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From globalization to reshoring? The role of Industry 4.0 in global supply chains across Europe

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ABSTRACT

Industry 4.0 (I4.0) technologies exhibit peculiar characteristics and can play a diverse role in the reconfiguration of global value chains (GVCs) and global sourcing geography. This paper explores the relationship between Industry 4.0 technologies and reshoring within Europe, focusing on additive manufacturing (AM), the Internet of Things (IoT), and advanced industrial robots (AIR). Utilizing data from the OECD Inter-Country Input-Output (ICIO) tables and Eurostat's Comext database (on international trade in goods) for 27 European countries and the UK from 2009 to 2018, the findings reveal a positive correlation between AIR adoption and reshoring. Conversely, increased IoT investment appears to reduce reshoring and the impact of AM on reshoring is negligible. The research also examines reshoring's geographical aspects, showing that AIR adoption promotes reshoring from Asia, whereas higher IoT investments correspond to a decrease in reshoring from the region. These results highlight the complexity of reshoring dynamics, which are influenced by both specific I4.0 technologies and geographic context. The study provides new insights into the reconfiguration of GVCs and manufacturing landscapes in the era of the Fourth Industrial Revolution.

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1. Introduction

Over the past few years, the contours of the global economic landscape have been shifting, leading to intense debates within the academic community. One pivotal question at the core of these discussions is whether the world is witnessing a substantive shift towards deglobalization (Altman and Bastian 2024; Casella, Bolwijn, and Casalena 2024; D'Ambrosio and Lavoratori 2025; Freund et al. 2024). Within this context, reshoring – or the practice of bringing back previously offshored production activities to the home country (De Backer et al. 2016) – has emerged as a significant phenomenon.

A growing body of literature explores the motivations of reshoring. Di Sano, Gunnella, and Lebastard (2023) view reshoring as a marker of deglobalization, reflecting a reversal of decades-long global economic integration. Key drivers include economic factors such as rising wages in traditionally low-cost countries (Antràs 2020; Li et al. 2025; Martínez-Mora and Merino 2014), as well as strategic

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considerations such as intellectual property protection and environmental factors (Dachs et al. 2019; Gray et al. 2017; McIvor et al. 2025). However, other scholars argue that the end of globalization is overstated (Baldwin 2022), framing the shift as a recalibration of global production networks rather than a retreat (Antràs 2020; Jaax, Miroudot, and van Lieshout 2023).

The debate is further shaped by macroeconomic events and disruptions. Recent developments, such as the second Trump administration threatening new tariffs, the US–China trade tensions, the Covid-19 pandemic, and Russia's invasion of Ukraine, have highlighted vulnerabilities in extended value chains, sparking renewed discussions on reshoring and localization. However, supply and demand disruptions are not unprecedented, having occurred over recent decades (Baldwin and Freeman 2022).

On top of these dynamics, the diffusion of new digital technologies is pushing companies to rethink their global production strategies (Javorcik 2020). While these technologies have varied impacts (UNCTAD 2020), they could also drive a new wave of hyper-globalization (Antràs 2020). For instance, robotics may encourage reshoring by enhancing domestic production efficiency, whereas IoT and AM may yield mixed or opposite effects (Strange and Zucchella 2017). Just as information and communication technologies (ICTs) facilitated earlier waves of globalization, IoT could reduce cross-border communication and transaction costs, potentially deepening the fragmentation of global value chains (GVCs).

Our study contributes to the literature in two main ways. First, a significant body of research has scrutinized the influence of robotics (or overall automation) on reshoring and offshoring dynamics, while a notable gap in the literature remains on the heterogeneous effect of different I4.0 technologies. The heterogeneous nature of these technologies means that their role in either facilitating or hindering reshoring is guided by different mechanisms and, hence, can vary greatly (Antràs 2020; Butollo 2021). Moreover, the few existing works on the effects of AM (or 3D printing) and IoT adoption on GVC reconfiguration are speculative in nature and lack robust empirical evidence. Building on this premise, this paper explores the heterogeneous relationship between reshoring and three I4.0 technologies – AM, IoT, and AIR. By investigating the direct effects of adopting these technologies, we offer a more granular understanding of how the Fourth Industrial Revolution contributes to the reconfiguration of the global manufacturing and production landscape.

Second, we place a special emphasis on geographical patterns of global sourcing for European countries, with Asia being a focal point due to its established role as a major offshoring destination over the recent decades. As production costs rose in advanced economies, labor-intensive processes were relocated to cost-effective offshore locations. This trend has characterized trade relationships between Western countries and East Asia for decades (Inomata and Taglioni 2019). As a result, the Asian region has emerged as a prominent hub for production offshoring for European and US companies, with China being the primary destination (Antràs 2020; Dachs et al. 2006, 2019). Indeed, East Asian economies now account for one-third of global exports, underscoring their significant role in international trade (European Parliament 2021). Our investigation delves into the effects of reshoring from and offshoring toward Asia. By exploring this geographic heterogeneity, our research contributes to a more detailed understanding of the reshoring phenomenon and underscores the importance of context-specific analyses.

The empirical analysis is based on OECD's Inter-Country Input-Output (ICIO) tables[1], which provide data to examine reshoring and offshoring activities at the country-industry level for 10 manufacturing industries across the 27 European Union (EU) countries plus the United Kingdom (UK), spanning the period 2009–2018. Additionally, we employ secondary data from Eurostat's Comext database, allowing measurement of adoption dynamics for AM, the IoT, and AIR technologies. Our results highlight a positive relationship between the adoption of AIR and reshoring. These findings align with existing research which argues that robotics can act as a labor substitute for offshoring destinations. The results also suggest that increased IoT adoption is linked to a reduction in reshoring, likely due to the technology's capacity to improve coordination and reduce transaction costs. For AM, we find no statistically significant results, indicating no clear impact on reshoring activities at the industry level. Furthermore, the analysis on reshoring from Asian economies distinguishes between developing (for example, China, Vietnam, Cambodia) and developed economies (for example, Japan, Korea). Our findings suggest that the adoption of AIR encourages reshoring from and reduces offshoring to Asia overall, while increased IoT investments per thousand workers correlate with a decline in the reshoring growth rate from Asia, particularly from developing countries.

The rest of the paper is organized as follows. Section 2 presents the related literature and our hypotheses. Section 3 describes the data sources and illustrates the descriptive statistics and the econometric strategy. Section 4 discusses the results, and Section 5 concludes.

2. Related literature and hypotheses

2.1. From offshoring to reshoring

The creation of final products or intermediates involves a variety of tasks. These tasks can be broken down based on geographical locations (either within or across countries) and organizational structures (within and/or across firms). Offshoring refers to the reallocation of these production tasks across different geographical regions (Hummels, Munch, and Xiang 2018). In turn, the global fragmentation of production processes has led to a surge in task-based trade (Grossman and Rossi-Hansberg 2008) or trade of intermediate goods and services.

The concept of global value chains has been in use extensively since the early 2000s to describe the global organization and geographical fragmentation of supply chains. This framework provides a comprehensive approach for identifying the full range of activities (and related tasks) and their geographic distribution (Gereffi and Lee 2012). From a historical perspective, the surge in production fragmentation took place during the 1990s and 2000s, influenced by several key developments (Baldwin 2016). First, the ICT revolution stood at the forefront of these changes. This technological shift introduced cost-effective and reliable telecommunications, more powerful computers, and advanced information management software. As a result, the costs associated with coordinating and overseeing activities across distances diminished significantly. Second, the 1970s marked the beginning of a drop in costs for both air and sea freight, facilitating firms in spreading their production activities across the globe. Alongside these two main drivers, another significant factor determined the rapid growth of GVCs – trade liberalization and agreements, above all, China's inclusion in the World Trade Organization (WTO). Specifically, during the period 1986–2008 several trade liberalization efforts reduced barriers for both developed and emerging nations, leading to lower trade costs (Antràs 2020). The development of the European single market, combined with the inclusion of major economies like China and India in the global trade scene, expanded the available markets for goods and labor. On the one hand, this allowed companies to serve a larger customer base and benefit from economies of scale; on the other hand, the availability of cost-effective labor led many companies to either move their production or to partner with suppliers in these low-cost economies, resulting in a surge in the offshoring trend (Antràs 2020; Baldwin 2013, 2016; World Bank 2020).

