From Globalisation to Reshoring? The role of Industry 4.0 in Trasforming Global Supply Chains within the EU

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Abstract: This paper investigates the relationship between Industry 4.0 technologies—specifically, additive manufacturing (AM), the Internet-of-Things (IoT), and advanced industrial robots (AIRs)—and reshoring and offshoring activities within the European Union (EU). We employ data from the OECD Inter-Country Input-Output (ICIO) tables and the Eurostat's Comext database for 27 EU countries and the United Kingdom for the period 2009–2018. Our findings indicate a positive relationship between the adoption of AIRs and the reshoring of supply activities. In contrast, increased investment in IoT appears to reduce reshoring in production, while the impact of AM adoption on reshoring remains inconclusive. The study also delves into the geographical aspects of reshoring. We document that the Asian region still represents the main destination for offshoring of both production and supply activities. The econometric results highlight that AIRs adoption encourages reshoring of activities back from Asia, whereas increased IoT investments relate with a decline in reshoring growth from the region. This study contributes to the reshoring literature by distinguishing between supply and production reshoring and by examining their geographical variations. Our results reveal that the dynamics of reshoring are complex and relates with both the specific Industry 4.0 technology and the geographic context. These insights offer a new perspective on the reconfiguration of global supply chains 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 of the pivotal questions at the core of these discussions is whether the world is witnessing a substantive shift towards deglobalisation.

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 in this context. A growing body of the literature seeks to understand the motivations, implications, and long-term consequences of reshoring. However, consensus remains elusive. For instance, Di Sano et al. [2023] argue that reshoring is a clear sign of deglobalisation, as it signifies a reversal of the decades-long trend of increasing global economic integration. The literature points to various drivers for this shift, ranging from economic factors like rising wages in traditionally low-cost countries [Martínez-Mora and Merino, 2014] to strategic considerations and the desire to protect intellectual property [Dachs et al., 2019]. Conversely, other authors contend that claims stating the end of globalization are significantly overstated [Baldwin, 2022], and that what we are observing is just a recalibration of global production networks [Antràs, 2020; Jaax et al., 2023]. Indeed, while certain industries or firms might be reshoring, the broader momentum of global integration continues unabated, driven by technology, trade agreements, and the (global) division of production activities at the very basis imperatives of global value chains.

The debate is further complicated by external events and disruptions. The recent global events, such as the US-China trade tensions, the COVID-19 pandemic, and the Russian invasion of Ukraine, have raised questions about the vulnerability of extended supply chains, reigniting discussions about the merits of reshoring and localisation choices. At the same time, the diffusion of new digital technologies is pushing companies to rethink their approach to global production [Javorcik, 2020]. Specifically, automation offers firms in developed countries a way to reduce labour costs without resorting to offshoring. In theory, if automation continues to advance, we might see more companies choosing to reshore their operations, possibly leading to a trend of reduced globalization in the future. However, as Antràs [2020] argues, the significant sunk costs that firms bear when establishing their global sourcing strategies usually imply that location decisions are relatively inflexible and therefore stable. Furthermore, the real-world effects of these technologies are more nuanced [UNCTAD, 2020]. While each technology has its unique influence on international production, emerging digital innovations hold the promise of reinvigorating hyper-globalization in the near future [Antràs, 2020]. For instance, while robotics may incentivise reshoring by enhancing the efficiency and competitiveness of domestic production, other technologies such as IoT may not have the same effect [Strange and Zucchella, 2017]. Indeed, just as information and communication technologies (ICTs) paved the way to earlier waves of globalisation, IoT could further lower the costs of cross-border communication and transactions, potentially leading to increased production fragmentation and a deepening of the global supply chains.

As production costs rise in advanced economies, there is a shift towards more capital-intensive manufacturing, while labour-intensive processes tend to relocate to cost-effective offshore locations. Such trend has characterised 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 by European and US companies, with China being the primary destination [Dachs et al., 2006, 2019]. Indeed, East Asian economies now accounts for one-third of global exports, underscoring its significant role in international trade [European Parliament, 2021].

