is included in a New Member State (CY, CZ, EE, HU, LT, LV, MT, PL, SI, SK), and equal to zero otherwise	Eurostat		

Appendix C: Data and method used for the analysis of Intra- and extra-European GVCs, their impact on the EU regions' economies and skill demand

C.1. Estimation Method for Regional Value-added Trade

The estimation of regional value-added trade is based on a multi-regional input-output table tracking the flows of goods and services across regions and industries, with each individual regions, across the regions of one country as well as across the regions of different countries. Schematically, this can be represented as follows, using matrix notation:

$$\begin{bmatrix} \boldsymbol{Z}^{11} & \boldsymbol{Z}^{12} & \boldsymbol{Z}^{13} & \boldsymbol{f}^{11} & \boldsymbol{f}^{12} & \boldsymbol{f}^{13} & \boldsymbol{x}^{1} \\ \boldsymbol{Z}^{21} & \boldsymbol{Z}^{22} & \boldsymbol{Z}^{23} & \boldsymbol{f}^{21} & \boldsymbol{f}^{22} & \boldsymbol{f}^{23} & \boldsymbol{x}^{2} \\ \boldsymbol{Z}^{31} & \boldsymbol{Z}^{32} & \boldsymbol{Z}^{33} & \boldsymbol{f}^{31} & \boldsymbol{f}^{32} & \boldsymbol{f}^{33} & \boldsymbol{x}^{3} \\ (\boldsymbol{w}^{1})' & (\boldsymbol{w}^{2})' & (\boldsymbol{w}^{3})' & & & & \\ (\boldsymbol{x}^{1})' & (\boldsymbol{x}^{2})' & (\boldsymbol{x}^{3})' & & & & \end{bmatrix} \text{ or } \begin{bmatrix} \boldsymbol{Z} & \boldsymbol{F} & \boldsymbol{x} \\ \boldsymbol{w}' & & \\ \boldsymbol{x}' & & \end{bmatrix}$$

$\boldsymbol{Z}^{rs}$ is a N × N intermediate input matrix (with being the number of industries) listing the (nominal values) of goods and services from region r used in the production of region s by each industry. The matrices where $\boldsymbol{r} = \boldsymbol{s}$, e.g. $\boldsymbol{Z}^{11}$, then indicate the within regional flows of goods and services coming from and used by the different industries within the respective region. The vectors $\boldsymbol{f}^{rs}$ indicate the flows of final goods from a region that are either consumer in the respective region itself, i.e. if $\boldsymbol{r} = \boldsymbol{s}$, e.g. $\boldsymbol{f}^{\mathbf{11}}$, or consumed in other regions, if $\boldsymbol{r} \neq \boldsymbol{s}$. Also, the multi-regional input-output table contains information on the total value-added produced in each region (by industries), denoted by $\boldsymbol{w}^{\boldsymbol{r}}$ as well as the gross output of each region (by industries), denoted by $\boldsymbol{x}^{\mathbf{1}}$.

The main ingredients for input-output analysis in general and the estimation of value-added trade are the coefficient matrix of intermediary inputs and the Leontief inverse. The intermediary inputs matrix, denoted by A, shows the intermediary use (by region and industry) as unit of gross output. Formally, it can be estimated using

$$\boldsymbol{A} = \boldsymbol{Z}\widehat{\boldsymbol{x}}^{-\mathbf{1}}$$

where $\hat{x}$ is the diagonalised output vector.

From this, the Leontief inverse L that shows the gross output directly and indirectly needed to produce one unit of output (in a respective region and industry) is given by

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}}$$

where I is an identity matrix of the same dimension as A.

In a standard demand-driven Leontief model multiplying the Leontief matrix (i.e. the gross output multiplier matrix) with the vector of final demand yields gross output (by industries and regions), i.e. x $= \boldsymbol{Lf}$=$(\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}}\boldsymbol{f}$.

Since we are interested in valued added trade instead of gross output trade, we convert the Leontief matrix into a matrix of value-added multipliers that shows the amount of value-added is needed to produce one unit of final output. Technically this is solved by using by defining value-added coefficients, represented by a vector v (for each region and industry). The vector v is given by $\boldsymbol{v} = \widehat{\boldsymbol{x}}^{-\mathbf{1}}\boldsymbol{w}$, i.e. the inverse of the diagonalised gross output vector times the value-added level (all by region and industry).

From this, the value-added multiplier matrix, denoted by B, can be directly derived using $\boldsymbol{B} = \widehat{\boldsymbol{v}}\boldsymbol{L}$, i.e. multiplying the diagonalised vector of value-added coefficients with the Leontief inverse. Given this, value-added trade flows can then be estimated by combining the value-added multiplier matrix B with final demand. In matrix notation, for a multi-regional input-output table this is:

$$\boldsymbol{T} = \boldsymbol{BF}$$

The row sums of matrix T are identical to the regions' value-added (by industries) and hence vector w, while the column sums are identical to each region's final demand (by industries).

Regional Value-added Exports: Correspondingly, in each row, all elements where $\boldsymbol{r} \neq \boldsymbol{s}$ indicate the value-added produced in region r but consumed in region s (by a certain industry), and hence value-added exports from region r to region s.

Regional Value-added Imports: Looking at the columns, each element where $\boldsymbol{r} \neq \boldsymbol{s}$ indicates the region r's consumption of value-added produced in region s, and hence value-added imports from s to r.

Regional Net Value-added Exports: This is the difference between regional value-added imports and regional value-added exports.

C.2. Estimation Method for the Nexus between Regional Value-added Exports and Imports

The paper uses a spatial error econometric model to the test the relationship between the regions' value-added trade share (in the regions total value added, i.e. GDP) and their net value-added exports (exports – imports). For this, we estimate the following model:

$$NVAX = \beta \cdot X + \gamma VAX + \varepsilon$$

with $\varepsilon = \lambda W \mu$, i.e. a spatial dependence in the error terms, as the descriptive analysis has shown strong country effects, so that the regions within a country tend to be more similar than regions of other countries.

In the regression, $NVAX$ is our dependent variable and represents the net value-added trade of the regions (in percent of the regions total value-added trade, excluding domestic trade). VAX is our main explanatory variable, i.e. the value-added exports share in the regions' total value added. To model the spatial dependence, we use a normalised distance-based spatial weight W matrix, using a spectral normalisation. Furthermore, X is a matrix of covariates that are assumed to affect the regions value-added trade performance. These explanatory variables include the levels of GDP in 2010 (in logs), the population density to account for agglomeration effects, the investment rate (i.e. gross fixed capital formation in percent of GDP), the R&D intensity (i.e. total R&D expenditures in percent of GDP), the sectoral employment shares for high and low technology intensive manufacturing as well as for knowledge intensive services to control for the pattern of specialisation in the regions) and an accessibility indicator. Importantly the control variables also include two variables measuring the regions' skill endowments, i.e. the share of highly educated (i.e. those with completed tertiary education) and the respective share of medium educated (i.e. completed secondary education) in the population. Table C.1 shows the results of the estimation.

Table C.1: Spatial regression results, net value-added trade and value-added trade intensity, full sample, total value-added trade

Variables	Global exports	EU exports	RoW exports
Initial GDP (2010)	7.857*** (2.158)	3.924** (1.619)	3.282*** (1.032)
Population density	0.000174 (0.000837)	0.000580 (0.000452)	2.21e-05 (0.000386)
High skill share in population	-0.173 (0.135)	-0.109 (0.0926)	-0.0405 (0.0661)
Medium skilled share in population	0.108 (0.0725)	0.0854 (0.0570)	0.0260 (0.0358)
Research and development	-1.263 (0.782)	-0.509 (0.442)	-0.658* (0.364)
Accessibility	-0.0112 (0.0341)	-0.00596 (0.0191)	-0.00530 (0.0159)
Investment rate (2010)	-0.646*** (0.203)	-0.380*** (0.122)	-0.255*** (0.0943)
Share of high-tech intensive manufacturing in total employment	0.139 (0.336)	0.102 (0.205)	0.0241 (0.156)
Share of low-tech intensive manufacturing in total employment	0.325 (0.248)	0.0855 (0.147)	0.228** (0.116)
Share of knowledge intensive services in total employment	0.522** (0.253)	0.190 (0.154)	0.276** (0.121)
VAX Global - total value-added exports in VA	0.609*** (0.101)		
VAX EU - total value-added exports in VA		0.619*** (0.116)	
VAX RoW - total value-added exports in VA			0.784*** (0.0709)
Constant	16.42 (10.77)	6.818 (7.871)	3.293 (5.098)
λ	1.061 (0.845)	3.506* (1.971)	1.522 (1.104)
Observations	246	246	246

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C.3. Estimation Method for the Nexus between Regional Value-added (Net) Exports and Regional Growth

For this, we analyse the relation of value-added exports and economic growth, using again a spatial econometric approach. In more detail, we estimate a typical regional growth model, including the most important (and data-wise available) indicators that determine regional growth, with value-added exports being one of them. In contrast to the econometric specification above, we estimate the following spatial autoregressive model (SAR model[4]) instead:

$$Y = \rho \cdot WY + \beta \cdot X + \varepsilon$$

with $\varepsilon \sim N(0, \sigma^2)$.

[4] A fundamental aspect in the SAR model is the presence of spatial feedback loops. By way of illustration: a change in region r's growth affects, through spatial spillovers, growth in the neighbouring regions. The additional growth in the neighbouring regions (caused by the initial growth in region r) feeds back again into the original region r, and so on. Thus, to estimate the growth effects correctly, these feedback loops need to be considered through the estimation of direct and indirect effects.

Here, Y denotes average regional GDP growth for the EU over a certain period of time, $\rho \cdot WY$ is the spatially weighted GDP growth of neighbouring regions, as we assume that the change in the economic development has impacts on its neighbouring regions. Furthermore, X is a matrix of covariates representing factors determining regional growth performance, including the regions' value-added exports. Since we are interested in medium-run growth dynamics, we estimate a cross-section model covering the period 2010-2019, i.e. after the global and financial crisis of 2008/2009 and before the COVID-crisis. Table C.2 presents the results of the estimation.