However, in the aftermath of the 2008 global financial crisis, terms such as *reshoring* and *nearshoring* (and *regionalization*) have gained prominence in both academic circles and broader public discussions. Central to these terms is the idea that reshoring involves bringing back to the home country activities once offshored (De Backer et al. 2016; D'Ambrosio and Lavoratori 2025). Overall, evidence on reshoring is still mixed and mostly bound to firm-specific studies based on surveys or newspapers (e.g. Ancarani, Mauro, and Mascali 2019; Barbieri et al. 2022; Dachs et al. 2019) and some studies suggest that it is unlikely that reshoring or nearshoring will grow on a large-scale trend (e.g. Casadei and Iammarino 2023; Di Berardino et al. 2025). Nonetheless, at the foundation of this shift is the reversal of many factors that had previously spurred the rapid geographic dispersion of production. Contrary to the 1986–2008 liberalization era, the momentum in the decrease of tariff rates has since slowed. Simultaneously, there has been a rise in the implementation of regulatory measures and non-tariff barriers, resulting in an overall increase in trade distortions (Cigna, Gunnella, and Quaglietti 2022).

A second important factor driving this reversal wave lies in the reduction of cross-country wage differentials. Indeed, over the last two decades, wages in most emerging economies have increased, implying that the cost benefits of producing there have decreased when compared to more developed countries, along with the increase in shipping and insurance costs (Antràs 2020; Cigna, Gunnella, and Quaglietti 2022; De Backer et al. 2016).[2] Furthermore, while the advent of ICTs has been a primary driver of offshoring, the diffusion of new digital technologies of the I4.0 may hold different premises. The adoption of AIR, IoT, and AM is guided by specific economic rationales, resulting in distinct implications for sourcing strategies and, therefore, the international fragmentation of production. While some of these I4.0 technologies might promote reshoring, others – especially those linked to increased digitalization and platform adoption – could further reduce cross-border communication and transaction costs, and therefore intensify production fragmentation (Antràs 2020; UNCTAD 2020).

2.2. Advanced industrial robots

The last decade has witnessed the growing relevance of advanced robotics in academic and policy debates. While much attention has focused on the potential labor-displacing role of AIR and other automation technologies (e.g. Acemoglu and Restrepo 2020), its impact on GVCs has received comparatively less scrutiny. Robotics presents opportunities for reshoring as industries pursue optimization strategies. However, the literature provides mixed evidence, pointing in two opposing directions: the adoption of robots can either increase offshoring or increase reshoring.

Automation technologies, particularly AIR, can expand production by enabling internationalized firms to scale up, thereby increasing demand for inputs from suppliers in developing countries. Following this premise, Artuc, Bastos, and Rijkers (2023) find that higher robot density in advanced regions (e.g. USA, EU countries) correlates with increased imports and exports involving less developed economies. At the firm level, Stapleton and Webb (2020) argue that automation lowers marginal costs, enabling firms to reduce prices and boost demand for offshored components whose production is difficult to automate. Using data on Spanish firms, they find that AIR usage positively affects imports from, and the number of affiliates in, lower-income countries. This evidence indicates a certain level of complementarity between automation and offshoring (Antràs 2020). Ma, Wu, and Fang (2025) argue that the positive relationship between robots and offshoring can be explained by a 'production expansion' mechanism, in which robots enhance firms' demand for production factors, boost productivity, and improve export capabilities. These effects, in turn, encourage offshoring and reduce the likelihood of reshoring. However, Kamp and Gibaja (2021) find no direct link between domestic automation adoption and reshoring efforts, suggesting that factors like declining sales, institutional uncertainty, and production rationalization may play a greater role in reshoring decisions.

Conversely, automation can significantly boost productivity (Lamperti, Lavoratori, and Castellani 2023) making it more attractive for companies to reshore stages of their production processes where the economic benefits of offshoring have diminished. Caséfalvay and Gkotsis (2022), who analyze in detail the robotization process across Europe, emphasize this substitution effect between capital and labor.

Hallward-Driemeier and Nayyar (2019) explore how robotization in high-income countries (HICs) affects foreign direct investment (FDI) in low – and middle-income countries (LMICs). They find that as robot density in HICs rises, FDI from HICs to LMICs initially grows, but beyond a threshold further automation leads to a decline in FDI, suggesting a shift towards reshoring. Carbonero, Ernst, and Weber (2020) report that robotization in developed countries reduces offshoring, causing a 5%

employment drop in developing nations. Similarly, De Backer et al. (2018) observe that industrial robots slow offshoring in developed economies but do not yet drive substantial reshoring. Conversely, findings from Krenz, Prettner, and Strulik (2021) suggest that for an increase of one robot per thousand workers, there is a 3.5% rise in reshoring activities within the manufacturing sectors.

In the USA, findings from Artuc, Christiaensen, and Winkler (2019) support the idea that automation could potentially serve as a substitute for offshoring, as every additional robot per thousand workers reduces import growth from Mexico by 6.7%. Similarly, Faber (2020) found that around 270,000 fewer jobs existed in Mexico between 1990 and 2015, suggesting that about 5% of US robots are in direct competition with Mexican labor. This impact on employment is also reflected in decreased export values and a reduced number of export-producing facilities. Bonfiglioli et al. (2022) observe that the adoption of AIR corresponds with a decline in offshoring activities. Chen and Frey (2024) demonstrate that robots drive some reshoring in local markets that are more exposed to offshoring from China, particularly in countries like Germany, though significant variations exist across other European nations.

Survey and firm-level data provide further evidence of automation's positive link with reshoring, particularly when firms prioritize quality (Ancarani, Mauro, and Mascali 2019) or when home countries promote I4.0 policies (Barbieri et al. 2022).

Summing up, extant literature suggests that, on the one hand, AIR increases productivity and value added (e.g. Acemoglu, Lelarge, and Restrepo 2020; Lamperti, Lavoratori, and Castellani 2023), therefore the scale of the company and further imports of components difficult to reshore; on the other hand, by reducing the labor share, the share of production workers in employment and, in turn, marginal costs, robots act as a substitute for labor in offshoring destinations (Artuc, Christiaensen, and Winkler 2019; Faber 2020), making reshoring a valuable alternative. Building on this premise, our first hypothesis is formulated following the two competing alternatives:

H1a. Higher AIR adoption negatively relates with an increase in reshoring, driven by lower marginal costs and an increase in productivity and scale.

H1b. Higher AIR adoption positively relates with an increase in reshoring, driven by a substitution effect for labor in offshoring destinations.

2.3. Industrial internet of things

The concept of IoT originated in the late 1990s (Egwuonwu et al. 2022) but began expanding rapidly after 2010 (ITU 2018). IoT refers to interconnected systems of everyday objects that communicate over the Internet. These systems are '*[…] equipped with (a) sensing, storing and processing capabilities that allow these objects to understand their environments; and (b) networking capabilities that allow them to communicate information about themselves and make autonomous decisions*' (ITU 2018). In essence, IoT connects devices ranging from household appliances to industrial machines, representing a transformative phase in the evolution of ICTs.

The key strengths of IoT lie in its ability to provide real-time transparency, traceability, adaptability, scalability, and flexibility (Zhou, Chong, and Ngai 2015). Real-time transparency ensures accurate, instantaneous information flows essential for streamlining operations and tracking goods, thereby enhancing overall business performance (Haddud et al. 2017). Moreover, this transparency fosters trust between trading partners (Rejeb, Keogh, and Treiblmaier 2019).

The high level of communication and integration characterizing IoT enhances productivity (Edquist, Goodridge, and Haskel 2021; Espinoza et al. 2020; Lamperti, Lavoratori, and Castellani 2023), the efficiency of industrial management and promotes digital collaboration between firms (Wang et al. 2016). Empirical studies primarily focus on IoT's role within organizational systems and its impact on efficiency and productivity. Specifically, Edquist, Goodridge, and Haskel (2021) found a 10% increase in IoT connections led to a 0.23% rise in productivity. Espinoza et al. (2020) estimated IoT investments contributed 0.01 percentage points (p.p.) to US productivity growth and 0.006 p.p. in Europe. Lamperti, Lavoratori, and Castellani (2023) highlighted IoT capital goods boosted productivity by 0.06 p.p. in advanced European economies, though gains were limited in less developed regions.