In this scenario, a significant body of research has scrutinized the influence of robotics on reshoring and offshoring dynamics, while a notable gap in the literature remains on the combined effects of different Industry 4.0 (I40) technologies. The heterogeneous nature of these technologies means that their role in either facilitating or hindering reshoring is guided by several different mechanisms and, hence, can vary greatly [Butollo, 2021]. Building on this premise, the aim of this paper is to explore the heterogeneous impacts of those capital-embodied I40 technologies that are expected to have a great impact on manufacturing operations [Eurofound, 2018]—specifically, additive manufacturing (AM; or 3D printing), the Internet-of-Things (IoT), and advanced industrial robots (AIRs)—and to delineate how each technological advancement contributes to the reshaping of global supply chains (GSCs). By investigating the distinct and combined effects of these technologies, we offer a more holistic understanding of how the fourth industrial revolution is reconfiguring the global manufacturing and production landscape. Specifically, we analyse reshoring and offshoring activities at the country-sector level across the 27 European Union (EU) countries plus the United Kingdom (UK) for the period 2009–2018. We further place a special emphasis on geographical patterns for the EU, with Asia being a focal point due to its established role as a major offshoring destination over the last decades. 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 the OECD Inter-Country Input-Output (ICIO) tables (2021 edition), which provide data to examine reshoring and offshoring activities at the country-industry level for 10 manufacturing industries, spanning the period 2009–2018. Additionally, we employ secondary data from the EUROSTAT Comext database, which serves as an essential tool for measuring our independent variables pertaining AM, the IoT, and AIRs technologies.

We consider the EU28 economy to be a peculiar setting for our investigation for several reasons. Firstly, over the observation period, EU member states have actively implemented policies designed to foster the adoption of I40 technologies. These efforts are further reflected in the objectives of the European Union's Strategies for Smart Specialization, which aim to enhance innovation and the competitiveness of member states. Additionally, the European Commission's Digitizing European Industry Initiative has reinforced the push towards utilizing I40 enabling technologies [Teixeira and Tavares-Lehmann, 2022]. Secondly, the EU provides an ideal setting due to its high degree of trade openness [International Monetary Fund, 2018] and significant involvement in global supply chains [European Central Bank, 2019], making it a microcosm for examining the broader implications of technological advancements on reshoring and supply chain dynamics.

Moreover, we contribute to the current empirical research on the GSCs by differentiating between the reshoring of supply and production. To bridge this gap, our investigation employs two distinct reshoring metrics. The first metric, named *supply reshoring*, encompasses all aggregate intermediate inputs sourced by each manufacturing sector from its various counterparts, in other words, all suppliers involved. Meanwhile, the second metric, called *production reshoring*, concentrates on intermediate imports that are sourced from the same focal industry.

We observe a positive relationship between the adoption of robots and the reshoring of supply activities. However, the relationship between AIRs adoption and production reshoring, while positive, is not statistically significant. These findings align with existing research which argues robots as a labour substitute in offshoring destinations. The results also suggest that increased IoT adoption is linked to a reduction in reshoring within production, likely due to the technology's capacity to improve coordination and reduce transaction costs. However, this negative relationship is not statistically significant for the supply measure of reshoring. For AM, we find no statistically significant results, indicating no clear impact on reshoring activities at the aggregate industry level. Therefore, the potential impact of AM on the reconfiguration of international production activities remains puzzling and unclear.

Our study goes further, examining the geographical nuances of reshoring, particularly focusing on the Asian context. The nuanced analysis across Asian economies distinguishes between developing and developed economies. The evidence suggests that the adoption of AIRs encourages reshoring from Asia, thereby making domestic production more appealing and competitive compared to outsourcing to Asia. Increased IoT investments per employee correlate with a decline in the reshoring growth rate from Asia for the supply of intermediates and not for the production. Finally, to enhance the robustness of our analysis, we incorporate the offshoring measure into our framework. The results support our main findings.