Table C.2: Spatial regression results, Full sample of regions, total value-added exports to the EU and the RoW

	Global VAX	EU VAX	RoW VAX
Initial GDP (2010)	-1.330*** (0.143)	-1.276*** (0.144)	-1.335*** (0.143)
Population density	2.49e-05 (5.40e-05)	8.43e-06 (5.51e-05)	2.30e-05 (5.31e-05)
High skill share in population	0.0471*** (0.00832)	0.0455*** (0.00835)	0.0442*** (0.00849)
Change in high skill share	-0.000606 (0.0194)	-0.00535 (0.0198)	-0.00739 (0.0195)
Medium skilled share in population	0.000634 (0.00604)	0.000898 (0.00622)	-0.000461 (0.00598)
Change in medium skill share	-0.0555*** (0.0186)	-0.0558*** (0.0188)	-0.0542*** (0.0182)
Research and development	0.108** (0.0498)	0.101** (0.0493)	0.123** (0.0497)
Accessibility	0.00398* (0.00214)	0.00401* (0.00213)	0.00440** (0.00213)
Investment rate (2010)	0.0253* (0.0134)	0.0321** (0.0141)	0.0245** (0.0124)
Change in investment rate	0.0870*** (0.0104)	0.0932*** (0.00989)	0.0824*** (0.00992)
Share of high-tech intensive manufacturing in total employment	0.00881 (0.0216)	0.0137 (0.0216)	0.00580 (0.0213)
Change in high tech intensive manufacturing share	0.0913 (0.0671)	0.0956 (0.0671)	0.0887 (0.0665)
Share of low-tech intensive manufacturing in total employment	0.0824*** (0.0160)	0.0826*** (0.0160)	0.0788*** (0.0159)
Change in low tech intensive manufacturing share	0.148*** (0.0532)	0.150*** (0.0532)	0.142*** (0.0526)
Share of knowledge intensive services in total employment	-0.00835 (0.0172)	-0.00323 (0.0173)	-0.0102 (0.0169)
Change in knowledge intensive services share	0.0713* (0.0425)	0.0738* (0.0425)	0.0632 (0.0421)
VAX Global - total value-added exports in VA	0.000949 (0.00769)		
Net exports Global - total value added	0.00270 (0.00404)		
VAX EU - total value-added exports in VA		-0.0146 (0.0145)	
Net exports EU - total value-added exports		-0.00127 (0.00705)	
VAX RoW - total value-added exports in VA			0.00456 (0.0120)
Net exports Row - total value-added exports			0.0143* (0.00847)
Constant	-7.099*** (0.737)	-7.034*** (0.737)	-7.011*** (0.733)
rho	0.301 (0.210)	0.485* (0.259)	0.346* (0.198)
Observations	246	246	246

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

C.4. Measuring Skill Intensity

In the final part of the analysis, we estimate the skill intensity of the EU regions exports and compare it to the available skills in order to evaluate to what extent this skill supply matches skill demand. Skill intensity in our analysis is defined as the share of highly educated employed to produce the regions' value-added exports in percent of total regional employment. In this respect, the skill intensity is also understood as the current skill demand of the regions. Skill supply is measured as the share of highly educated population aged 25-34 years in total population of the same age group. This age cohort is assumed to represent the medium run skill supply for the regions' economic activities. Combining both indicators, we estimate our skill match indicator as the simple ratio

$$POP_{25-34}^{HS} / EMP^{HS}$$

Where POP_{25-34}^{HS} represents the high skill supply of the population and EMP^{HS} the high skill demand, defined through the number of high skilled employed in the regions' exports to the EU and the RoW. In comparison to other skill indices available, e.g. from the OECD[5] or CEDEFOP[6], this is a highly simplified index. The reason for this is the lack of data availability at the regional level, making it extremely difficult, beyond the scope of this paper, to estimate more detailed and nuanced indices for an EU wide regional comparison. And, as will be shown below, even this simple index is not completely straightforward to estimate with the data at hand.

From a technical perspective to estimate skill demand of exports we go to back to the input/output analysis methodology above, recalling that the value-added trade matrix T was defined as

$\boldsymbol{T} = \boldsymbol{BF}$ with $\boldsymbol{B} = \hat{\boldsymbol{v}}\boldsymbol{L}$

With $\hat{\boldsymbol{v}}$ being the (diagonalised) value-added coefficients, defined as $\boldsymbol{v} = \hat{\boldsymbol{x}}^{-1}\boldsymbol{w}$, i.e. the inverse of the diagonalised gross output vector times the value-added levels (all by region and industry). To estimate skill intensity at the regional level we use this and substitute $\boldsymbol{w}$, i.e. the value-added levels first with total employment by sector and region, denoted by $\boldsymbol{l}$ and secondly high skilled employment by sector and region, denoted by $\boldsymbol{h}$. From this we estimate total employment and high skill employment coefficients, denoted by $\boldsymbol{c}$ and $\boldsymbol{d}$, respectively as

$\boldsymbol{c} = \hat{\boldsymbol{x}}^{-1}\boldsymbol{l}$ and $\boldsymbol{d} = \hat{\boldsymbol{x}}^{-1}\boldsymbol{h}$

5 https://www.oecd.org/en/publications/a-new-approach-to-skills-mismatch_e9563c2a-en.html
6 https://www.cedefop.europa.eu/en/tools/european-skills-index/skills-matching

in analogy to the value-added coefficients estimation. The total and high skill employment coefficient are then used to estimate the total employment exports $\boldsymbol{E}$ and high skill employment exports $\boldsymbol{K}$ as

$$\boldsymbol{E} = \boldsymbol{MF} \text{ with } \boldsymbol{M} = \hat{\boldsymbol{c}}\boldsymbol{L} \text{ and } \boldsymbol{K} = \boldsymbol{NF} \text{ with } \boldsymbol{N} = \hat{\boldsymbol{d}}\boldsymbol{L}$$

As in the case of value-added trade, the row sums of matrix $\boldsymbol{E}$ and $\boldsymbol{K}$ are identical to the regions' the total employment and high skill employment exports (by industries). Correspondingly, in each row, all elements where $\boldsymbol{r} \neq \boldsymbol{s}$ indicate the total or high skill employment inputs in region r but "consumed" in region s (by a certain industry), and hence total or high skill exports from region r to region s. Looking at the columns, each element where $\boldsymbol{r} \neq \boldsymbol{s}$ indicates the region r's consumption of total or high skill exports produced in region s, and hence total or high skill exports imports from s to r.

In the next step we analyse, whether differences in the high skill intensities of exports matter for the regions' capacity to export, i.e. whether there is a correlation between the high skill intensities and the regional total value-added trade shares in the regions GDP. Additionally, we test whether the skill intensities affect the net value-added export performance of the regions. For this, we use the same spatial error econometric as above (Appendix C.2), including the same control variables, and we additionally include our indicator for high skill intensity as main variable of interest. Table C.3 presents the results.

Table C.3: Spatial regression results, Full sample of regions, the high skill effect, global value-added exports

Variables	Net value-added trade	Value-added exports
Initial GDP (2010)	7.703*** (2.216)	2.504* (1.331)
Population density	0.000234 (0.000852)	-0.00123*** (0.000439)
High skill share in population	-0.0704 (0.334)	-0.552*** (0.182)
Medium skilled share in population	0.0913 (0.0888)	0.369*** (0.0476)
Research and development	-1.289 (0.784)	-0.692* (0.416)
Accessibility	-0.0107 (0.0341)	-0.00558 (0.0179)
Investment rate (2010)	-0.656*** (0.204)	0.215* (0.114)
Share of high-tech intensive manufacturing in total employment	0.116 (0.343)	0.727*** (0.183)
Share of low-tech intensive manufacturing in total employment	0.314 (0.251)	0.267** (0.135)
Share of knowledge intensive services in total employment	0.520** (0.253)	0.233* (0.137)
VAX Global - total value-added exports in VA	0.620*** (0.106)	
High skill intensity - global exports	-0.0981 (0.297)	0.808*** (0.157)
Constant	16.96 (10.87)	0.565 (6.523)
λ	1.123 (0.861)	2.971*** (1.136)
Observations	246	246

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Estimating the impact of "working from home" and outsourcing (by occupation and sector)

To estimate the long-term trends in employment by occupations over the period 2011-2022, the shifts during the Covid period, the impacts of the intensity of 'work-from-home' (by occupations and by sectors) as well as sector involvement in outsourcing, the following regression equation has been estimated:

$$\Delta lnEMPL_{oict} = \alpha + \beta COVID + \theta \Delta lnGVC_{ict} + \pi_i COVID\boldsymbol{\vartheta} + +\pi_i \Delta lnGVC_{ict}\boldsymbol{\tau} + COVID\Delta lnGVC_{ict}\boldsymbol{\varphi} + \pi_i * COVID * \Delta lnGVC_{ict}\boldsymbol{\tau} + \mu_c + \pi_i + \epsilon_{oict} \quad (1)$$

where $\Delta lnEMPL_{oict}$ refers to the annual employment growth rate of workers aged 15+ in occupation o in industry i country c and time t. $COVID$ refers to the COVID-19 pandemic period and is a dummy that is equal to one for the years 2020-2022 and zero otherwise. $\Delta lnWFH'_{oct}$ and $\Delta lnWFH'_{ict}$ refer to the annual growth rates of the share of workers aged 15+ who work from home, measured at the one-digit occupation level (ISCO-08) as the share of workers in occupation o who work from home and the one-digit industry level (NACE Rev. 2) as the share of workers in industry i who work from home, respectively. $\Delta lnGVC_{ict}$ refers to the annual growth rate of global value chain (GVC) trade in industry i country c and time t. Specifically, we use the concept of offshoring – i.e. the international outsourcing of production stages – to measure the expansion of GVCs. Finally, μ_c and π_i are country and industry fixed effects while ϵ_{oict} is the error term.

Offshoring is measured using information from international input-output tables, from which intermediate input purchases by each sector and country from each sector and country can be measured. In our analysis, we distinguish between two offshoring measures. Our initial indicator for offshoring is a measure of total offshoring, defined as the share of imported intermediate inputs from all industries as a share of gross output:

$$IIM_{i,c}^{T} = \frac{\sum_{j=1}^{J} O_{j,c}}{GO_{i,c}}, \quad (2)$$

where $O_{j,c}$ refers to imported intermediate purchases by industry i from industry j in country c and GO refers to gross output of industry i in country c. This initial offshoring measure is broken down further by sourcing region, where we distinguish the following four regions: (i) advanced Europe, (ii) developing Europe, (iii), developed non-Europe, and (iv) developing non-Europe.[7]

[7] The group of advanced European countries comprises Austria, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal and Sweden. The group of developing European countries comprises Bulgaria, Cyprus, Czechia, Estonia, Croatia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, Slovakia and Turkey. The group of developed non-European countries comprises Australia, Canada, Japan, South Korea and the United States. The group of non-EU developing countries comprises Argentina, Brazil, China, India, Indonesia, Mexico, Russia, South Africa and Saudi Arabia.

NEW REGIONS: Europe, non-Europe[8] on the one hand and developed countries and developing countries[9] on the other, defined as follows:

$$IIM_{i,c}^{Europe} = \frac{\sum_{w=1}^{W} O_{w,c}}{GO_{i,c}} \quad \text{and} \quad IIM_{i,c}^{Non-Europe} = \frac{\sum_{x=1}^{X} O_{x,c}}{GO_{i,c}} \tag{3a}$$

$$IIM_{i,c}^{Developed} = \frac{\sum_{y=1}^{Y} O_{y,c}}{GO_{i,c}} \quad \text{and} \quad IIM_{i,c}^{Developing} = \frac{\sum_{z=1}^{Z} O_{z,c}}{GO_{i,c}} \tag{3b}$$

Methodologically, we use a pooled OLS approach with industry and country fixed effects and robust standard errors clustered at the industry level to allow for correlation in the error terms across industries. Equation (1) is calculated separately for all occupations, except for occupation 0, which pertains to the armed forces.

The data for this part of the analysis come from two different sources, i.e. the Labour Force Survey (EU-LFS) and the *Full International and Global Accounts for Research in input-output analysis* (FIGARO), which provides information on international linkages of production processes and structures of trade in final goods across 64 industries (NACE Rev. 2, A64) and 64 commodities, covering all 27 EU member states, the United Kingdom, the United States and 16 main EU partners[10], plus a rest of the work aggregate. It is available from 2010 to 2021. We use information for both domestic and imported inputs at the one-digit industry level to construct the different offshoring measures described above.

Information on working from home (WFH) is calculated from EU-LFS (SUF-files). Specifically, we use the following question to calculate WFH indicators: with respect to the reference week, 'How often did you work from home during this time?'. A person was considered to work from home if s/he (i) usually works at home or (ii) sometimes works at home. The countries in our sample refer to all EU member states (as of 2020) except for Germany due to the break in the data. The data in the analysis refer to persons aged 15+ who were employed during the reference week.