IoT also helps organizations manage information and transaction costs, which represent barriers to firms' business activities, especially when operating internationally. These costs arise from identifying trading partners, understanding regulations, gathering consumer data, and fulfilling contractual obligations (WTO 2018). As advocated by several academics (e.g. Hallward-Driemeier and Nayyar 2017; Strange and Zucchella 2017), by reducing coordination and transaction costs, IoT strengthens GVCs (UNCTAD 2020; World Bank 2020), creating transparent, reliable information flows crucial for minimizing barriers in international manufacturing and trade (WTO 2018). In fact, the WTO (2018) estimates that the adoption of digital technologies by developing countries could significantly increase their share in global trade, rising from 46% in 2015–57% by 2030.

However, despite these advantages, empirical evidence on the impact of IoT adoption on reshoring and offshoring – and, more broadly, on GVCs – remains notably scarce. Building on ICT advancements and productivity gains, IoT has the potential to reduce coordination costs and expand GVCs, directing production activities toward offshoring destinations, particularly in developing countries. In light of this evidence and the unique features of IoT just discussed, our second hypothesis posits:

H2. Higher IoT adoption negatively relates with an increase in reshoring activities, driven by improved coordination and communication channels among actors.

2.4. Additive manufacturing

AM, or 3D printing, originated in the 1970s but only began to mature in the early 2000s, primarily within R&D departments, and is defined as '*the general term for those technologies that based on a geometrical representation create physical objects by successive addition of material*' (ISO 2015). A turning point for the technological maturity of AM came between 2009 and 2013 when key patents expired, triggering cost reductions in 3D printers and related innovations (Buonafede et al. 2018; Felice, Lamperti, and Piscitello 2022; Laplume, Petersen, and Pearce 2016). This cost drop accelerated AM's diffusion, and advancements have since made basic models increasingly affordable (Laplume, Petersen, and Pearce 2016).

The transformative impact of AM on production stems from its ability to eliminate multiple stages and intermediate inputs (Buonafede et al. 2018). By combining manufacturing and assembly in a single step (Hannibal and Knight 2018; Strange and Zucchella 2017), it reduces costs, time, inventories, and quality issues (Delic and Eyers 2020; Weller, Kleer, and Piller 2015). AM simplifies GVCs by consolidating multiple production stages – ranging from raw material processing to final product creation – into fewer components, decreasing supplier reliance and chain complexity (Buonafede et al. 2018; Hallward-Driemeier and Nayyar 2017; Laplume, Petersen, and Pearce 2016; UNCTAD 2020). Furthermore, since AM is a capital-intensive technology and, due to relatively small differences in capital costs across countries, it diminishes the benefits of offshoring to labor-abundant regions while making advanced economies more competitive (Laplume, Petersen, and Pearce 2016). Therefore, AM stands as a transformative technology with the potential to revolutionize GVCs by altering their scope and distribution, eventually enhancing the potential for re-bundling.

Economists and management scholars have only recently turned their attention to AM. Quantitative studies have revealed its economic impact. For example, Felice, Lamperti, and Piscitello (2022) show that a 1% increase in AM patent stock growth raises OECD manufacturing labor demand by 0.07%–0.1%. Ben-Ner, Urtasun, and Taska (2023) find AM creates skill-intensive jobs, while Lamperti, Lavoratori, and Castellani (2023) highlight a 0.31 percentage-point productivity gain, particularly for lagging European manufacturers. However, the impact of AM on GVC structure and location remains underexplored, with most evidence limited to theoretical and qualitative

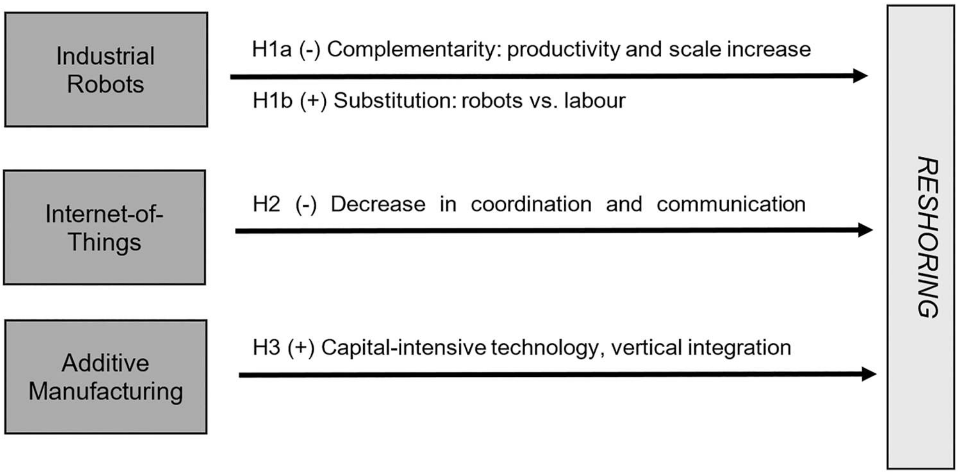

Figure 1. Conceptual scheme of AIR, IoT, and AM, and reshoring.

analyses. Buonafede et al. (2018) find that increased AM adoption, measured by patent applications, correlates with reduced GVC participation, particularly in sectors highly exposed to the capabilities of AM. De Beule, Van Assche, and Nevens (2022) show that AM-adopting firms are more likely to establish foreign subsidiaries and operate in more countries due to AM's ability to decentralize production by separating design from manufacturing, shortening value chains, and localizing production closer to consumers.

Another key feature of AM is its potential for mass customization, enabling on-demand production of complex, personalized goods (Delic and Eyers 2020; Felice, Lamperti, and Piscitello 2022). Building on this technological specificity, Abeliansky, Martínez-Zarzoso, and Prettner (2020) theorize and provide evidence that widespread AM adoption may reduce trade volumes, particularly for goods efficiently produced by local affiliates using 3D printers, aligning with findings from Hannibal and Knight (2018) and De Beule, Van Assche, and Nevens (2022).

In summary, evidence suggests that AM leads to a substantial reorganization of GVCs, with reduced intra-firm trade in intermediates. However, this shift may not necessarily result in reshoring but rather in the localization of production in end markets (Abeliansky, Martínez-Zarzoso, and Prettner 2020; Buonafede et al. 2018; De Beule, Van Assche, and Nevens 2022). Given its capital-intensive nature and vertically integrated production capabilities, AM is poised to significantly impact the geography and organization of GVCs. This can be formulated in the following third hypothesis:

> **H3.** Higher AM adoption positively relates with an increase in reshoring activities, driven by substitution and vertical integration.

We summarize our conceptual arguments in Figure 1.

3. Data and empirical strategy

3.1. Data sources

Our empirical analysis relies on two main sources of data. First, to investigate the aggregate reshoring activities, we use country-sector data on transactions of intermediate goods for manufacturing sectors from the OECD's Inter-Country Input-Output (ICIO) Tables (2021 edition).[3] One of the primary advantages of ICIO compared to alternative sources (e.g. the World Input-Output Database – WIOD) is its extensive coverage in terms of countries, sectors, and years. It encompasses 66 countries, plus the 'Rest of the World' and 45 industries at the 2-digit ISIC4 level (corresponding to 2-digit NACE Rev.

2), and notably, its data spans 1995–2018. The information for the 66 economies represents 93% of the world's GDP, 92% of global exports, 90% of global imports, and 70% of the world's population.

Second, we gather data to measure adoption related to AIR, AM, and IoT technologies from Eurostat's Comext database. Comext offers in-depth statistics on international trade in goods collected electronically through customs when goods transit borders for EU 27 and the UK, ensuring comprehensive coverage of trade data for Europe. It captures trade both within and between member states and non-EU countries. Goods in Comext are classified using the Combined Nomenclature (CN) system, an extension of the 6-digit Harmonized Commodity Description and Coding System (HS). The CN classification, built on the HS, provides an impressive level of granularity, offering information up to the 8-digit level of disaggregation, encompassing around 9,500 8-digit product codes. To maintain its relevance, the CN undergoes annual updates reflecting technological shifts and global trade patterns (European Commission and Eurostat 2020).