The rest of the paper is organized as follows. Section 3.2 presents the related literature and our hypotheses. Section 3.3 describes the data sources. Section 3.4 illustrates the descriptive statistics while in Section 3.5 we illustrate the empirical strategy. Section 3.6 discusses the results, and in Section 3.7 we conclude.

2. Related literature and hypotheses

In this section, we briefly review the literature that addresses the determinants of offshoring and reshoring. Following that, we elaborate on the three pivotal technologies: AIRs, IoT, and AM, and explore the associated literature to develop/derive our main hypotheses.

2.1. From offshoring to reshoring

The creation of final products or intermediates involves a myriad 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 essentially refers to the reallocation of these productive tasks across different geographical regions [Hummels et al., 2018]. The global fragmentation of production processes has led to a surge in task-based trade or trade of intermediate goods and services. In turn, such phenomenon has been largely studied taking different theoretical and measurement perspectives, e.g. *offshoring* [Feenstra and Hanson, 1996b], *global commodity chain* [Gereffi, 1999], *fragmentation* [Arndt and Kierzkowski, 2001], *vertical specialisation* [Hummels et al., 2001], *global production network* [Henderson et al., 2002], *international production networks* [Borrus et al., 2003], *global value chain* [Gereffi et al., 2005], *trading task* [Grossman and Rossi-Hansberg, 2008] and, lately, *functional specialization* [Timmer et al., 2019].

From an historical perspective, fragmentation first emerged during the period between 1820 and 1913, often referred to as the "first globalization unbundling" [Baldwin, 2017]. The 19th century featured a distinct shift with the separation of production from consumption. This era marked a notable expansion in international trade flows, largely driven by reductions in trade costs, as a direct consequence of the steam revolution. The subsequent surge in production fragmentation during the 1990s and 2000s, known as the "second unbundling" [Baldwin, 2017], was influenced by several key developments. 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, with the '70s it started a marked decrease in costs for both air and sea freight. This substantial dip in transportation costs facilitated firms in spreading their production activities across the globe. Alongside these two main drivers, another significant factor determining the rapid growth of global supply chains lies in trade liberalization and agreements, above all, the China inclusion in the World Trade Organisation (WTO). During the period 1986-2008—defined by Antràs [2020] as the "golden age of trade liberalisation" —several trade liberalisation efforts reduced barriers for both developed and emerging nations, leading to lower trade costs. The development of the European single market, combined with the inclusion of major economies like China, India, and former Soviet Union countries into the global trade scene, expanded the available markets for goods and labour. 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 labour led many companies to either move their production or partner with suppliers in these low-cost economies [Antràs, 2020; Baldwin, 2013, 2017; World Bank, 2020].

However, since the 2008 financial crisis, global trade has experienced a slowdown. Consequently, terms such as *reshoring*, *onshoring*, *backshoring*, and *nearshoring* have gained prominence in both academic circles and broader public discussions[4]. Unsurprisingly, the increased intricacy of domestic and international sourcing processes has given rise to a plethora of terms and definitions (see, for instance, Ancarani et al. [2015]; Arik [2013]; Arlbjørn and Mikkelsen [2014]; Ellram [2013]; Foerstl et al. [2016]; Fratocchi et al. [2014]; Gray et al. [2013]; Kazmer [2014]; Kinkel and Maloca [2009]; Kinkel and Zanker [2013]). Central to these definitions is the idea that reshoring involves bringing back activities once offshored, as highlighted by De Backer et al. [2016]. This is the interpretation we will adopt in this paper.

[4] Cranfrield University [2015] tracks the growing interest in reshoring since 2008 by counting the media articles that reference it.