[8] The group of European countries comprises Austria, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Sweden, Bulgaria, Cyprus, Czechia, Estonia, Croatia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, Slovakia and Turkey. The group of non-European countries comprises Australia, Canada, Japan, South Korea, the United States, Argentina, Brazil, China, India, Indonesia, Mexico, Russia, South Africa and Saudi Arabia.

[9] The group of developed countries comprises Austria, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Sweden, Australia, Canada, Japan, South Korea and the United States. The group of developing countries comprises Bulgaria, Cyprus, Czechia, Estonia, Croatia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovenia, Slovakia, Turkey, Argentina, Brazil, China, India, Indonesia, Mexico, Russia, South Africa and Saudi Arabia.

[10] The 16 main trading partners are Argentina, Australia, Brazil, Canada, Switzerland, China, Indonesia, India, Japan, South Korea, Mexico, Norway, Russia, Saudi Arabia, Turkey, and South Africa.

Table D.1: Estimation with outsourcing and Covid period effects – NorthWest (NW) Europe: Results for total offshoring (TO), offshoring to Europe (TOEUROPE) and to non-Europe (TOnonEUROPE)

	Managers		Professionals		Technicians		Clerical		Sales workers		Craft workers		Plant and assembly		Elementary occupations	
	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU	TO	EU-nonEU
Aggregate																
Trend	-0.006	-0.004	0.049***	0.050***	0.008	0.008	-0.019	-0.023*	-0.007	-0.009	0.002	0.003	-0.005	-0.006	0.021	0.018
Covid Impact	-0.017	-0.022	0.013	0.010	0.002	0.007	0.060*	0.053*	-0.011	-0.016	0.007	-0.003	0.012	0.013	0.017	0.015
grTO	0.055		0.143***		-0.070**		0.044		-0.044		-0.079		0.018		0.182***	
grTOEUROPE		0.319		0.080		-0.101**		-0.108		0.019		-0.059		-0.054		-0.046
grTOnonEUROPE		-0.415		0.080		0.048		0.203**		-0.091		-0.061		0.116		0.326***
COVperiod*grTO	0.033		0.042		-0.084		0.505		0.253		0.735***		0.039		0.031	
COVperiod*grTOEUROPE		-0.044		0.064		-0.488		-0.290		0.205		-0.081		0.399		-0.252
COVperiod*grTOnonEUROPE		0.126		-0.108		0.310		0.331		0.090		0.430***		-0.648*		0.083
Manufacturing (4)																
4.ind	0.010	0.009	-0.027*	-0.024*	-0.016	-0.020*	-0.012	-0.011	-0.004	-0.005	-0.023***	-0.022***	-0.012	-0.012	-0.042***	-0.042***
4.ind*grTO	-0.059		-0.109		-0.20***		0.005		0.064		0.022		0.044		-0.150	
4.ind*grTOEUROPE		-0.330		0.229		-0.431***		0.037		-0.119		0.046		0.012		-0.058
4.ind*grTOnonEUROPE		0.485		-0.252**		0.056		-0.073		0.141		0.052		-0.033		-0.252
4.ind#COVperiod	-0.080	-0.068	0.028	0.029	-0.039	-0.038	-0.017	-0.013	0.044	0.056	0.007	0.018	-0.033	-0.032	-0.070	-0.080
4.ind#COVperiod*grTO	-1.373		-0.281		-0.634		0.518		0.652		-0.381		0.203		-0.377	
4.ind#1.COVperiod*grTOEUROPE		-0.316		-0.474		0.587		1.184*		0.872		-0.350		-0.523		0.972
4.ind#1.COVperiod*grTOnonEUROPE		-0.693		0.196		-0.932**		0.035		0.325		-0.175		0.773*		-0.531
Information & communication Industry (10)																
10.ind	0.018	0.016	-0.004	-0.004	-0.011	-0.009	-0.004	-0.001	0.024	0.013	-0.032	-0.027	-0.039**	-0.033*	-0.113	-0.095
10.ind*grTO	-0.027		-0.183***		0.068		-0.247		-0.442		0.260*		-2.837***		0.208	
10.ind*grTOEUROPE		-0.274		-0.069		0.083		0.191		-0.445*		0.053		-2.352***		0.301
10.ind*grTOnonEUROPE		0.406		-0.144		-0.063		-0.577***		0.173		0.173		-1.124***		-0.446
10.ind*COVperiod	0.026	0.018	0.023	0.042	0.084*	0.117*	-0.042	-0.029	-0.030	-0.035	0.169	0.070	-0.067	-0.086*	0.219	0.287
10.ind*COVperiod*grTO	0.406		0.060		0.284		-0.303		0.312		0.804		1.031*		1.690	
10.ind*COVperiod*grTOEUROPE		0.149		-0.536**		-0.663		-0.029		0.825		1.067		17.76***		-1.728
10.ind*COVperiod*grTOnonEUROPE		-0.180		0.424		0.401		0.350		-0.673		-0.560		N/A		0.636
Professional, scientific/technical activities (13)																
13.ind	0.028*	0.025	-0.010	-0.012	0.019*	0.021*	0.001	0.002	0.026**	0.020*	0.007	0.005	0.038	0.007	-0.009	-0.003
13.ind*grTO	-0.049		-0.11***		0.034		-0.042		0.048		0.078		-1.03***		-0.357**	
13.ind*grTOEUROPE		-0.487*		-0.097		0.007		0.139		-0.639**		0.135		-1.504***		-0.271
13.ind*grTOnonEUROPE		0.531*		-0.028		-0.024		-0.216**		0.698**		0.033		0.929***		-0.280
13.ind*COVperiod	0.017	0.045	-0.014	-0.009	-0.010	-0.022	-0.056	-0.043	-0.053	-0.062	0.109	0.099	-0.057	-0.077	-0.068*	-0.059
13.ind*COVperiod*grTO	-1.27**		-0.185		0.442		-0.909		0.251		0.667		1.807		2.390	
13.ind*COVperiod*grTOEUROPE		0.941		-0.089		0.634		0.455		2.461		-0.887**		2.470***		-0.021
13.ind*COVperiod*grTOnonEUROPE		-0.620		0.099		-0.189		-0.353		-1.054		0.464		-1.316*		0.793
Country FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,232	1,232	1,408	1,408	1,540	1,540	1,405	1,405	1,155	1,155	1,010	1,010	824	824	1,212	1,212
R^2	0.092	0.143	0.071	0.137	0.086	0.102	0.071	0.130	0.099	0.144	0.116	0.164	0.100	0.211	0.114	0.166
Adjusted R^2	0.0273	0.0510	0.0132	0.0569	0.0341	0.0264	0.0144	0.0502	0.0358	0.0543	0.0391	0.0548	0.0110	0.0947	0.0523	0.0780

Note: Wholesale and Retail Trade (NACE G) is the base to which other industries are compared. Robust standard errors are not reported, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D.2: Estimation with outsourcing and Covid period effects – NorthWest (NW) Europe: Results for total offshoring (TO), offshoring to Developed (TODeveloped) and to Developing (TODeveloping) countries

	Managers		Professionals	Technicians		Clerical		Sales workers	Craft workers		Plant and assembly			Elementary occupations		
	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding	TO	Ded-Ding
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Aggregate																
Trend	-0.006	-0.004	0.049***	0.050***	0.008	0.008	-0.019	-0.023*	-0.007	-0.009	0.002	0.003	-0.005	-0.006	0.021	0.018
Covid Impact	-0.017	-0.022	0.013	0.010	0.002	0.007	0.060*	0.053*	-0.011	-0.016	0.007	-0.003	0.012	0.013	0.017	0.015
grTO	0.055		0.143***		-0.070**		0.044		-0.044		-0.079		0.018		0.182***	
grTODeveloped		0.181		0.178**		-0.099		0.063		-0.043		-0.097		0.141		0.064
grTODeveloping		-0.149		-0.032		0.028		-0.029		-0.012		0.001		-0.185		0.162
Covid*grTO	0.033		0.042		-0.084		0.505		0.253		0.735***		0.039		0.031	
Covid*grTODeveloped		0.027		0.328		0.777***		0.811***		0.337		0.543***		-0.190		0.405**
Covid*grTODeveloping		0.123		-0.094		-0.616***		-0.421***		0.021		-0.125***		0.253		-0.358***
Manufacturing (4)																
4.ind	0.010	0.010	-0.027*	-0.030*	-0.016	-0.020*	-0.012	-0.014	-0.004	-0.003	-0.023***	-0.021***	-0.012	-0.016	-0.042***	-0.038***
4.ind*grTO	-0.059		-0.109		-0.201***		0.005		0.064		0.022		0.044		-0.150	
4.ind*Covid	-0.080	-0.074	0.028	0.041	-0.039	-0.032	-0.017	0.011	0.044	0.050	0.007	0.017	-0.033	-0.028	-0.070	-0.074
4.ind*Covid*grTO	-1.373		-0.281		-0.634		0.518		0.652		-0.381		0.203		-0.377	
4.ind*grTODeveloped		-0.076		-0.267		-0.287		-0.146		0.178		0.144		-0.125		0.045
4.ind*Covid*grTODeveloped		-1.788		-0.279		-1.729**		-0.006		0.085		-0.577		0.519		-1.018
4.ind*grTODeveloping		0.085		0.231**		0.118		0.256**		-0.154		-0.161		0.266*		-0.319**
4.ind*Covid*grTODeveloping		-0.398		-0.144		0.187		0.630**		0.381		0.385**		-0.251		0.209
Information & communication Industry (10)																
10.ind	0.018	0.017	-0.004	-0.005	-0.011	-0.010	-0.004	-0.002	0.024	0.015	-0.032	-0.024	-0.039**	-0.036*	-0.113	-0.103
10.ind*grTO	-0.027		-0.183***		0.068		-0.247		-0.442		0.260*		-2.837***		0.208	
10.ind*Covid	0.026	0.020	0.023	0.031	0.084*	0.078*	-0.042	-0.032	-0.030	-0.016	0.169	0.083	-0.067	-0.061	0.219	0.230
10.ind*Covid*grTO	0.406		0.060		0.284		-0.303		0.312		0.804		1.031*		1.690	
10.ind*grTODeveloped		-0.123		-0.201		0.069		-0.131		-0.204		0.462**		-2.865***		0.515
10.ind*Covid*grTODeveloped		0.493		-0.673		-2.267***		-0.786		0.842		-0.436		1.067		-2.451
10.ind*grTODeveloping		0.120		0.009		-0.020		-0.214		-0.180		-0.383		-0.452***		-0.848
10.ind*Covid*grTODeveloping		-0.567		0.361		1.876***		0.835		-0.693		0.868*		N/A		1.630
Professional, scientific/technical activities (13)																
13.ind	0.028*	0.034**	-0.010	-0.012	0.019*	0.022*	0.001	-0.002	0.026**	0.018	0.007	0.004	0.038	0.024	-0.009	-0.000
13.ind*grTO	-0.049		-0.1***		0.034		-0.042		0.048		0.078		-1.032***		-0.357**	
13.ind*Covid	0.017	0.032	-0.014	-0.004	-0.010	-0.008	-0.056	-0.025	-0.053	-0.022	0.109	0.104	-0.057	-0.008	-0.068*	-0.048
13.ind*Covid*grTO	-1.266**		-0.185		0.442		-0.909		0.251		0.667		1.807		2.390	
13.ind*grTODeveloped		0.095		-0.170**		0.066		-0.142		-0.213*		0.075		0.536		-0.314
13.ind*Covid*grTODeveloped		0.188		-0.474		-0.492		-0.154		2.181**		-1.827***		5.448***		2.764
13.ind*grTODeveloping		-0.261		0.080		-0.063		0.157*		0.410**		0.076		-1.080		-0.201
13.ind*Covid*grTODeveloping		0.213		0.149		0.622**		0.032		-1.299**		0.826		-2.004**		-0.431
Country FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,232	1,232	1,408	1,408	1,540	1,540	1,405	1,405	1,155	1,155	1,010	1,010	824	824	1,212	1,212
R-squared	0.092	0.128	0.071	0.125	0.086	0.140	0.071	0.122	0.099	0.130	0.116	0.178	0.100	0.216	0.114	0.178
Adj. R^2	0.0273	0.0349	0.0132	0.0433	0.0341	0.0669	0.0144	0.0413	0.0358	0.0397	0.0391	0.0704	0.0110	0.100	0.0523	0.0913

Note: Wholesale and Retail Trade (NACE G) is the base to which other industries are compared. Robust standard errors are not reported, *** p<0.01, ** p<0.05, * p<0.1.