Our study focuses on the period from 2009 to 2018. The 2009 year is a meaningful starting point for several reasons: (i) only after the 2008 global financial crisis did these technologies begin to receive heightened attention from European policymakers, and global demand for advanced mechanical and automation equipment returned to pre-crisis levels (De Backer et al. 2018; Kagermann, Wahlster, and Helbig 2013); (ii) between 2009 and 2014, several foundational patents for AM technologies, such as fused deposition modeling and selective laser sintering, expired (Felice, Lamperti, and Piscitello 2022; Laplume, Petersen, and Pearce 2016), spurring a wave of spillover inventions and an increase in AM machinery producers. Unfortunately, our sample does not cover the most recent years due to the availability of ICIO data.

3.2. Measuring reshoring and offshoring

To determine our variable of reshoring intensity, we employ ICIO data, drawing upon the methodology established by Krenz and Strulik (2021) and Krenz, Prettner, and Strulik (2021).[4] Their approach captures the relative increase in domestic inputs to foreign input flows, dynamically accounting for the relocation of inputs from abroad back to the home country from t –1 to t. The basic reshoring index is given by:

$$Reshoring = R_t = \left(\frac{DI_t}{FI_t}\right) - \left(\frac{DI_{t-1}}{FI_{t-1}}\right) \quad (1)$$

where ***DI*** and ***FI*** represent domestic and foreign inputs for a specific sector and country in year t, respectively. Building on this formula, the $\boldsymbol{R_t}$ index can assume either negative or positive values; a necessary condition for reshoring is a positive input differential, that is $\boldsymbol{R_t} > 0$. Negative values, however, do not infer offshoring but merely denote the non-occurrence of reshoring (Krenz and Strulik 2021). Conversely, positive values explicitly indicate reshoring activities. To isolate the impact of reshoring, we follow Krenz, Prettner, and Strulik's (2021) approach and normalized negative values to zero. However, positive $\boldsymbol{R_t}$ values might still falsely signal reshoring in situations where it does not actually occur. For example, if both domestic and foreign inputs decrease but foreign inputs decline more sharply, this measure might mistakenly indicate reshoring. To avoid this pitfall, we implement additional conditions that control for production fluctuations, both downward and upward, over time. Specifically, this narrowly defined reshoring measure (Krenz, Prettner, and Strulik 2021) requires that the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

As posited by Krenz and Strulik (2021), dividing by foreign inputs often results in an asymmetric distribution. To address this, we apply a logarithmic transformation to the terms in Equation 1, yielding:

$$\Delta R_t = ln\left(\frac{DI_t}{FI_t}\right) - ln\left(\frac{DI_{t-1}}{FI_{t-1}}\right) \quad (2)$$

The final form of our reshoring dependent variable – formally corresponding to a growth rate – will adopt the values from Equation 2, when the above-mentioned conditions are met.

Figure 2 shows the distribution of the logarithmic change of reshoring intensity for all country-sector-year observations in our data set. The plots on the left panel of the figure show that our data follows a normal distribution. The distribution reveals that reshoring remains a relatively rare phenomenon, with only a quarter of the observations showing a positive reshoring index. To provide a clearer visualization of this phenomenon, the panel on the right of the figure shows the distribution of the measures with the condition discussed above (i.e. setting negative values to zero).

While reshoring signals a shift in production dynamics, it does not necessarily indicate a complete reversal of offshoring or the repatriation of all tasks previously outsourced (De Backer and DeStefano 2021). In a complementary vein, Krenz and Strulik (2021) underscore that a drop in the offshoring rate does not necessarily equate to reshoring. This is because the decline in the share of foreign inputs might be due to a decrease in production, without necessarily bringing production activities back to the home country. Additionally, firms can engage in both offshoring and reshoring simultaneously, suggesting that the two activities can coexist. The authors show a weak negative correlation, which is about –0.0936, between reshoring and offshoring growth rates. Consequently, to enhance the robustness of our analysis, we include the offshoring measure in our empirical analysis, to complement the investigation on the reshoring phenomenon. Drawing upon the approach outlined by Feenstra and Hanson (1996), we compute the offshoring measure as the logarithmic change in the share of imported manufacturing intermediate inputs relative to the total manufacturing intermediate inputs[5]:

$$\Delta Off_t = ln\left(\frac{FI_t}{DI_t + FI_t}\right) - ln\left(\frac{FI_{t-1}}{DI_{t-1} + FI_{t-1}}\right) \tag{3}$$

where ***DI*** and ***FI*** represent domestic and foreign inputs for a specific sector and country in year *t*. We compute reshoring and offshoring measures for the EU 27[6] plus the UK and 10 manufacturing

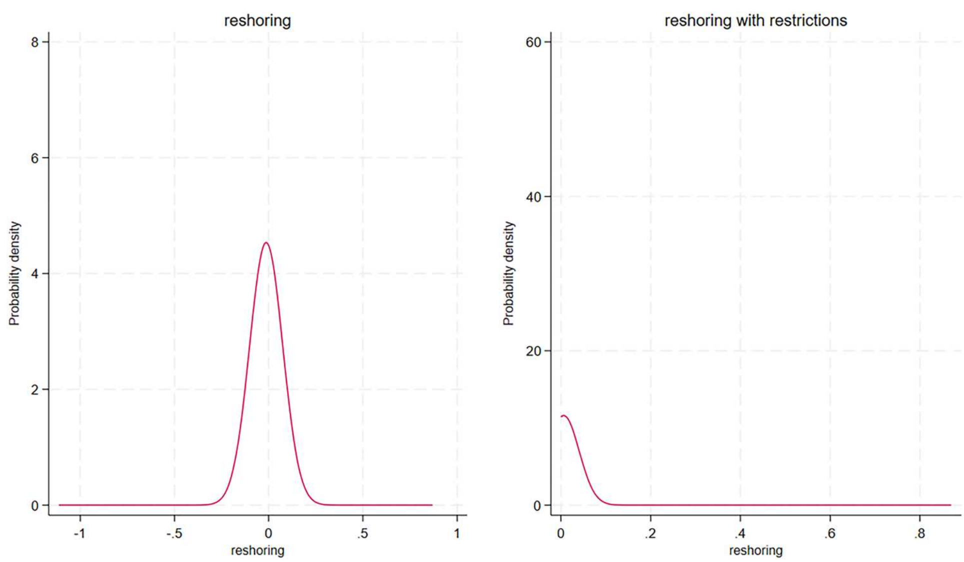

Figure 2. Reshoring probability density function.

Notes: restrictions require that $\boldsymbol{R_t} > 0$ and the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero. Source: own elaboration using ICIO data.

industries[7], spanning 2009–2018. The Online Appendix reports figures illustrating the evolution of the reshoring and offshoring measures over time, across sectors and countries.

3.3. Measuring adoption of advanced manufacturing technologies

To measure the adoption of the three I4.0 technologies central to our study (i.e. AM, IoT, and AIR), we use import flows of products and machinery that embody these technologies, hence requiring the physical installation of specialized capital goods.[8] This approach is consistent with well-established methods in the literature where the import of capital goods is used as a proxy of technology adoption (e.g. Acemoglu, Lelarge, and Restrepo 2020; Bonfiglioli et al. 2022; Caselli and Coleman 2001; Domini et al. 2021). We identify the 8-digit product codes in the CN that specifically capture imports of I4.0 technologies following Castellani, Lamperti, and Lavoratori (2022)[9] and exploit the measurement methodology delineated by Lamperti, Lavoratori, and Castellani (2023), which is similar to the adoption measurement used in related research (e.g. Acemoglu and Restrepo 2020; Felice, Lamperti, and Piscitello 2022). We acknowledge that I4.0 encompasses a broad spectrum of technologies, including artificial intelligence, cloud computing, and big data analytics. However, our analysis specifically targets AM, IoT, and AIR since these are hardware technologies, enabling their adoption to be proxied by trade data (Lamperti, Lavoratori, and Castellani 2023).

To measure the adoption of I4.0 technologies using Comext data, we first aggregate import values for all 8-digit product codes related to each individual technology at the country-year level. Then, following Lamperti, Lavoratori, and Castellani (2023), we use intermediate-weighted proportions of technology imports to create country-sector-year adoption measures. This is achieved by: (a) analyzing the fraction of a country's I4.0-relevant imports relative to its total imports originating from sectors producing each I4.0 technology; and (b) incorporating cross-national and cross-sectoral data on imported intermediate goods sourced from sectors producing each technology abroad and used by all domestic manufacturing sectors.[10] We mathematically formalize the computation process in the Online Appendix.