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 liberalisation era from 1986 to 2008, 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 et al., 2022]. Notable events, like the 2018's implementation from the US of multiple rounds of tariff hikes on specific products and nations [Amiti et al., 2019; Fajgelbaum et al., 2020][5] have become ever more frequent.
A second important factor driving this reversal wave lies in the lowering 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 [Antràs, 2020; Cigna et al., 2022; De Backer et al., 2016][6].
Finally, while the advent of ICTs—and the economic mechanisms behind it—have been a primary driver of offshoring, the diffusion of new digital technologies may hold different premises. The adoption of robots, IoT, and 3D printing is guided by specific economic rationales, resulting in differential expected impacts on sourcing strategies and the international fragmentation of production characterizing GSCs. Surely, some of these I40 technologies might promote reshoring; conversely, others—especially those linked to increased digitalisation and platform adoption—could further reduce cross-border communication and transaction costs, and as a consequence intensify production fragmentation [Antras, 2020b; UNCTAD, 2020].

2.2. Advanced Industrial Robots

The last decades have been characterised by the growing prominence of advanced robotics in academic and policy debates. Most concerns revolve around this automation representing a cost-effective alternative to traditional labour. Taking an internationalisation perspective, as industries seek optimisation strategies, the potential for robotics to drive reshoring becomes increasingly feasible. However, the existing literature offers mixed viewpoints on this subject. The increasing adoption of robots can either increase reshoring or increase offshoring.
New automation technologies—above all, AIRs—may induce a scaling-up in production by allowing internationalised firms to expand and, in turn, demand more inputs from supplier located in developing countries. Following this premise, Artuc et al. [2023] use country-industry panel data and show that a higher robot density in the northern (advanced) regions corresponds to a surge in imports from less developed economies in the same industry and a notable growth in exports to these countries. At the firm level, Stapleton

[5] Amiti et al. [2019] and Fajgelbaum et al. [2020] document that these tariffs affected 12,043 products, causing import tariffs to surge from 2.6% to 16.6%, covering $303 billion (or 12.7%) of annual U.S. imports. In retaliation, trading partners levied tariffs on U.S. exports, increasing tariffs from 7.3% to 20.4% on 8,073 export products, impacting $127 billion (or 8.2%) of annual U.S. exports.
[6]Antràs [2020] shows that, excluding Mexico, most emerging countries in Asia and Europe have seen their labour 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 labour costs have grown
about 2.5 times as fast as those in Germany and the United States.

and Webb [2020] offer a fresh perspective on how automation in high-income countries influences trade and multinational engagements with lower-income countries. The authors suggest that increased automation leads to lower marginal costs, enabling firms that automate to reduce prices, eventually increasing demand for both offshore and domestic labour. Using data on Spanish firms, they find that robot usage positively affects imports from, and the number of affiliates in lower-income countries. Another important mechanism poses that automation can boost productivity, making it attractive for companies to reshore those stages of their production process for which the economic advantages of offshoring are no longer effective. Findings from Krenz et al. [2021] support this view, indicating that for an increase of one robot per 1000 workers, there is a 3.5% rise in reshoring activities within the manufacturing sectors.

Robust empirical investigations of these phenomena still provide mixed evidence. Hallward-Driemeier and Nayyar [2019] analyse the relationship between AIRs adoption in high-income countries (HICs) and offshoring—measured by the growth of FDI from HICs to low- and middle-income countries (LMICs)—finding an inversed U-shape relationship once robot density in HICs exceeds the threshold of 578 robots per 1,000 employees. Kamp and Gibaja [2021] find no direct link between domestic automation adoption and reshoring efforts, suggesting that other factors (e.g., declining sales projections offshoring destination countries, institutional uncertainty, rationalisation of global production apparatuses) might play a more influential role in backshoring decisions. Drawing from data spanning 41 countries and 15 sectors between 2005-2014, Carbonero et al. [2020] investigate the influence of robots on offshoring/reshoring decisions in high-income countries and the subsequent effects on employment in middle- and low-income nations. Their findings indicate that the adoption of robots in developed countries leads to a reduction in offshoring, which in turn results in a 5% employment drop in developing economies. Conversely, De Backer et al. [2018] show that use of industrial robots in developed economies may be slowing offshoring, but it does not lead to backshoring yet.