Appendix E: Robot, (re-)shoring and employment

Table E.1: Grouping of occupation by task content

	Routine	Non-routine
Manual	Craft workers and machine operators [71–74, 81–82, 93], Agricultural workers [60-61, 92], Other, including armed forces [01-03, 90,99]	Personal service workers [51, 910, 912–916] Drivers [83]
Analytic	Clerical support workers [41–42]	Legislators [11], Managers [12–13], Engineering professionals [21, 31], Health professionals [22, 32], Teaching professionals [23, 33], Other professionals [24, 34], Sales workers [52, 911]

To investigate the association between employment and robots, the following regression equation has been estimated:

$$\Delta EMPN_{ci} = \beta_1 \, \Delta Robot\ intensity_{ci} + Z'_{ci}\gamma + \delta_c + \varepsilon_{ci}$$

where i and c indicate industries and countries, respectively, and Z is a vector of potential control variables; δc refers to the country's fixed-effect. A Weighted Least Square (WLS) approach has been used, weighting industries using their initial employment shares within each country. Note that this approach still gives equal weight to all countries in the analysis. We also follow those studies by using heteroscedasticity-robust standard errors that are two-way clustered by country and industry, which is facilitated by the *ivreg2* command in STATA 18. Table E.2 reports the results of this exercise.

Table E.2: Robotisation and employment by occupational groups

	(1) Δln (EMPN)	(2) Δ Routine EMP share	(3) Δ Non-Routine EMP share	(4) ΔRoutine manual EMP share	(5) ΔRoutine analyt EMP share
Percentile of changes in robot adoption	0.143 (0.09)	-0.011*** (0.00)	0.011*** (0.00)	-0.013* (0.01)	0.001 (0.01)
r2	0.029	0.003	0.003	0.003	0.000
Observations	509	509	509	509	509
#Countries	35	35	35	35	35

Notes: WLS estimates. Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

Table E.3: Robot adoption and (re-)shoring

	(1) Δln (Value Added)	(2) Δln (VA/FI)	(3) ln(RI^O)	(4) ln(RI^O)
% changes in robot adoption	0.201***	0.048	-0.136**	-0.222***
	(0.06)	(0.07)	(0.07)	(0.07)
x RI^O>0				1.274***
				(0.18)
r2	0.035	0.002	0.005	0.277
Observations	509	509	509	509
#Countries	35	35	35	35

Notes: VA= value added; FI; foreign input use; RI^0= reshoring intensity index. Robust standard errors in parentheses. Multi-way clustering by country and industry. Country fixed effects are included in all regressions and partialled out in the reported r2.

Table E.4: Reshoring and employment by occupational groups

	(1) Δln (EMPN)	(2) Δ Routine EMP share	(3) Δ Non-Routine EMP share	(4) ΔRoutine manual EMP share	(5) ΔRoutine analyt EMP share
ln(RI^O)	0.031	-0.007	0.007	-0.008	0.008
	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)
r2	0.004	0.004	0.004	0.004	0.004
Observations	509	509	509	509	509
#Countries	35	35	35	35	35

Notes: WLS estimates. Robust standard errors in parentheses. Multi-way clustering by country and industry.
Country fixed effects are included in all regressions and partialled out in the reported r2.

Table E.5: Robotisation, employment and reshoring intensity

	(1) Δln (EMPN)	(2) Δln (EMPN)	(3) Δln (EMPN)	(4) Δln (EMPN)
% of changes in robot adoption	0.143	0.146*	0.139*	0.144*
	(0.09)	(0.09)	(0.08)	(0.05)
x RI^O>0		-0.036		
		(0.05)		
ln(RI^O)			0.053	0.055
			(0.04)	(0.04)
Perc Δ in robot adoption x ln(RI^O)			-0.032	
			(0.05)	
RI^O<0: Perc Δ in robot adoption x ln(RI^O)				-0.022
				(0.07)
RI^O>0: Perc Δ in robot adoption x ln(RI^O)				-0.067
				(0.17)
r2	0.029	0.030	0.036	0.036
Observations	509	509	509	509
#Countries	35	35	35	35

Notes: WLS estimates. Robust standard errors in parentheses. Multi-way clustering by country and industry.
Country fixed effects are included in all regressions and partialled out in the reported r2.

Appendix F: Export quality upgrading, employment and GVCs

Export quality at the firm level

We estimated the quality of exports by using the International Trade in Goods Statistics (IHG) on the 6-digit harmonised system (HS) product classification. In particular, quality is extracted as the residual of a log-linearized CES demand system (Khandelwal et al., 2013). This approach reflects the idea that if a consumer is willing to pay a higher price for variety h_A than for variety h_B of a given good h, conditional on essential demand shifters, variety h_A must be of superior quality. With each firm f producing a variety of good h, demand q of this variety by the importing country c at time t is given in this CES framework as:

$$q_{fhct} = \lambda_{fhct}^{\sigma-1} p_{fhct}^{-\sigma} P_{hct}^{\sigma-1} Y_{ct} \quad (1)$$

where the importer's income level, Y, and price level, P, are demand shifters that reflect that demand rises with income, and what matters for demand is that e product-specific price p is in relation to the importing country price level, p/P. Given σ>1, higher quality λ (and lower price p) are associated with higher demand ceteris paribus. Taking logs, and after a simple re-arrangement and parameterisation of eq. (1) to allow for a more flexible form, we get:

$$\ln q_{fhct} + \sigma \ln p_{fhct} = \beta_1(\sigma - 1)\ln P_{hct} + \beta_2 \ln Y_{ct} + (\sigma - 1)\ln \lambda_{fhct}. \quad (2)$$

With data for q, p, P, Y, and σ available, one can estimate quality λ residually. Since international price levels are not available for the relative product categories and it is not a priory clear how to best proxy the income level, we follow the literature by absorbing those factors with a fixed effect and estimate:

$$\ln q_{fhct} + \sigma \ln p_{fhct} = \alpha_h + \alpha_{ct} + \epsilon_{fhct} \quad (3)$$

Quality can then be inferred as the transformed residual $\ln \hat{\lambda}_{\mathrm{fhct}} = \frac{\hat{\epsilon}_{fhct}}{\sigma-1}$. We rely on estimates of σ from Ghodsi (2021) and, since firms usually export several products to various country, we aggregate them at the firm level: $Exp\_Qual\_agg_{ft} = \sum_h \sum_c w_{hct} \ln \hat{\lambda}_{hct}$.

Methodology

We are interested in how changes in firm fs export quality affects its subsequent employment. For our baseline specification, we model this relationship as a stacked difference equation:

$$\Delta \ln(emp)_{ft} = b_1 \Delta \ln(Exp\_Qual\_agg)_{f,t} + X_{ft}\theta + \Delta\delta_i + \Delta\varepsilon_{ft} , \quad (4)$$

where *emp* is the number of employees (in full-time equivalents) in firm f at time t, *Exp_Qual_agg* is the measure of export quality, and X is a vector of firm-level control variables, which include firms' initial employment levels, export shares, and labour productivity, as well as changes in labour productivity. Industry-specific dummies δ_i account for sector-specific employment trends common to all firms. The main results are shown in Tables F1-F4.

Table F.1: Employment changes

VARIABLES	(1) Δln(EMP FTE)	(2) Δln(EMP FTE)	(3) Δln(EMP FTE)	(4) Δln(EMP FTE)	(5) Δln(EMP FTE)	(6) Δln(EMP FTE)
Initial ln(EMP FTE)	-0.0221***	-0.0266***	-0.0274***	-0.0160***	-0.0223***	-0.0228***
	(0.00214)	(0.00205)	(0.00206)	(0.00196)	(0.00196)	(0.00198)
Initial export share	-6.00e-05***	0.000632*	0.000660*	-6.24e-05***	0.00100***	0.000993***
	(5.43e-06)	(0.000326)	(0.000338)	(2.94e-06)	(0.000205)	(0.000212)
Δ Exp_Qual_agg	0.0208***	0.0182***	0.0180***	0.0210***	0.0185***	0.0186***
	(0.00410)	(0.00366)	(0.00368)	(0.00420)	(0.00368)	(0.00369)
Initial GVC wide			-0.00147			-0.000541
			(0.000898)			(0.000804)
Δ Exp_Qual_agg x			-0.00142*			-0.00123
initial GVC wide			(0.000728)			(0.00107)
Initial export quality	0.0101***	0.00829***	0.00783**	0.00895***	0.00824***	0.00831***
	(0.00354)	(0.00315)	(0.00315)	(0.00347)	(0.00301)	(0.00301)
Δ ln (labor productivity)		-0.109***	-0.111***		-0.119***	-0.121***
		(0.0119)	(0.0121)		(0.0150)	(0.0152)
Initial ln (labor productivity)		0.0421***	0.0434***		0.0353***	0.0363***
		(0.00349)	(0.00352)		(0.00345)	(0.00351)
Observations	21,016	20,104	19,825	21,016	20,104	19,825
R-squared	0.028	0.087	0.090	0.022	0.081	0.083

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector FEs included. (1)-(3) estimated with OLS, (4)-(6) with WLS.

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Table F.2: Changes in average wages

VARIABLES	(1) Δln(mean wage)	(2) Δln(mean wage)	(3) Δln(mean wage)	(4) Δln(mean wage)	(5) Δln(mean wage)	(6) Δln(mean wage)
Initial ln(wage)	-0.0438***	-0.121***	-0.122***	-0.0308***	-0.0941***	-0.0961***
	(0.00406)	(0.00779)	(0.00783)	(0.00479)	(0.00902)	(0.00893)
Initial export share	4.21e-06***	7.56e-05	2.36e-05	3.04e-06***	4.78e-05	-1.22e-05
	(1.11e-06)	(7.20e-05)	(6.30e-05)	(8.67e-07)	(5.85e-05)	(5.55e-05)
Δ Exp_Qual_agg	-0.000310	-0.000184	-3.03e-05	0.00113	0.00126	0.00132
	(0.00156)	(0.00153)	(0.00153)	(0.00165)	(0.00162)	(0.00163)
Initial GVC wide			0.00169***			0.00233***
			(0.000489)			(0.000404)
Δ Exp_Qual_agg x initial GVC wide			0.00123***			0.00126***
			(0.000245)			(0.000356)
Initial export quality	0.00323**	0.00249*	0.00286**	0.00503***	0.00404***	0.00427***
	(0.00142)	(0.00136)	(0.00137)	(0.00149)	(0.00143)	(0.00144)
Δ ln (labor productivity)		0.0646***	0.0647***		0.0544***	0.0551***
		(0.00457)	(0.00462)		(0.00496)	(0.00492)
Initial ln (labor productivity)		0.0584***	0.0585***		0.0484***	0.0496***
		(0.00397)	(0.00395)		(0.00454)	(0.00435)
Observations	21,014	20,102	19,823	21,014	20,102	19,823
R-squared	0.070	0.122	0.123	0.088	0.131	0.133

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector FEs included. (1)-(3) estimated with OLS, (4)-(6) with WLS.