In our regression analysis, we normalize our variables by measuring the stock of AIR, AM, and IoT imports (in thousands €) per worker. We source the number of persons engaged, encompassing both employees and the self-employed, at the country-sector level from the EU KLEMS database 2023 release. Table 1 presents summary statistics for our dependent and independent variables.

3.4. Econometric strategy

Our analysis sets out to investigate the distinct effects of the adoption of AIR, AM, and IoT on reshoring and offshoring phenomena spanning 2009–2018, for the EU 27 countries and the UK. For this

Table 1. Summary statistics of the main variables.

	Mean	SD	Min	Max	Obs.	Correlations: *AM*	*IoT*	*AIR*
ΔR	0.007	0.038	0.000	0.870	5,320	−0.007	−0.035	−0.140
Δf	0.013	0.087	−0.870	1.113	5,040	−0.014	0.033	0.082
$AM = ln\left(\frac{K^{AM}}{emp}\right)$	−7.965	1.564	−13.390	−3.022	2,620	1.000	0.382	0.298
$IoT = ln\left(\frac{K^{IoT}}{emp}\right)$	−0.456	2.279	−7.691	8.978	2,705		1.000	0.504
$AIR = ln\left(\frac{K^{AIR}}{emp}\right)$	−9.100	2.386	−17.875	−3.504	2,666			1.000

Notes: *the ΔR reshoring measure requires that $R_t > 0$ and the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero. $\Delta Off =$ change in offshoring; AM = additive manufacturing; IoT = Internet of Things; AIR = advanced industrial robots.*

purpose, we estimate the following baseline reduced-form equation:

$$Y_{i,j,t} = \beta_0 + \beta_1 AM_{i,j,t-1} + \beta_2 IoT_{i,j,t-1} + \beta_3 AIR_{i,j,t-1} + \gamma_{i,j} + \tau_t + u_{i,j,t} \quad (4)$$

where $Y_{i,j,t}$ is our dependent variable for industry j in country i at time t, namely, $\Delta R_{i,j,t}$ and $\Delta Off_{i,j,t}$ in two distinct regressions; $AM_{i,j,t-1}$, $IoT_{i,j,t-1}$, $AIR_{i,j,t-1}$, are our log-transformed explanatory variables, normalized per thousand workers. Our identification strategy is based on the use of the within-group estimator (i.e. we include country-sector dummies $\gamma_{i,j}$ in each of our specifications) to account for the potential unobserved heterogeneity. We further incorporate additional fixed effects (FE) in our model: in our baseline specifications we include time effects τ_t to capture common, time-variant shocks and cyclical components that might influence all country-sectors in a particular year. We also test specifications in which we control for sector-specific time trends $\theta_{j,t}$ capturing potentially unobserved factors that vary across sectors and over time, for example, the evolution of specific sectoral dynamics such as industry growth and profitability, the evolution of specific technological trajectories, and the level of scale economies and product differentiation. These additional controls should ensure that our results are not confounded by unobserved characteristics, which might simultaneously correlate with both our outcome variables and our key regressors.

We use one-year lagged values of all our regressors to mitigate simultaneity bias. This should also partially alleviate the problems that reverse causality may introduce into our regressions. Furthermore, to ease concerns that our results might capture spurious correlations, we also check for stationarity of the process described by all our dependent and explanatory variables by means of unit root tests (Im, Pesaran, and Shin 2003) and by testing for long-run cointegration in our specifications using Pedroni's (2004) procedure.

In addition to the baseline analysis, we aim to identify potential sources of heterogeneity in the reshoring phenomenon. Following our discussion in Section 2.1, a region of particular interest is Asia which, in recent decades, has emerged as a primary hub for offshoring by European companies (Dachs et al. 2006, 2019). The data in Figure 3 illustrates a significant trend in offshoring towards Asia in the initial decade of the 2000s, emphasizing its importance relative to other regions. This trend indicates that as companies increasingly shift their operations to Asia, there may be a potential for a subsequent movement towards reshoring. However, post-financial crisis, this growth seems to stabilize. Furthermore, as Castellani, Lamperti, and Lavoratori (2022) note, the year 2009 is usually recognized as the starting point of a global wave of technological innovation around I4.0. These considerations highlight the importance of focusing on Asia as a pivotal region for analyzing the dynamics of offshoring and the potential for reshoring activities.

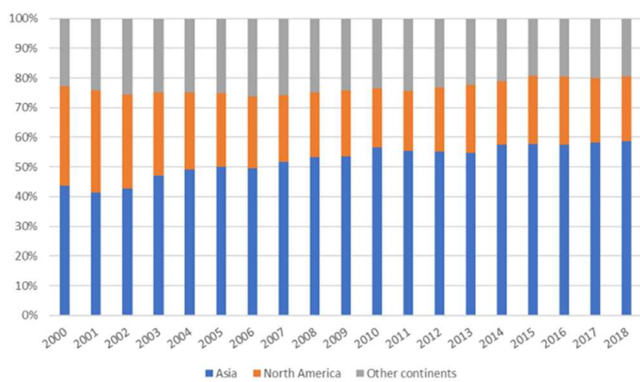

Figure 3. Offshoring toward Asia. Source: own elaboration using ICIO data.

To measure reshoring from Asia, we employ the domestic – foreign (i.e. Asia) input differential:

$$\Delta R_t^{Asia} = ln\left(\frac{DI_t}{FI_t^{Asia}}\right) - ln\left(\frac{DI_{t-1}}{FI_{t-1}^{Asia}}\right) \tag{5}$$

Further, for offshoring, we compute the following variable:

$$\Delta Off_t^{Asia} = ln\left(\frac{FI_t^{Asia}}{DI_t + FI_t}\right) - ln\left(\frac{FI_{t-1}^{Asia}}{DI_{t-1} + FI_{t-1}}\right) \tag{6}$$

To further understand the complexity of reshoring and offshoring trends, our research will highlight the geographical distinctions between developing and developed countries in Asia.[11] This approach will help to delve into the diverse economic landscapes and how they influence the movement of production across these regions. Indeed, different stages of economic development correspond to varying levels of specialization, skill availability, and labor costs. These factors can significantly influence a company's decisions about where to locate its production. For instance, while developed countries may offer advanced technological infrastructure and a skilled workforce, developing countries might present cost advantages through lower wages. Such dichotomies, coupled with varying levels of domestic I4.0 technology adoption, could lead to divergent decisions regarding the relocation of production back to European countries.

4. Results

Before introducing our main findings, we first assess the presence of unit roots in our data by applying the procedure used by Im, Pesaran, and Shin (2003) (Table D.1 in the Online Appendix). Results confirm the stationarity of all variables within our models. Furthermore, to investigate the cointegrating relationship of the model's variables, we apply the panel test by Pedroni (2004) (Table D.2 in Appendix). Our findings substantiate a significant long-run cointegrating relationship among the model variables, evidenced by residuals from both Phillips – Perron and Augmented Dickey – Fuller tests, significant at the 1% level. While our econometric strategy does not allow us to claim causal relation, these preliminary results suggest the estimated relationships are not affected by spurious correlations in the data.

4.1. Industry 4.0, reshoring, and offshoring

Table 2 presents the regression results for changes in reshoring and offshoring activities. Columns (1) and (2) assess the link between I4.0 technologies and our measure of reshoring.[12] In line with our

Table 2. I4.0 technology and effects on reshoring and offshoring.

	Reshoring (ΔR_t)		Offshoring (ΔOff_t)	
	(1)	(2)	(3)	(4)
AIR	0.00950***	0.00934***	−0.00598	−0.00680
	(0.00338)	(0.00338)	(0.00797)	(0.00795)
IoT	−0.00432	−0.00449	0.0121*	0.0123*
	(0.00297)	(0.00323)	(0.00651)	(0.00668)
AM	0.00175	0.00156	−0.00465	−0.00542
	(0.00180)	(0.00177)	(0.00517)	(0.00518)
Country-sector FE	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Time-sector FE		Yes		Yes
N Obs.	2,358	2,358	2,358	2,358
R^2	0.141	0.158	0.192	0.212

Notes: *Robust SE are clustered at the country-industry level. All the independent variables are lagged by one year. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.*

hypotheses, we find that on average the adoption of AIR positively correlates with an increase in reshoring, with a strong statistical significance (columns (1) and (2)): a 10% increase in robot investment associates with about a 0.1 p.p. increase in ΔR_t (significant at the 1% level). This provides some evidence rejecting hypothesis H1a and supporting H1b, suggesting the prevailing mechanisms driving reshoring could be a substitution effect for labor in offshoring destinations. Conversely, the adoption of IoT technology is negatively related to reshoring. The coefficients in columns (1) and (2) suggest that a 10% increase in IoT investment leads to a decrease in the growth rate of ΔR_t of about 0.04 p.p. Overall, as IoT adoption rises, reshoring tends to grow at a slower rate. However, the estimated coefficients are not statistically significant, suggesting that they are not precise estimates and we cannot find strong statistical support for H2. For AM, we find a positive, small (about 0.01 p.p.), but not statistically significant relationship with reshoring. These findings are in line with the literature discussed in Section 2.4, overall indicating that this technology has, at least over the observation period, no clear average relationship with reshoring activities at the country-industry level.