Empirical evidence seems more converging when looking at the US. Findings from Artuc et al. [2019] support the idea that automation and offshoring could potentially serve as substitutes, impacting similar job categories, highlighting that every additional robot per thousand workers in the US correspond to a 6.7% decrease in the growth of imports per worker from Mexico. The authors argue that such results are consistent with the notion that automation might be accelerating reshoring while decelerating offshoring. Similarly, Faber [2020] find that around 270,000 fewer jobs exist in Mexico between 1990 and 2015, suggesting that about 5% of US robots appear to be in direct competition with Mexican labour. This significant impact on employment is also reflected in decreased export values and a reduced number of export-producing facilities, further supporting the idea that robotic integration encourages reshoring. Similarly, Bonfiglioli et al. [2023] observe that the adoption of robots corresponds with a decline in offshoring activities.

Further insights drawn from survey data reveal a positive link between reshoring and automation adoption, particularly when a firm prioritizes high quality [Ancarani et al., 2019] or when firms' home countries actively advocate for I40 policies [Barbieri et al., 2022]. Given this background, we posit that robots can potentially act as a substitute for labour in offshoring destinations. Building on this premise, our first hypothesis is:

H1. *Higher AIRs adoption positively correlates with an increase in reshoring*.

2.3. Industrial Internet-of-Things (IoT)

The notion of the IoT dates back almost two decades, first emerging in the late 1990s [Egwuonwu et al., 2022]. However, the IoT ecosystem has only grown rapidly since 2010 [ITU, 2018]. IoT can be define as "*as systems containing ubiquitous everyday objects accessible through the Internet and equipped with (a) sensing, storing and processing capabilities that allow these objects to understand their environments; and (b) identifying and networking capabilities that allow them to communicate information about themselves and make autonomous decisions*[7]" [ITU, 2018]. More simply, IoT refers to the interconnected nature of devices and systems that communicate with each other over the internet. It represents a new stage in the evolution of ICT, where various devices, from household appliances to industrial machines, are networked together.

The cornerstone of IoT's strength lies in its ability to offer real-time transparency, traceability, adaptability, scalability, and flexibility [Zhou et al., 2015]. This real-time transparency ensures accurate and instantaneous information flow, vital for streamlining operations and transactions associated with the movement of goods. IoT's capability to track and trace products enhances overall business operations [Haddud et al., 2017]. Furthermore, the heightened information transparency fostered by IoT fosters greater trust between trading partners [Rejeb et al., 2019].

Information and transaction costs are essentially barriers that firms encounter during their business operations, especially when operating internationally. These costs arise when companies need to identify suitable trading partners, gather data on consumer preferences, familiarize themselves with regulations and technical specifications, and ensure contractual obligations are met [WTO, 2018]. As noted by Hallward-Driemeier and Nayyar [2017], IoT technology has the potential to reinforce GSCs through a reduction in coordination and transaction costs [UNCTAD, 2020; World Bank, 2020]. When integrated into supply chains, IoT allows companies to closely monitor and track their products, activities, and operations. This high level of communication and integration enhances the efficiency of industrial management and promotes digital collaboration between firms within the value chain [Wang et al., 2016]. Essentially, IoT ensures a transparent and trustworthy information flow about goods and services. Especially in manufacturing, where minimizing information and transaction costs is crucial, IoT becomes indispensable[8]. It effectively addresses challenges like a shortage of information and trust barriers in international transactions [WTO, 2018]. To the best of our knowledge, while there is plenty of speculation on the topic, empirical evidence regarding the impact of IoT adoption on reshoring, and offshoring, remains notably absent.