Table F.3: Changes in the standard deviation of wages (at the firm level)

VARIABLES	(1) Δ SD wage	(2) Δ SD wage	(3) Δ SD wage	(4) Δ SD wage	(5) Δ SD wage	(6) Δ SD wage
Initial SD wage	-0.878***	-0.782***	-0.783***	-0.873***	-0.775***	-0.775***
	(0.0700)	(0.116)	(0.116)	(0.0731)	(0.116)	(0.116)
Initial export share	5.70e-05	-0.00268	-0.00758	-0.000167	-0.00190	-0.00826
	(0.000187)	(0.00391)	(0.00466)	(0.000291)	(0.00820)	(0.00920)
Δ Exp_Qual_agg	0.673	0.633	0.638	1.081	1.008	1.010
	(0.469)	(0.489)	(0.498)	(0.783)	(0.814)	(0.823)
Initial GVC wide			0.0809			0.165**
			(0.0597)			(0.0694)
Δ Exp_Qual_agg x			-0.0122			0.0118
initial GVC wide			(0.0481)			(0.0564)
Initial export quality	1.010***	0.695*	0.692*	1.343**	0.842	0.837
	(0.344)	(0.358)	(0.365)	(0.560)	(0.582)	(0.589)
Δ ln (labor productivity)		3.816***	3.881***		5.965***	6.073***
		(1.002)	(1.024)		(1.992)	(2.025)
Initial ln (labor productivity)		4.123***	4.206***		5.732***	5.881***
		(0.771)	(0.792)		(1.319)	(1.358)
Observations	20,785	19,908	19,636	20,785	19,908	19,636
R-squared	0.469	0.275	0.275	0.485	0.290	0.290

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector FEs included. (1)-(3) estimated with OLS, (4)-(6) with WLS.

Table F.4: Export quality and GVC participation

	(1) Δ Exp Qual_agg	(2) Δ Exp Qual_agg	(3) Δ Exp Qual_agg	(4) Δ Exp Qual_agg	(5) Δ Exp Qual_agg	(6) Δ Exp Qual_agg	(7) Δ Exp Qual_agg	(8) Δ Exp Qual_agg
Initial GVC wide	-.0034881*	-.0038175***						
	(.0019226)	(.0012692)						
Δ GVC wide			.0015793	.0003327	.0002142***	.000204***		
			(.0014897)	(.0016934)	(.0000141)	(.0000153)		
Δ imp qual							.18663***	.1957588***
							(.0335735)	(.0330052)
Initial export share	.0005173	-.0001231	.0003851	-.0002776				
	(.0005073)	(.000251)	(.0004895)	(.0003066)				
Initial export quality	-.6333***	-.6390***	-.6332***	-.6393***				
	(.0092)	(.0102)	(.0093)	(.0103)				
Δ Labor productivity	-.0072084	-.010872	-.0032852	-.0071823				
	(.0129347)	(.0154758)	(.0133561)	(.0157584)				
Initial Labor productivity	-.008476	.0026619	-.0075163	-.0006434				
	(.0071606)	(.0081469)	(.0072355)	(.0082244)				
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Obs	19,842	19,842	19,562	19,562	19,872	19,872	17,467	17,467
R squared	0.4491	0.4618	0.4488	0.4619	0.0154	0.0204	0.0484	0.0339
Estimation	OLS	WLS	OLS	WLS	OLS	WLS	OLS	OLS

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector FE included. (1)-(3) estimated with OLS, (4)-(6) with WLS.

Appendix G: Covid, GVCs, and employment strategies

GVC participation

To indicate whether organisations participate in GVCs, we use the World Bank Enterprise Survey (WBES) to construct four different indicators (Dovis & Zaki, 2020; Elsharaawy & Ezzat, 2022). These indicators are based on export status, import status, international quality certification, and foreign ownership. According to Dovis & Zaki (2020), the least strict definition contains companies that export and import simultaneously. Definitions two and three are seen as substitutes. These companies are two-way traders and either have an international quality certification or are owned by a foreign firm. The strictest definition combines the four dimensions and hence consists of companies that are two-way traders, have an international quality certificate, and are foreign-owned.

Table G.1: Logistic multilevel regression analysis of formal training programs

		(1)			(2a)			(2b)			(2c)			(2d)	
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
HC obstacle															
None	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Minor	0.105	0.026	0.000	0.077	0.027	0.005	0.077	0.027	0.005	0.081	0.027	0.003	0.084	0.027	0.002
Moderate	0.315	0.026	0.000	0.295	0.027	0.000	0.288	0.027	0.000	0.302	0.027	0.000	0.300	0.027	0.000
Major	0.387	0.029	0.000	0.357	0.030	0.000	0.364	0.030	0.000	0.373	0.030	0.000	0.382	0.030	0.000
Very severe	0.522	0.038	0.000	0.486	0.039	0.000	0.478	0.039	0.000	0.507	0.039	0.000	0.501	0.039	0.000
Multisite	0.501	0.025	0.000	0.499	0.025	0.000	0.478	0.026	0.000	0.478	0.025	0.000	0.473	0.026	0.000
Sector															
Manufacturing	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Construction	0.132	0.037	0.000	0.162	0.038	0.000	0.162	0.038	0.006	0.122	0.038	0.001	0.112	0.038	0.004
Services	0.256	0.033	0.000	0.316	0.034	0.000	0.324	0.034	0.000	0.249	0.034	0.000	0.235	0.035	0.000
Organization size															
Small	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Medium	0.622	0.021	0.000	0.578	0.022	0.000	0.655	0.022	0.000	0.608	0.022	0.000	0.612	0.022	0.000
Large	1.230	0.026	0.000	1.133	0.028	0.000	1.063	0.028	0.000	1.175	0.028	0.000	1.163	0.028	0.000
Unknown	0.940	0.058	0.000	0.908	0.058	0.000	0.850	0.059	0.000	0.940	0.059	0.000	0.931	0.059	0.000
EU	0.653	0.214	0.002	0.586	0.211	0.001	0.573	0.215	0.000	0.644	0.215	0.000	0.748	0.213	0.000
Year															
2019	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
2020	0.223	0.071	0.002	0.203	0.073	0.010	0.188	0.073	0.010	0.225	0.072	0.002	0.207	0.073	0.005
2021	-0.010	0.078	0.896	-0.015	0.080	0.732	-0.028	0.080	0.732	-0.017	0.079	0.828	-0.038	0.080	0.639
2022	-0.033	0.085	0.696	-0.055	0.088	0.412	-0.072	0.088	0.412	-0.087	0.087	0.318	-0.102	0.088	0.249
2023	-0.130	0.043	0.003	-0.103	0.045	0.012	-0.111	0.045	0.012	-0.109	0.044	0.013	-0.105	0.044	0.018
2024	0.241	0.100	0.016	0.266	0.102	0.003	0.307	0.102	0.003	0.266	0.101	0.008	0.324	0.101	0.001

GVC participation															
Two-way trade				0.423	0.023	0.000									
+ Certificate							0.741	0.029	0.000						
+ Foreign owned										0.741	0.029	0.000			
All													0.776	0.053	0.000
Constant	-1.715	0.130	0.000	-1.753	0.130	0.000	-1.709	0.132	0.000	-1.724	0.131	0.000	-1.730	0.132	0.000
-2 Log Likelihood	36286.360			34637.784			33644.147			34530.896			33692.778		
Deviance	2497.453			1648.576			2642.213			1755.464			2593.582		

(1) Two way traders; (2a) two-way traders + certification; (2b) two-way traders foreign owned; (2d) all. 68,945 companies in 70 countries
-2 log likelihood of the empty model: 38783.813

Table G.2: Multinomial regression of the number of permanent workers (COVd3a)

	Increased			Decreased		
	b	s.e.	p	b	s.e.	p
Two-way trade	0,153	0,052	0,003	0,151	0,043	0,000
+ Certification	0,135	0,058	0,020	0,002	0,049	0,975
+ Foreign owned	-0,120	0,082	0,145	-0,010	0,067	0,880
All	-0,181	0,096	0,060	-0,117	0,078	0,132

17175 companies in 12 countries
Analyzes are controlled for sector, organization size, year, and country

Table G.3: Multinomial regression of the number of temporary workers (COVd3b)

	Increased			Decreased		
	b	s.e.	p	b	s.e.	p
Two-way trade	-0,108	0,068	0,110	0,210	0,046	0,000
+ Certification	-0,061	0,077	0,428	0,340	0,051	0,000
+ Foreign owned	-0,231	0,106	0,030	-0,036	0,070	0,606
All	-0,227	0,122	0,061	-0,046	0,079	0,561

17175 companies in 12 countries
Analyzes are controlled for sector, organization size, year, and country

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Appendix H: Citizens' perceptions of costs and benefits of GVCs

H1. List of sectors for the calculation of the indicator of regional GVCs exposure

The indicator of regional GVCs specialization is calculated using employment data for the following 21 NACE-Rev2 sectors:

A - Agriculture, Forestry and Fishing

BDE - Mining and Quarrying (B) + Electricity, Gas, Steam and Air Conditioning Supply (D) + Water Supply; Sewerage, Waste Management and Remediation Activities (E)

C10-12 - Manufacture of food, beverages and tobacco products

C13-15 - Manufacture of textile, wearing apparel, leather and related products

C16-18 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of paper and paper products; Printing and reproduction of recorded media

C20-21 - Manufacture of chemicals and chemical products; Manufacture of basic pharmaceutical products and pharmaceutical preparations

C22 - Manufacture of rubber and plastic products

C23 - Manufacture of other non-metallic mineral products

C24-25 - Manufacture of basic metals; Manufacture of fabricated metal products, except machinery and equipment

C26-27 - Manufacture of computer, electronic and optical products; Manufacture of electrical equipment

C28 - Manufacture of machinery and equipment n.e.c.

C29-30 - Manufacture of motor vehicles, trailers and semi-trailers and other transport equipment;

C31-33 - Manufacture of furniture; Other manufacturing; Repair and installation of machinery and equipment

F - Construction

G-I - Wholesale and retail trade, transport, accommodation and food service activities

J - Information and communication

K - Financial and insurance activities

L - Real estate activities

M-N - Professional, scientific and technical activities; administrative and support service activities

O-Q - Public administration, defence, education, human health and social work activities

R-U - Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organisations and bodies

Data on trade in employment come from the OECD TiM database (2023 Ed.: https://stats.oecd.org/Index.aspx?DataSetCode=TIM_2021). Data on the regional sectoral specialisation come from the Eurostat Labor Force Survey. Sector C19 (Manufacture of coke and refined petroleum products) is not included in the analysis, since regional employment data are unavailable.