Columns (3) and (4) in Table 2 extend our investigation to the effects of I4.0 technologies on offshoring activities. Across the models, the coefficients for AM and AIR are consistently negative, although not statistically significant. Conversely, a positive and significant (at the 10% level) relationship emerges between the IoT and offshoring activities. Specifically, an increment of 10% in IoT capital per thousand workers is associated with around 0.12 p.p. increase in the growth rate of offshoring.

While certain nuances are present, there is a general coherence between the results of our reshoring and offshoring measures. Specifically, when a positive relationship is observed between a given technology and reshoring, there tends to be a concomitant negative relationship with offshoring. Our results corroborate the idea that digital and automation technologies of the Fourth Industrial Revolution do not entail common implications for the organization and the geography of GVCs, but rather multifaceted and composite mechanisms are in place, depending on the specific technology.

4.2. Robustness checks

4.2.1. Weighted regressions

Our baseline econometric strategy is based on the within-group estimator, namely we estimate OLS-FE regressions with heteroskedasticity-robust standard errors (SE), augmented with additional FE, depending on the specification. However, heteroskedasticity is pervasive in the country-sector data used, hence our baseline estimates could lead to unprecise SE and unreliable confidence intervals. Specifically, hypothesis testing (Greene 2000) highlights that variances are unequal across individual (i.e. country-sector) groups. Therefore, to validate the robustness of our results, we re-estimate our main specifications by means of Weighted Least Squares (WLS) regression using sectoral employment shares in total manufacturing employment as weights.

Results from our main specifications for reshoring and offshoring are reported in panel A of Table 3, highlighting the overall robustness of our main findings. In particular, looking at columns (1) and (2), there is a negative and significant relationship between IoT adoption and reshoring, which is quantitatively more important than that found in our baseline estimates (about 0.06 p.p. increase from a 10% rise in technology adoption) and significant at the 5% level.

4.2.2. Cross-sectional dependence

Our baseline OLS-FE models are estimated using a set of time dummies to capture the effect of common exogenous shocks potentially affecting both technology adoption and reshoring (offshoring) trends. In so doing, we assume that unobservable factors characterizing co-movements across country-sector groups have identical effects across individual groups, thus representing a source of weak cross-sectional (or 'spatial') dependence (Pesaran 2006). Moreover, in these regressions,

Table 3. Robustness checks: weighted regressions and cross-sectional dependence adjustments.

	Reshoring (ΔR_t)		Offshoring (ΔOff_t)	
	(1)	(2)	(3)	(4)
Panel A: Weighted regressions				
AIR	0.0104***	0.0100***	−0.00508	−0.00610
	(0.00373)	(0.00368)	(0.00883)	(0.00887)
IoT	−0.00565**	−0.00598**	0.0133**	0.0134**
	(0.00254)	(0.00273)	(0.00629)	(0.00652)
AM	0.00151	0.00141	−0.00415	−0.00514
	(0.00181)	(0.00179)	(0.00479)	(0.00490)
Panel B: D-K standard errors	Reshoring (ΔR_t)		Offshoring (ΔOff_t)	
AIR	0.00950**	0.00934*	−0.00598	−0.00680
	(0.00410)	(0.00405)	(0.00899)	(0.00913)
IoT	−0.00432	−0.00449	0.0121***	0.0123**
	(0.00262)	(0.00305)	(0.00341)	(0.00407)
AM	0.00175	0.00156	−0.00465	−0.00542
	(0.00111)	(0.00107)	(0.00482)	(0.00399)
Country-sector FE	Yes	Yes	Yes	Yes
Time FE	Yes		Yes	
Time-sector FE		Yes		Yes
Panel C: Common correlated effects	Reshoring (ΔR_t)		Offshoring (ΔOff_t)	
AIR	0.00934***	0.00934**	−0.00659	−0.00659
	(0.00347)	(0.00397)	(0.00785)	(0.00876)
IoT	−0.00431	−0.00431	0.0121*	0.0121***
	(0.00297)	(0.00261)	(0.00650)	(0.00340)
AM	0.00175	0.00175	−0.00465	−0.00465
	(0.00180)	(0.00111)	(0.00519)	(0.00482)
CSD AIR	−0.00703	−0.00703**	0.0182	0.0182
	(0.00961)	(0.00239)	(0.0207)	(0.0112)
CSD IoT	0.0135	0.0135	−0.0270	−0.0270
	(0.0189)	(0.00835)	(0.0585)	(0.0225)
CSD AM	−0.0512	−0.0512***	0.0126	0.0126
	(0.0410)	(0.0120)	(0.0976)	(0.0224)
CSD Reshoring	0.924***	0.924***		
	(0.183)	(0.0370)		
CSD Offshoring			1.067***	1.067***
			(0.104)	(0.0348)
CCE	Yes	Yes	Yes	Yes
D-K SE		Yes		Yes
N Obs.	2,358	2,358	2,358	2,358

Notes*: Robust SE are clustered at the country-industry level. All the independent variables are lagged by one year. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.*

heterogeneity is limited to country-sector specific FE – and industry-specific time trends, in some specifications – and the estimated coefficients for the three technologies are considered homogeneous across countries. Since hypothesis testing via the Breusch and Pagan (1980) LM test and the Pesaran (2021) CD test suggests the presence of cross-sectional dependence in our panel data, we implement two robustness checks.

First, in panel B of Table 3, we control for the robustness of our main results to the presence of weak forms of spatial dependence by re-estimating our main OLS-FE models with time FE (or sectoral trends) and computing Driscoll and Kraay (1998) standard errors, assuming the error structure to be heteroskedastic, autocorrelated up to the third lag, and correlated between country-sector groups. Since the underlying models are identical to those estimated in Table 2, coefficients are identical too. However, SE are more precisely estimated, yielding lower statistical significance (5% level) in columns (1) and (2) for the AIR adoption coefficients, but higher significance (1% level) in columns (3) and (4) for IoT adoption coefficients.

Second, in panel C, we account for stronger levels of cross-sectional dependence than normally controlled for by including time FE. We adopt the common correlated effects (CCE) by Chudik and

Pesaran (2015). In our data, high levels of spatial correlation may result from increasing market integration underlying GVCs, as well as the diffusion of new technologies. All these factors may be imperfectly measured by trade statistics used to compute our variables, creating a strong error dependence across them and hence producing evidence of rising reshoring from AIR adoption or higher offshoring from IoT adoption. Following Chudik and Pesaran (2015), we construct CEE terms as annual averages, across country-sector groups, of the dependent variable – either reshoring or offshoring – and the three technology adoption variables, adding them to our baseline specifications of the OLS-FE model. In so doing, we account for all existing forms of unobservable co-movements across country-sector groups. Also, the estimated coefficients are virtually identical to those reported in Table 2, suggesting that spatial dependence does not add any substantial bias to our model results, and supports the overall robustness of our findings.

4.3. Industry 4.0 and sourcing from Asia

The offshoring wave observed over the past two decades has shown Asia as a prominent hub for production offshoring by European companies, with China and other Asian countries being the primary destinations (Dachs et al. 2006, 2019). Consequently, given the established trend of European countries offshoring production to Asia, Table 4 and 5 investigate the effects of I4.0 technologies on the restructuring of value chains with Asia.

Table 4 shows that the coefficients for AIR are positive and statistically significant across all models, indicating a robust relationship between the adoption of robotics in Europe and reshoring activities from Asia. This trend is observed for both developing and developed Asian countries. The positive impact of AIR suggests that advanced automation technologies in Europe are enhancing production efficiency and cost-effectiveness (Lamperti, Lavoratori, and Castellani 2023), therefore reducing the reliance on offshore manufacturing even from developed Asian countries. These countries, despite their advanced industrial capabilities, may potentially face increasing competition from Europe's technological advancements, prompting European firms to leverage these efficiencies and maintain a competitive edge in the global market in the home country. Specifically, a 10% increase in AIR adoption is correlated with a higher reshoring growth rate of 0.3 p.p. (on average) for all Asian countries, 0.23 p.p. for developing Asian countries, and 0.34 p.p. for developed Asian countries (significant at the 5% and 10% level).

Looking at IoT adoption, the analysis reveals that an increase in related investment is associated with a decrease in the growth rate of reshoring, mostly across developing Asian countries. IoT coefficients are always negative and statistically significant in models related to all Asian countries and developing ones (at the 10% and 5% levels, respectively). The larger magnitude of coefficients in developing Asian economies, indicates that results for Asia are primarily driven by developing

Table 4. I4.0 technology and effects on reshoring from Asia.

	Asia		Asia developing		Asia developed	
	(1)	(2)	(3)	(4)	(5)	(6)
AIR	0.0296**	0.0289**	0.0234**	0.0229**	0.0335*	0.0329*
	(0.0123)	(0.0121)	(0.0112)	(0.0110)	(0.0175)	(0.0176)
IoT	−0.0165*	−0.0174*	−0.0202**	−0.0203**	−0.00240	−0.00387
	(0.00895)	(0.00947)	(0.00914)	(0.00952)	(0.0172)	(0.0175)
AM	0.00564	0.00398	0.00354	0.00217	0.00345	0.00328
	(0.00692)	(0.00686)	(0.00537)	(0.00545)	(0.0137)	(0.0133)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes		Yes		Yes	
Time-sector FE		Yes		Yes		Yes
N Obs.	2,358	2,358	2,358	2,358	2,358	2,358
R^2	0.145	0.169	0.140	0.162	0.157	0.178

Notes: *Robust SE are clustered at the country-industry level. All the independent variables are lagged by one year. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.*

Table 5. I4.0 technology and effects on offshoring towards Asia.

	Asia		Asia developing		Asia developed	
	(1)	(2)	(3)	(4)	(5)	(6)
AIR	−0.0541***	−0.0573***	−0.0455***	−0.0501***	−0.0669**	−0.0642**
	(0.0170)	(0.0173)	(0.0175)	(0.0174)	(0.0261)	(0.0262)
IoT	0.0108	0.0129	0.00547	0.00625	0.00590	0.0171
	(0.0132)	(0.0140)	(0.0135)	(0.0147)	(0.0261)	(0.0270)
AM	−0.00360	−0.00236	−0.00883	−0.00844	0.0131	0.0162
	(0.0103)	(0.0101)	(0.00971)	(0.00961)	(0.0209)	(0.02)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes		Yes		Yes	
Time-sector FE		Yes		Yes		Yes
N Obs.	2,358	2,358	2,358	2,358	2,358	2,358
R^2	0.119	0.160	0.112	0.160	0.0916	0.121

Notes: Robust SE are clustered at the country-industry level. All the independent variables are lagged by one year. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

countries. Specifically, a 10% increase in IoT adoption relates to a drop in the growth rate of reshoring by approximately 0.17 p.p. (on average) in the case of all Asian countries, and by approximately 0.2 p.p. for developing economies. As for the aggregate investigation, AM coefficients are positive, but small in magnitude and never statistically significant, suggesting that the technology has no clear relationship with reshoring activities over the observation period, even when focusing on the Asian region.

Table 5 complements our examination by presenting the findings for offshoring variables. The data indicates that there is a negative average relationship between the adoption of AIR and offshoring activities across all Asia, as well as when distinguishing between developing and developed countries within the region. In detail, a 10% increase in AIR adoption is associated with a decrease in offshoring activities towards Asia by approximately 0.55 p.p., larger in magnitude (about –0.66 p.p.) in the case of developed countries in the region, smaller (around –0.46 p.p.) in the case of developing ones. Table 5 further shows that, although the sign of IoT adoption coefficients is consistent with our expectations (proposing a positively growing trend in offshoring towards Asia), they are never statistically significant. This suggests that the positive effect seen in our baseline results is due to IoT-enabled growing digital ties with other Western regions. Finally, our findings for AM mirror previous results on the technology, yet also highlight some heterogeneity in the sign of the coefficients when looking at different country groups in Asia (developed vs developing).[13]

5. Discussion and conclusions

In recent years, in the aftermath of global turmoil and economic shocks, the dynamics of the global economy have undergone significant changes, sparking debate both within and outside academic circles about a potential shift towards deglobalization and more resilient global value chains. Central to this discussion is the concept of reshoring – the process of moving previously offshored activities back to the home country. While the actual economic relevance and consequences of the reshoring phenomenon is yet to be fully evaluated in manufacturing (Casadei and Iammarino 2023; Di Berardino et al. 2025; D'Ambrosio and Lavoratori 2025), it has gained momentum against the backdrop of the Fourth Industrial Revolution, characterized by advancements in AIR, IoT, and AM.

These technological innovations are recognized as drivers of reshoring (Javorcik 2020). The existing, limited literature is dominated by a preponderance of studies examining the impact of robotics, or automation more broadly, on reshoring and offshoring, while there is a relative paucity of comprehensive analyses that consider the collective influence of multiple I4.0 technologies. The oversight is significant and our work bridges this gap in the literature – despite the transformative potential of AIR, the real-world implications of I4.0 transformation are complex and varied. Indeed, these technologies are distinct in their characteristics and functionalities, they operate at different stages of the production process and affect distinct aspects of manufacturing, thereby influencing global value chains in diverse ways (Antràs 2020). The heterogeneous nature of these technologies means that their role in either facilitating or hindering reshoring can vary greatly (Butollo 2021). As the debate on deglobalization continues, it is essential to develop a nuanced understanding of how each I4.0 technological advancement contributes to the reshaping of GVCs. Therefore, our contribution provides a multifaceted exploration of I4.0 technologies, offering a broader perspective on their implications for reshoring.

Our results indicate a significant positive average relationship between AIR adoption in European countries and reshoring. This supports the argument of substitution between automation (capital) and labor, therefore the shift in the production process configuration can impact the geography of production operations, moving from offshoring to reshoring. Automation competes with low-skilled workers abroad because it serves as a substitute for low-skilled labor. An improvement in automation efficiency, where industrial robots become more productive, may lead firms to opt for production using industrial robots at home, relying less on offshore labor. This can also reflect some vertical integration, with the ability of advanced robots to perform flexibly and be employed on multiple complex tasks (Martinelli, Mina, and Moggi 2021). Our findings corroborate the existing literature on AIR, reshoring, offshoring, and their broader impact on GVCs (Artuc, Christiaensen, and Winkler 2019; Carbonero, Ernst, and Weber 2020; Faber 2020; Krenz, Prettner, and Strulik 2021).

Looking at the impact of IoT, to the best of our knowledge, we provide the first empirical evidence supporting the notion that IoT adoption relates to a diminishing trend in reshoring activities and a rising offshoring trend, although with limited and geographically localized evidence. Prior studies on ICTs suggest this is probably due to IoT's role in reducing coordination and transaction costs (Hallward-Driemeier and Nayyar 2017).

Finally, despite extensive theoretical discussion and some preliminary evidence that AM could reverse the fragmentation patterns characterizing GVCs, we find no evidence of such influence on reshoring or offshoring activities over the decade leading up to the outbreak of the Covid-19 pandemic. While AM adoption has grown significantly and the technology has reached widespread maturity (Felice, Lamperti, and Piscitello 2022; Laplume, Petersen, and Pearce 2016), its impact on GVC reconfiguration appears limited to a few highly exposed industries (Buonafede et al. 2018) and the production of niche, highly customized, finished products. Subsequently, our results on the insignificant role of AM in influencing reshoring/offshoring patterns across countries and industries suggest that AM technology has a complex role in shaping GVC patterns. AM technology can also enable vertically integrated and localized production processes close to single (or regional) end markets, particularly where traditional economies of scale become less relevant.