Table H.1: List of variables, definition, source and summary statistics

Variable name	Description	Source	Mean	S.d.
Individual characteristics				
Anti-trade sentiment	Dummy = 1 if the respondent stated that he/she did not benefit from trade	EB	0.392	0.488
Occupation	Set of dummy variables for the different categories of workers, low-skilled (ISCO 08-09, 12.35%), high-skilled (ISCO 01-02, 13.22%), medium-skilled (ISCO 03-07, 23.7%), unemployed (6.58%), retired (30.53%), student (7.16%), house-worker (6.46%)	EB		
Low education	Dummy = 1 if the maximum educational achievement of the respondent is equal or less than middle school	EB	0.488	0.500
Difficult with bills	Dummy = 1 if the respondent encountered most of times difficulties in paying the bills in the last 12 months	EB	0.089	0.285
Political views	Set of dummy variables for the respondents who, on a 1-10 scale from left to right, placed themselves either on the extreme left (1, 4.63%) or on the extreme right (10, 4.48%)			
Foreigner	Dummy = 1 if the respondent has a nationality different from the country of residence	EB	0.023	0.152
No internet access	Dummy equal to 1 if the respondent does not use/has no access to internet	EB	0.271	0.444
Female	Dummy equal to 1 if the respondent is a woman	EB	0.546	0.498
Age	Age of the respondent	EB	49.857	18.323
Marital status	Set of dummy variables for the marital status of the respondent, among married (53.42%) single with partner (10.97%), single alone (17.54%), separated/divorced (8.05%), widower (10.02%)	EB		
Regional characteristics				
Regional functional specialization ISCO 01-02	Share of high-skilled workers over total regional employment (see Equation [3])	Eurostat LFS	0.249	0.075
Regional GVCs exposure	Indicator of regional GVCs exposure (see Equation [2])	Author's calculation based on OECD TiM and Eurostat LFS	0.299	0.093
Change in region. GDP per capita (t-8)	% change in regional GDP per capita in the 8 years before the survey	Eurostat	0.417	0.379
Change in regional employment (t-8)	% change in regional employment in the 8 years before the survey	Eurostat	0.054	0.092
Population density	Resident population per square km	Eurostat	0.001	0.969
Rank 1 region	Dummy = 1 for regions with more than 1 million inhabitants	Eurostat		
Eastern Europe	Dummy = 1 if the region is part of a New Member State	Eurostat	0.383	0.468
Year == 2010	Dummy = 1 if the year of the survey is 2010	EB	0.502	

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Table H.2: Anti-trade sentiment as a function of individual and contextual factors: regression results

	[1]	[2]	[4]	[5]	[6]	[7]	[8]
Regional functional specialization ISCO 01-02	-0.040***		-0.041***	-0.028***	-0.011*	-0.008	-0.011*
	(0.006)		(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Regional GVCs exposure		0.006	-0.004	0.005	-0.008	-0.009	-0.006
		(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Individual characteristics							
Occupation							
Low-skilled (ISCO08-09)				0.035***	0.036***	0.036***	0.037***
				(0.008)	(0.008)	(0.008)	(0.009)
*Low-skilled * Reg. functional special. ISCO 01-02*						-0.003	
						(0.008)	
*Low-skilled * Reg. GVCs exposure*							-0.003
							(0.007)
High-skilled (ISCO01-02)				-0.041***	-0.041***	-0.036***	-0.033***
				(0.008)	(0.008)	(0.008)	(0.008)
*High-skilled * Reg. functional special. ISCO 01-02*						-0.012*	
						(0.007)	
*High-skilled * Reg. GVC exposure*							-0.020***
							(0.007)
Unemployed				0.069***	0.069***	0.069***	0.069***
				(0.010)	(0.010)	(0.010)	(0.010)
Retired				0.022***	0.022**	0.021**	0.022**
				(0.009)	(0.008)	(0.009)	(0.008)
House worker				0.055***	0.054***	0.054***	0.055***
				(0.012)	(0.012)	(0.012)	(0.012)
Student				0.010	0.009	0.009	0.010
				(0.012)	(0.012)	(0.012)	(0.012)
Low education				0.069***	0.069***	0.070***	0.069***
				(0.005)	(0.005)	(0.005)	(0.005)
Difficult with bills				0.089***	0.089***	0.089***	0.089***
				(0.009)	(0.009)	(0.009)	(0.009)
Political views							
Extreme left				0.047***	0.047***	0.047***	0.047***
				(0.011)	(0.011)	(0.011)	(0.011)
Extreme right				0.016	0.016	0.016	0.016
				(0.011)	(0.011)	(0.011)	(0.011)
Foreigner				-0.037*	-0.035	-0.034	-0.035*
				(0.021)	(0.021)	(0.021)	(0.021)
No internet access				0.099***	0.099***	0.100***	0.099***
				(0.007)	(0.007)	(0.007)	(0.007)

	[1]	[2]	[4]	[5]	[6]	[7]	[8]
Female				-0.003	-0.003	-0.003	-0.003
				(0.005)	(0.005)	(0.005)	(0.005)
Age				0.002***	0.002***	0.002***	0.002***
				(0.000)	(0.000)	(0.000)	(0.000)
Marital status							
Single with partner				-0.013	-0.013*	-0.013*	-0.013*
				(0.008)	(0.008)	(0.008)	(0.008)
Single alone				0.013*	0.013*	0.013*	0.013*
				(0.007)	(0.007)	(0.007)	(0.007)
Separated/divorced				0.023***	0.023***	0.023***	0.023***
				(0.009)	(0.009)	(0.009)	(0.009)
Widower				0.048***	0.049***	0.049***	0.049***
				(0.009)	(0.009)	(0.009)	(0.009)
Regional characteristics							
Change in region. GDP per capita (t-8)					-0.027	-0.027	-0.027
					(0.017)	(0.017)	(0.017)
Change in regional employment (t-8)					-0.279***	-0.280***	-0.274***
					(0.057)	(0.057)	(0.057)
Population density					-0.004	-0.004	-0.004
					(0.007)	(0.007)	(0.007)
Rank 1 region					-0.053***	-0.054***	-0.054***
					(0.017)	(0.017)	(0.017)
Eastern Europe					0.053	0.053	0.053
					(0.041)	(0.041)	(0.041)
Year == 2010	0.011***	0.013***	0.011***	0.010***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	23.131***	26.717***	22.518***	20.295***	18.766***	18.689***	18.703***
	(1.315)	(1.706)	(1.786)	(1.781)	(1.928)	(1.928)	(1.928)
Observations	41,268	41,268	41,268	40,243	40,243	40,243	40,243

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
Reference categories: medium-skilled (occupation), married (marital status).
Variables of regional functional specialisation, regional GVC exposure, and population density are mean-standardized.

Appendix I: Do Global production networks increase job polarization? The EU experience

We create an Index of labour polarization, to be used as dependent variabel as follow:

$$\boldsymbol{Polarisation_{i,t}} = ln\frac{\sum \boldsymbol{E}_{i,t}^{high} + \sum \boldsymbol{E}_{i,t}^{low}}{\sum \boldsymbol{E}_{i,t}^{medium}}$$

where low skill workers are those holding a job in sales and service and elementary occupations (ISCO 9), medium skill workers are those holding a job in clerical, craft, plant and machine operators and assembler occupations (ISCO 4- 8). High skill workers are those holding a job in managerial professional, technicians and associate professional occupations (ISCO 1-2-3).
t= 2008, 2015, 2018, 2022
i=EU NUTS2 regions

Outward internationalization

Network of European Global Ultimate Owners (GUOs), that is, the independent companies at the top of the corporate structure, and their foreign affiliates (SUBs).

- $GUO_{i,t}$*: number of GUO*
- $SUB_{i,t}$*: number of subsidiaries controlled by GUO*
- $SUBSAME_{i,t}$: Number of subsidiaries with the same 1-digit sector as the GUO

Moreover, to capture the different mechanisms: efficiency seeking is captured by the presence of subsidiaries in the same 4-digit sector, market seeking by subsidiaries in the same 2-digit sector but a different 4-digit sector; strategic seeking refers to the presence of subsidiaries in sectors with high technological and knowledge intensity (OECD classification). Finally, diversification is captured by the presence of subsidiaries in a different 2-digit sector from that of the GUO.

Table I.1: Classification of sector of activities

TECHNOLOGICAL AND KNOWLEDGE INTENSITY	NACE
Industry	
HIT	21, 26, 30.3, 32.5
HITS	53, 58, 60-63, 72
KWNMS	50, 51, 68, 69-71, 73-74, 77-78, 80-82

Inward attraction

Subsidiaries located in European NUTS2 regions controlled by foreign GUOs.

- $subsIN_{i,t}$

Following Autor et al. (2015) we create a **measure of the routine task-intensity RTI** of each occupation and, through this, we calculate the regional average:

$$meanRTI_{i,t} = \ ln(task\_routine_{i,t}) - ln(task\_manual_{i,t}) - \ ln(task\_abstract_{i,t})$$

Economic complexity indicators are based on the ubiquity of each industry and the diversity of each region in term of industry specialization (Hidalgo and Hausmann, 2009).

$$ECI_{i,t} = \boldsymbol{f}(diversity,\ rarity)$$

We estimate the following equations:

$$Polarisation_{\boldsymbol{i,t}} = \ \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} Mechanism_{i,t-1} + X_i\,\boldsymbol{\theta} + \ \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} \qquad (1)$$

We create SUBSAME (same 1-digit sector) as the sum of efficiency and market variables. And we estimate the following equations:

$$\boldsymbol{Polarisation_{i,t}} = \ \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} GUO_{i,t-1} + \boldsymbol{\beta_2} SUBSAME_{i,t-1} + \boldsymbol{\beta_3} subsIN_{\boldsymbol{i,t-1}} + \ \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} \qquad (2)$$

$$\boldsymbol{Polarisation_{i,t}} = \ \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} GUO_{i,t-1} + \boldsymbol{\beta_2} SUBSAME_{i,t-1} + \boldsymbol{\beta_3} subsIN_{\boldsymbol{i,t-1}} + X_i\,\boldsymbol{\theta} + \ \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} \ (3)$$

Where *i* denotes the EU NUTS2 region, *c* the EU NUTS0 country; *t* time=2008, 2015, 2018 and 2022; and $\boldsymbol{\alpha_i}\ and\ \boldsymbol{\gamma_t}$ region and time fixed effects. And where $\boldsymbol{X_i}\,\boldsymbol{\theta}$ represents a set of **control variables,** such as RTI, eci, degree of urbanization and the country trend. Additionally, all covariates are expressed in standard deviation.

Table I.2: The effect of globalization on job polarization. Fixed-effect model. 2007-2022

VARIABLES	(2) polarization	(3) polarization
GUO	-0.00925	-0.00964
	(0.00908)	(0.00935)
SUBSAME	0.0323***	0.0311***
	(0.00902)	(0.00928)
subsIN	0.0259**	0.0311**
	(0.0121)	(0.0127)
Degurba		-0.00793
		(0.0384)
meanRTI		-0.0293
		(0.0497)
Eci		0.00330**
		(0.00138)
Constant	0.888***	0.699***
	(0.0116)	(0.172)
Observations	787	734
R-squared	0.548	0.541
Number of id	212	204
Years Fes	YES	YES
Region Fes	YES	YES

Country Trends	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The OECD indicators of employment protection legislation (EPL) evaluate the regulations on the dismissal of workers on regular contracts and the hiring of workers on temporary contracts.
LowEPL: *if below the median*
HighEPL: *if above the median*

$$\boldsymbol{Polarisation_{i,t}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} GUO_{i,t-1} + \boldsymbol{\beta_2} SUB_{i,t-1} * EPL_{c,t-1} + \boldsymbol{\beta_3} subsIN_{\boldsymbol{i,t-1}} * EPL_{c,t-1} + X_i \boldsymbol{\theta} + \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} \quad (4)$$

Table I.3: The heterogeneous effect of globalization on job polarization: the role of Employment Protection

VARIABLES	(4) polarization
GUO	-0.0124
	(0.0143)
SUBSAME	0.125***
	(0.0380)
2. HighEPL #c.SUBSAME	-0.0993***
	(0.0367)
subsIN	0.152***
	(0.0334)
2.HighEPL#c.subsIN	-0.148***
	(0.0407)
Constant	0.704***
	(0.176)
Observations	681
Number of id	184
R-squared	0.553
Region FEs	YES
Years FEs	YES
Country Trends	YES
Controls	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.