We further contribute to the literature by shedding light on the geographical heterogeneity of reshoring activities, with an emphasis on Asian countries. This focus is informed by the region's central role in the narrative of global offshoring, where it has been a primary beneficiary due to its competitive labor markets and favorable manufacturing environments. We provide a nuanced insight into how I4.0 technologies are influencing economic behaviors across diverse economic landscapes: our findings suggest that the integration of AIR within European industries may be incentivizing reshoring by enhancing the appeal and competitiveness of domestic production relative to foreign inputs sourced from Asia. This trend holds true for both developing and developed Asian economies. IoT investments seem to lower the growth rate of reshoring from the region, although this trend is limited to developing countries in the region. The results further highlight an inverse relationship between investment in robots and the propensity for European manufacturing industries to offshore to Asian markets, suggesting that as automation spreads, these industries tend to bring production processes closer to their operational base, reducing reliance on foreign manufacturing owing to the higher productivity.

Finally, our analysis illustrates that the adoption of I4.0 technologies may incentivize movements both towards the relocation of production domestically or towards enhanced fragmentation and offshoring. Therefore, each technology exerts distinct effects on these dynamics, in turn, implying a multifaceted – rather than unidirectional – influence on the geography of manufacturing activities.

5.1. Policy implications

Policymakers aiming to devise strategies to encourage reshoring must consider a variety of factors. First and foremost, industrial policies at the EU and national level should address disparities in the production and adoption of new digital and automation technologies, as countries at different stages of industrial development experience varying benefits from automation (Lamperti, Lavoratori, and Castellani 2023). Second, actionable policies will require subsidies and tax incentives aimed at providing equitable access to I4.0 technologies, which would also boost research and development, and faster adoption. This goes hand in hand with targeted education policies and reskilling programs, which are crucial to ensuring workforce readiness for technologically advanced production environments.

As complete reshoring of manufacturing activities is unlikely to be achieved (as it would require a costly and long transition due to the existing dependencies with Asian countries), European policymakers and firms should look at pursuing nuanced alternatives, such as nearshoring. This represents an intermediate approach between relocating the entire manufacturing chain back to the home country and maintaining it in the offshoring destination countries (Di Berardino et al. 2025). Nearshoring could represent a suitable option to address certain offshoring decisions (e.g. quality issues, transportation, and coordination costs), as well as gaining access to the advanced manufacturing standards of European neighbors and the related benefits (lower geographic and cultural distance, common standards, and the high technological integration made available by integrated I4.0 policies). As discussed by Di Berardino et al. (2025), such a shift would not only foster economic and organizational integration of firms across Europe but would also lower the EU dependence on external sourcing, while also improving and diversifying sources of production and technological innovation across the region.

Despite all these potential gains, policymakers should take into account and manage the broader implications of either reshoring or nearshoring strategies in view of the public debate on the effects of both GVCs and new technologies. Drawing on the extensive literature on the employment effects of automation, we can assume that previously offshored jobs are unlikely to return if the European reshoring trend is driven by robotization and other advanced technologies. As discussed by Cséfalvay and Gkotsis (2022), the returning manufacturing activities are likely to be performed by smart factories, thus requiring fewer but more skilled workers. This further emphasizes the need for policymakers to address both GVC-related, technological, and human capital factors with an eclectic approach to achieve a long-run effective transition across Europe.

5.2. Limitations and future research

While our study provides valuable insights, it does have drawbacks. First, our analysis is concentrated on the reconfiguration of GVCs within the EU. This focus offers a detailed view of trends characterizing Europe but does not account for internal heterogeneity within member states or compare these trends with other major economic players (such as the US). Future studies could address these gaps by investigating intra-EU variations and by drawing comparisons with the value chain dynamics in the US, which may exhibit different patterns due to distinct regulatory environments, labor market conditions, and technology adoption rates. Second, while our study investigates the relationship between three I4.0 technologies and reshoring/offshoring activities by exploiting differences over time in import stocks by technology, country, and sector, it does not encompass a more complete view that accounts for the local production of these technologies. Although existing studies highlight import-based adoption proxies to be highly correlated with overall adoption from both imports and local production (e.g. Caselli and Coleman 2001; more recently, Castellani, Lamperti, and Lavoratori 2022; Lamperti, Lavoratori, and Castellani 2023), future work is needed to provide a more comprehensive analysis that considers how overall adoption relates to GVC restructuring.

Finally, due to the limited availability of data and measures of reshoring and adoption of I4.0-related technologies at the firm level, the study resorts to sector-country data following similar approaches in the literature (Artuc, Bastos, and Rijkers 2023; Carbonero, Ernst, and Weber 2020; Krenz, Prettner, and Strulik 2021). Although this data is crucial as it provides preliminary evidence on a phenomenon that is under-investigated, it may hide several sources of heterogeneity across firms (D'Ambrosio and Lavoratori 2025; Stentoft, Mikkelsen, and Wickstrom 2024). As more data become available, future research should delve into this by developing firm-level measures of reshoring across countries and over time, including the geography of their sourcing.

Notes

1. Previous studies have measured reshoring using various data types. Country-sectoral analyses typically rely on trade and Input-Output (I-O) data (Faber 2020; Krenz, Prettner, and Strulik 2021), while micro-level studies often use ad hoc surveys or secondary data from newspapers (Ancarani, Mauro, and Mascali 2019; Dachs et al. 2019). A few exceptions use parent-subsidiary employment data as reshoring proxies (Delis, Driffield, and Temouri 2019). Offshoring, in the form of outsourcing or captive offshoring, is captured through import/export transactions (Feenstra and Hanson 1996) with independent firms or intra-firm (parent-subsidiary) flows. We use trade data to analyze reshoring as a whole, without focusing on specific governance forms.
2. Antràs (2020) shows that, excluding Mexico, most emerging countries in Asia and Europe have seen their labor costs going up over the last twenty years. These increases have been higher than in places like the US or the countries in the euro area. Since 1990, Chinese unit labor costs have grown about 2.5 times as fast as those in Germany and the United States.
3. Data available at https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm.
4. Differently from us, they use WIOD data.
5. Feenstra and Hanson (1996) referred to this metric as the foreign outsourcing of intermediate inputs imported by domestic firms, thus offshoring.
6. Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom.
7. Manufacture of food products (C10–C12); Manufacture of textiles, wearing apparel, leather and related products (C13–C15); Manufacture of wood, paper, printing, and reproduction (C16–C18); Coke and refined petroleum products and chemicals (C19–C21); Manufacture of rubber and plastic products and other non-metallic mineral products (C22–C23); Manufacture of basic metals and fabricated metal products, except machinery and equipment (C24–C25); Computer, electronic, optical products (C26–C27); Manufacture of machinery and equipment n.e.c. (C28); Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment (C29–C30); Manufacture of furniture (C31–C33).
8. Castellani, Lamperti, and Lavoratori (2022) develop two proxies to measure the adoption of I4.0 technologies. The first proxy is based on imports of I4.0 capital goods. The second one is calculated using the formula: net consumption = (production + import − export); hence, it considers both domestic and foreign sources of capital investments in I4.0 technologies. However, the authors note that the net consumption measure is not universally applicable due to the absence or unreliability of production data for goods embodying I4.0 technologies in some countries and for some products. Nonetheless, they document a strong correlation between the import-based adoption measure and the net consumption (which accounts for domestic production), with pairwise correlation coefficients of 0.83 for AIR, 0.78 for AM, and 0.66 for IoT.
9. See Table A.1 in the Online Appendix for the product codes related to I4.0 technologies.
10. Sourced from the WIOD dataset (Timmer et al. 2015).
11. As for UNCTAD classification, Asia developing includes the following countries: Brunei Darussalam, Cambodia, China, India, Hong Kong, Laos, Malaysia, Myanmar, Philippines, Singapore, Taiwan, Thailand, Vietnam, Kazakhstan, and Indonesia. Asia developed includes: Japan, South Korea.
12. We note that reported coefficients can be interpreted as semi-elasticities.
13. Additional robustness checks on the analysis of the Asian region are reported in the Online Appendix and are available upon request from the authors. Furthermore, we performed an additional empirical exercise by replicating the analysis using *narrow* measures of reshoring and offshoring, following the approach of Feenstra and Hanson (1996) (i.e. only based on inter-country 'vertical' links within the same sector, neglecting the wider network of inter-sectoral links). Results of this replication exercise are available upon request from the authors and support the robustness of our main findings.

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Data availability

Data are available from the authors upon request.

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