Table I.4: The effect of different globalization strategies on job polarization. Fixed-effect model. 2007-2022

VARIABLES	(1) polarization	(2) polarization	(3) polarization	(4) polarization
Efficiency	0.0170**			
	(0.00780)			
Market seeking		0.0245***		
		(0.00702)		
Diversification			0.00438	
			(0.00816)	
Strategic				0.00502
				(0.00880)
Constant	0.715***	0.711***	0.707***	0.709***
	(0.166)	(0.165)	(0.167)	(0.167)
Observations	720	720	720	720
R-squared	0.545	0.551	0.541	0.541
Number of id	195	195	195	195
Years FEs	YES	YES	YES	YES
Region FEs	YES	YES	YES	YES
Country Trends	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix L: Gender wage gaps, unemployment and job insecurity across countries by economics sectors

Gender pay gap

Table L.1 shows the results of the panel analysis of the gender wage gap in unadjusted form.

Table L.1: Panel analysis of the gender pay gap in unadjusted form

	Coeff	s.e.	p
Tertiary education	-0.127	0.009	0.000
Working time women	-0.096	0.054	0.074
Working time men	0.207	0.055	0.000
GVC participation	-0.036	0.021	0.084
Constant	15.785	2.584	0.000

Wald Chi²	250.81 (0.000)		
-2 Log Likelihood	154145.218		

Sources: Eurostat and TiVA

Precarious employment of women

The results for precarious employment of women are presented in Table L.2.

Table L.2: Panel analysis of percentage women in precarious employment in a sector

	Coeff	s.e.	p
Tertiary education	-0.008	0.002	0.000
Working time women	0.001	0.012	0.554
Working time men	0.035	0.012	0.005
GVC participation	0.018	0.005	0.000
Constant	1.015	0.578	0.078
Wald Chi²	46.06 (0.000)		
-2 Log Likelihood	5163.030		

Sources: Eurostat and TiVA

Job insecurity and GVC participation

Table L.3 shows the results for the analysis of GVC participation at the sectoral level and the job insecurity of men and women.

Table L.3: Multilevel regression analysis of job insecurity

		(1)			(2)	
	Coeff.	s.e.	p	Coeff.	s.e.	p
Location of work (ref = Client)						
Employer/own business	-0.125	0.035	0.000	-0.123	0.035	0.000
Also other places (not home)	-0.146	0.040	0.000	-0.145	0.040	0.000
Also from home	-0.115	0.037	0.002	-0.114	0.037	0.002
From home	-0.090	0.040	0.023	-0.093	0.040	0.019
Other combinations	0.007	0.040	0.860	0.008	0.040	0.839
Vehicle	-0.110	0.048	0.021	-0.108	0.048	0.024
From home and somewhere else	-0.069	0.040	0.086	-0.071	0.040	0.076
Teleworkable type (ref = Not tw, high SI)						
Not teleworkable, low social interaction	0.023	0.019	0.231	0.019	0.019	0.322
Teleworkable, high social interaction	-0.033	0.019	0.087	-0.029	0.019	0.132
Teleworkable, low social interaction	-0.025	0.022	0.246	-0.028	0.022	0.187
Autonomy	-0.033	0.002	0.000	-0.033	0.002	0.000
Educational level (ref = Primary education)						
Secondary education	-0.051	0.065	0.431	-0.052	0.065	0.428
Tertiary education	-0.087	0.066	0.188	-0.085	0.066	0.198
Employment contract (ref = Unlimited duration)						
Contract of limited duration	0.692	0.021	0.000	0.694	0.021	0.000
A temporary employment agency contract	0.961	0.056	0.000	0.959	0.056	0.000
An apprenticeship or other training scheme	0.221	0.060	0.000	0.221	0.060	0.000
No contract	0.360	0.052	0.000	0.359	0.052	0.000
Other (spontaneous)	0.514	0.054	0.000	0.517	0.054	0.000
Unknown	0.223	0.084	0.008	0.221	0.084	0.008
Age	0.000	0.000	0.725	0.000	0.000	0.735
Female	-0.125	0.015	0.000	-0.260	0.032	0.000
GVC participation	0.064	0.009	0.000	0.043	0.010	0.000
GVC participation X Female				0.097	0.020	0.000
Constant	2.264	0.084	0.000	2.280	0.084	0.000
Wald Chi^2			2050.90 (0.000)			2075.35 (0.000)
-2 Log Likelihood			50358.297			50346.829
Deviance						11.468 (0.001)
ICC			0.030			0.030

Sources: EWCTS 2021 and TiVA
33280 workers in 19 sectors in 28 countries. Empty model: ICC = 0.032

Appendix M: A multi-dimensional assessment of GVCs on jobs' quality developments in the EU

The results of the interaction models are best presented in tables (not as coefficient plots):

Table M.1: Working conditions and occupational differences: Total offshoring

	Physical environment				Work intensity				Worktime quality			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IIM^T	0.043	0.067	0.062	0.027	0.103**	0.213**	0.097***	0.077**	-0.092	-0.068	-0.021	-0.005
	(0.066)	(0.066)	(0.042)	(0.049)	(0.052)	(0.095)	(0.031)	(0.032)	(0.057)	(0.051)	(0.075)	(0.079)
Clerks*IIM^T	-0.031	-0.022	0.043	0.056	-0.065	0.021	0.079	0.056	-0.307**	-0.040	-0.015	-0.035
	(0.071)	(0.079)	(0.044)	(0.039)	(0.069)	(0.139)	(0.065)	(0.057)	(0.134)	(0.102)	(0.072)	(0.085)
Craft*IIM^T	-0.274	-0.228*	-0.143	-0.023	-0.115	-0.091	0.071	0.134**	0.189	0.022	0.048	0.011
	(0.173)	(0.120)	(0.109)	(0.088)	(0.139)	(0.152)	(0.089)	(0.060)	(0.181)	(0.144)	(0.113)	(0.072)
Manual*IIM^T	0.054	0.043	-0.019	-0.007	-0.170**	-0.209*	0.221	0.191	0.144*	0.135*	-0.031	0.018
	(0.099)	(0.100)	(0.086)	(0.111)	(0.079)	(0.110)	(0.160)	(0.179)	(0.081)	(0.080)	(0.110)	(0.132)
Clerks	-0.085***	-0.084***	-0.083***	-0.082***	-0.112***	-0.111***	-0.109***	-0.110***	-0.115***	-0.112***	-0.113***	-0.113***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.018)	(0.019)	(0.018)	(0.018)	(0.039)	(0.040)	(0.040)	(0.040)
Craft workers	-1.093***	-1.090***	-1.093***	-1.094***	0.250***	0.251***	0.252***	0.252***	0.112***	0.114***	0.114***	0.114***
	(0.042)	(0.043)	(0.043)	(0.042)	(0.059)	(0.060)	(0.058)	(0.058)	(0.034)	(0.033)	(0.034)	(0.034)
Manual workers	-0.648***	-0.648***	-0.648***	-0.648***	0.106**	0.108**	0.113**	0.113**	0.007	0.005	0.005	0.006
	(0.026)	(0.027)	(0.025)	(0.025)	(0.054)	(0.053)	(0.049)	(0.049)	(0.045)	(0.045)	(0.045)	(0.045)
No of obs.	43,083	43,082	43,082	43,079	41,671	41,670	41,670	41,667	43,557	43,556	43,556	43,553
No of groups	25	25	25	25	25	25	25	25	25	25	25	25
	Social environment				Skills and discretion				Prospects			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
IIM^T	-0.093	-0.110	-0.110***	-0.088**	0.048	-0.033	-0.004	-0.007	-0.134	-0.127	0.088	0.083
	(0.095)	(0.082)	(0.036)	(0.038)	(0.049)	(0.056)	(0.031)	(0.042)	(0.128)	(0.125)	(0.138)	(0.129)
Clerks*IIM^T	-0.016	-0.102	0.156	0.167*	-0.150	0.128	0.068**	0.091***	0.147	0.309	0.010	0.005
	(0.139)	(0.120)	(0.102)	(0.098)	(0.138)	(0.094)	(0.032)	(0.035)	(0.235)	(0.202)	(0.180)	(0.172)
Craft*IIM^T	0.148	0.132	0.063	0.031	-0.010	0.081	-0.051	-0.079	-0.430**	-0.204	-0.327*	-0.250
	(0.127)	(0.125)	(0.055)	(0.044)	(0.130)	(0.121)	(0.192)	(0.163)	(0.210)	(0.140)	(0.187)	(0.193)
Manual*IIM^T	0.060	0.244**	0.174***	0.167***	-0.012	0.060	0.064	0.070	-0.141	0.010	-0.102	-0.053
	(0.125)	(0.123)	(0.041)	(0.047)	(0.079)	(0.115)	(0.076)	(0.078)	(0.135)	(0.147)	(0.149)	(0.159)
Clerks	-0.095***	-0.094***	-0.090***	-0.089***	-0.433***	-0.433***	-0.430***	-0.429***	-0.206***	-0.210***	-0.206***	-0.206***
	(0.034)	(0.035)	(0.031)	(0.031)	(0.049)	(0.050)	(0.048)	(0.047)	(0.031)	(0.029)	(0.030)	(0.030)
Craft workers	0.077***	0.076***	0.081***	0.082***	-0.527***	-0.527***	-0.525***	-0.524***	-0.202***	-0.203***	-0.206***	-0.204***
	(0.024)	(0.025)	(0.024)	(0.024)	(0.020)	(0.020)	(0.020)	(0.021)	(0.042)	(0.044)	(0.041)	(0.041)
Manual workers	0.039*	0.038	0.043*	0.043*	-0.906***	-0.907***	-0.905***	-0.905***	-0.357***	-0.359***	-0.359***	-0.358***
	(0.022)	(0.024)	(0.023)	(0.022)	(0.037)	(0.036)	(0.036)	(0.036)	(0.043)	(0.044)	(0.044)	(0.045)
No of obs.	43,929	43,928	43,928	43,925	43,880	43,879	43,879	43,876	43,929	43,928	43,928	43,925
No of groups	25	25	25	25	25	25	25	25	25	25	25	25

Note: IIM^T refers to total offshoring. It is expressed as differences (D) in its log, with D1, D2, D3 and D4 referring to 1-, 2-, 3- and 4-year differences. All equations also control for gender, migrant status, age, education, the log of tenure, firm size, firm type, and ICT. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table M.2: Working conditions and occupational differences: Offshoring by source region (as deviations from annual changes of advanced Europe)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Physical environment				Work intensity				Worktime quality			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
$IIM^{DevngEUR}$	0.072	-0.025	-0.080	-0.028	0.026	0.101	0.112*	0.140*	-0.028	-0.169**	-0.271***	-0.248***
	(0.059)	(0.072)	(0.093)	(0.069)	(0.084)	(0.095)	(0.064)	(0.079)	(0.110)	(0.067)	(0.070)	(0.055)
Clerks*$IIM^{DevngEUR}$	0.068	0.078	0.053	-0.043	0.041	-0.001	0.036	0.093	0.011	0.250***	0.243***	0.136*
	(0.099)	(0.068)	(0.064)	(0.063)	(0.135)	(0.091)	(0.070)	(0.057)	(0.163)	(0.077)	(0.079)	(0.079)
Craft*$IIM^{DevngEUR}$	0.173	-0.109	0.149	0.101	-0.023	-0.019	-0.078	-0.040	0.300	0.078	0.020	0.146
	(0.205)	(0.190)	(0.160)	(0.125)	(0.296)	(0.272)	(0.166)	(0.173)	(0.236)	(0.145)	(0.141)	(0.107)
Manual*^{IIMDevngEUR}	0.226	-0.045	0.070	0.095	0.246	0.314*	0.045	-0.020	-0.223	-0.118	0.129	0.151
	(0.176)	(0.121)	(0.062)	(0.064)	(0.213)	(0.191)	(0.111)	(0.103)	(0.213)	(0.192)	(0.133)	(0.113)
$IIM^{DevdxEUR}$	0.042	0.057	0.051	0.045	-0.101	-0.056	-0.018	-0.016	-0.112	-0.038	0.028	0.063
	(0.085)	(0.049)	(0.047)	(0.045)	(0.111)	(0.075)	(0.068)	(0.051)	(0.069)	(0.059)	(0.085)	(0.086)
Clerks*$IIM^{DevdxEUR}$	0.075	0.016	0.005	0.014	-0.016	0.073	0.032	-0.007	0.118	-0.106	-0.132	-0.091
	(0.105)	(0.063)	(0.060)	(0.057)	(0.137)	(0.088)	(0.074)	(0.069)	(0.185)	(0.090)	(0.085)	(0.097)
Craft*$IIM^{DevdxEUR}$	0.276	-0.082	0.276**	0.182*	0.318*	0.198	0.069	0.054	0.051	0.143	-0.053	-0.070
	(0.168)	(0.124)	(0.128)	(0.104)	(0.182)	(0.166)	(0.106)	(0.084)	(0.101)	(0.101)	(0.145)	(0.129)
Manual*$IIM^{DevdxEUR}$	-0.254***	-0.157**	-0.103	-0.176*	0.430*	0.217	0.053	0.198	-0.135	-0.158	-0.110	-0.205*
	(0.088)	(0.075)	(0.075)	(0.092)	(0.225)	(0.141)	(0.160)	(0.131)	(0.098)	(0.105)	(0.101)	(0.120)
$IIM^{DevngxEUR}$	0.137**	0.076	0.019	-0.036	0.042	-0.008	0.020	-0.005	0.083	0.070*	0.037	0.021
	(0.060)	(0.055)	(0.046)	(0.041)	(0.050)	(0.066)	(0.048)	(0.032)	(0.083)	(0.042)	(0.048)	(0.037)
Clerks*$IIM^{DevngxEUR}$	-0.094	-0.022	-0.003	0.070	0.033	0.001	-0.032	-0.049	-0.452**	-0.346***	-0.214***	-0.139**
	(0.097)	(0.065)	(0.054)	(0.057)	(0.120)	(0.066)	(0.048)	(0.063)	(0.183)	(0.093)	(0.076)	(0.063)
Craft*$IIM^{DevngxEUR}$	-0.005	-0.218*	-0.192**	-0.122	0.146	0.228	0.001	0.049	0.055	0.013	0.089	0.055
	(0.309)	(0.132)	(0.093)	(0.090)	(0.227)	(0.189)	(0.105)	(0.076)	(0.165)	(0.177)	(0.135)	(0.086)
Manual*$IIM^{DevngxEUR}$	-0.332***	-0.194*	-0.050	0.002	0.269	0.363**	0.151	0.157**	0.140	-0.011	-0.046	-0.024
	(0.103)	(0.101)	(0.072)	(0.049)	(0.205)	(0.180)	(0.115)	(0.074)	(0.093)	(0.086)	(0.064)	(0.055)
Clerks	-0.081***	-0.083***	-0.089***	-0.092***	-0.115***	-0.115***	-0.111***	-0.115***	-0.092***	-0.099***	-0.101**	-0.102**
	(0.018)	(0.016)	(0.018)	(0.022)	(0.017)	(0.016)	(0.015)	(0.016)	(0.035)	(0.037)	(0.043)	(0.047)
Craft workers	-1.114***	-1.067***	-1.095***	-1.092***	0.232***	0.228***	0.256***	0.247***	0.097***	0.096**	0.091**	0.076*
	(0.041)	(0.047)	(0.038)	(0.043)	(0.053)	(0.051)	(0.054)	(0.055)	(0.037)	(0.038)	(0.037)	(0.041)
Manual workers	-0.630***	-0.634***	-0.644***	-0.658***	0.080*	0.076	0.081	0.077	0.009	0.015	0.004	-0.007
	(0.027)	(0.026)	(0.026)	(0.028)	(0.047)	(0.047)	(0.057)	(0.056)	(0.044)	(0.046)	(0.045)	(0.046)
No of obs	43,083	43,082	43,082	43,079	41,671	41,670	41,670	41,667	43,557	43,556	43,556	43,553
No of groups	25	25	25	25	25	25	25	25	25	25	25	25

Table M.2: continued

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	Social environment				Skills and discretion				Prospects			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
$IIM^{DevngEUR}$	-0.150***	-0.177**	-0.173***	-0.131*	-0.024	0.086	0.025	0.043	0.121	0.112	0.071	0.003
	(0.058)	(0.082)	(0.061)	(0.068)	(0.103)	(0.090)	(0.057)	(0.061)	(0.142)	(0.146)	(0.069)	(0.066)
Clerks*$IIM^{DevngEUR}$	0.219*	0.319***	0.206*	0.106	-0.002	0.099	0.135	-0.058	-0.100	-0.003	0.044	0.027
	(0.119)	(0.096)	(0.107)	(0.109)	(0.106)	(0.170)	(0.116)	(0.071)	(0.094)	(0.167)	(0.085)	(0.075)
Craft*$IIM^{DevngEUR}$	-0.074	0.169	0.101	0.072	0.318**	0.078	-0.116	-0.079	-0.168	-0.089	-0.087	-0.176
	(0.121)	(0.114)	(0.085)	(0.073)	(0.156)	(0.154)	(0.125)	(0.083)	(0.210)	(0.188)	(0.132)	(0.112)
Manual*$IIM^{DevngEUR}$	-0.047	0.088	0.155*	0.157*	-0.092	-0.018	-0.008	-0.086	0.142	0.227	0.164**	0.146
	(0.201)	(0.145)	(0.082)	(0.083)	(0.135)	(0.128)	(0.097)	(0.109)	(0.126)	(0.156)	(0.082)	(0.090)
$IIM^{DevdxEUR}$	-0.059	-0.024	-0.009	-0.001	-0.018	-0.060	0.028	0.056	0.193*	0.076	0.042	0.122**
	(0.052)	(0.048)	(0.034)	(0.037)	(0.068)	(0.063)	(0.046)	(0.052)	(0.109)	(0.070)	(0.056)	(0.054)
Clerks*$IIM^{DevdxEUR}$	-0.038	0.022	0.040	0.006	0.027	0.002	-0.079	-0.052	-0.003	-0.122*	-0.098	-0.090
	(0.093)	(0.070)	(0.065)	(0.085)	(0.092)	(0.065)	(0.073)	(0.065)	(0.091)	(0.074)	(0.066)	(0.069)
Craft*$IIM^{DevdxEUR}$	0.042	0.047	-0.037	-0.064	-0.126	-0.012	-0.078	-0.107	-0.257**	-0.338**	-0.327***	-0.279**
	(0.074)	(0.056)	(0.058)	(0.054)	(0.115)	(0.097)	(0.111)	(0.104)	(0.128)	(0.135)	(0.097)	(0.109)
Manual*$IIM^{DevdxEUR}$	-0.106	-0.091	-0.035	-0.064	-0.132	0.002	-0.066	-0.101	-0.174	-0.226***	-0.121*	-0.200**
	(0.103)	(0.077)	(0.068)	(0.069)	(0.143)	(0.083)	(0.094)	(0.111)	(0.142)	(0.073)	(0.072)	(0.096)
$IIM^{DevngxEUR}$	-0.084	-0.012	0.061	0.024	0.232**	0.109	0.056	-0.009	-0.168	0.045	0.022	0.080
	(0.060)	(0.056)	(0.043)	(0.033)	(0.100)	(0.080)	(0.048)	(0.056)	(0.124)	(0.085)	(0.062)	(0.049)
Clerks*$IIM^{DevngxEUR}$	0.160**	0.123	-0.033	0.017	-0.047	-0.020	-0.052	0.085	0.015	-0.015	0.006	-0.012
	(0.065)	(0.080)	(0.056)	(0.051)	(0.100)	(0.098)	(0.052)	(0.059)	(0.120)	(0.108)	(0.051)	(0.059)
Craft*$IIM^{DevngxEUR}$	0.187	0.108	-0.004	-0.002	-0.292	-0.108	-0.006	0.003	-0.473***	-0.260*	-0.084	-0.080
	(0.116)	(0.118)	(0.069)	(0.056)	(0.204)	(0.127)	(0.097)	(0.061)	(0.147)	(0.139)	(0.074)	(0.084)
Manual*$IIM^{DevngxEUR}$	0.186	-0.014	-0.037	-0.040	-0.013	0.058	0.046	0.123**	-0.226*	-0.128	-0.058	-0.105*
	(0.141)	(0.101)	(0.066)	(0.062)	(0.114)	(0.100)	(0.051)	(0.062)	(0.123)	(0.109)	(0.079)	(0.064)
Clerks	-0.104***	-0.103***	-0.106***	-0.110***	-0.429***	-0.432***	-0.435***	-0.442***	-0.206***	-0.203***	-0.210***	-0.208***
	(0.033)	(0.028)	(0.032)	(0.036)	(0.048)	(0.048)	(0.043)	(0.042)	(0.032)	(0.029)	(0.034)	(0.034)
Craft workers	0.067***	0.064***	0.072***	0.073***	-0.505***	-0.517***	-0.511***	-0.511***	-0.153***	-0.162***	-0.162***	-0.153**
	(0.017)	(0.016)	(0.018)	(0.015)	(0.018)	(0.018)	(0.016)	(0.017)	(0.047)	(0.048)	(0.060)	(0.067)
Manual workers	0.034*	0.041**	0.032*	0.028	-0.900***	-0.906***	-0.910***	-0.918***	-0.347***	-0.352***	-0.361***	-0.354***
	(0.020)	(0.021)	(0.017)	(0.020)	(0.037)	(0.036)	(0.037)	(0.037)	(0.042)	(0.039)	(0.043)	(0.042)
No of obs	43,929	43,928	43,928	43,925	43,880	43,879	43,879	43,876	43,929	43,928	43,928	43,925
No of groups	25	25	25	25	25	25	25	25	25	25	25	25

Note: $IIM^{DevngEUR}$ refers to offshoring to European developing countries, $IIM^{DevdxEUR}$ to offshoring to non-European developed countries and $IIM^{DevngxEUR}$ to offshoring to non-European developing countries. All offshoring measures are expressed as differences (D) in logs, with D1, D2, D3 and D4 referring to 1-, 2-, 3- and 4-year differences. All equations also control for gender, migrant status, age, education, the log of tenure, firm size, firm type, and ICT. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.