Building on the advancements in ICT, the IoT has the potential to facilitate an expansion of global supply chains, further directing production activities towards developing countries. Along with this, estimates from

[7] For an extended overview of definitions, refer to Haddud et al. [2017].

[8] Information and transaction costs account for around 7 per cent of total trade costs [WTO, 2018].

WTO [2018] project that adoption of digital technologies by developing countries could significantly increase their share in global trade, rising from 46% in 2015 to 57% by 2030. Considering the aforementioned premise and the unique features of IoT that we have discussed above, our second hypothesis is articulated as follows:

H2. *Higher IoT adoption is negatively associated with an increase in reshoring activities*.

2.4. Additive manufacturing

Additive manufacturing, also known as 3D printing, has its origins in the 1970s. However, it was not until the early 2000s that the technology began to mature, primarily within the research and development departments of a select few firms. A significant shift occurred between 2009 and 2013 when the costs of 3D printers plummeted, due to the expiring of key patents and the proliferation of related innovations [Felice et al., 2022]. This dramatic reduction in cost catalysed the widespread adoption and popularity of AM. Since then, the technology has seen rapid advancements, and the affordability of basic models has continued to improve [Laplume et al., 2016]. The International Organization for Standardization (ISO) in cooperation with the American Society for Testing and Materials (ASTM) defines additive manufacturing as "*the general term for those technologies that based on a geometrical representation creates physical objects by successive addition of material*" [ISO, 2015].

The transformative nature of AM on production processes stems from its inherent advantages over traditional production processes. With its start-to-finish capability, AM eliminates the need for multiple stages and machines. This technology allows for the creation of integrated components in one step, because manufacturing and assembly steps are combined when using AM [Strange and Zucchella, 2017], reducing assembly-related costs, time, and quality challenges [Tofail et al., 2018]. AM simplifies the supply chain by consolidating multiple components into a single part, thereby reducing the number of suppliers and supply chain complexity [Priyadarshini et al., 2023]. Therefore, AM stands as a transformative technology with the potential to revolutionise GSCs, altering their scope and distribution. This is primarily due to the inherent nature of the technology, which could promote rebundling. In essence, additive techniques might integrate all manufacturing stages—from raw material processing to the final product creation—into a singular, cohesive process, reversing the trend towards fragmented and globally dispersed supply chains [Buonafede et al., 2018; Felice et al., 2022; Hallward-Driemeier and Nayyar, 2017; Laplume et al., 2016; UNCTAD, 2020].

The interest of economists and management academics in AM has taken-off only in the last few years, while it has long been studied in engineering fields. Most of the debate about its influence on the structure and location of GSCs is based on theories, with limited concrete evidence to support them [Buonafede et al., 2018]. A notable study in this domain is by Freund et al. [2022], who highlighted a significant shift in the production of hearing aids from traditional manufacturing methods to 3D printing. This transition led to an approximate 60% surge in international trade of hearing aids. However, while the underlying mechanisms explored in the study are intriguing, it primarily focuses on a final product rather than trade in intermediates. A limited number of studies have directly examined the relationship between AM and GSCs. One such study by Buonafede et al. [2018] uses patent activity as an indicator for AM adoption across countries from 2000 to 2014. Their findings indicate that increased AM adoption is associated with reduced participation in GSCs, particularly in sectors most impacted by AM technologies. Their analysis suggests that the rise of AM may lead countries to rely less on intermediate products from abroad, instead boosting domestic production using AM techniques. De Beule et al. [2022] find that firms adopting AM are more likely to have a foreign production subsidiary compared to non-AM firms and operate them in more countries. This is attributed to AM technology favouring decentralised production, which is achieved by increasing the separability of design and production. Additionally, AM enables the shortening of supply chains and localisation of manufacturing closer to end-consumers. Finally, the authors suggest that concerns about knowledge appropriability prevent AM firms from outsourcing foreign production to other firms.

Given the unique characteristics of AM and the theories we have discussed above, we present our third hypothesis as follows:

> **H3.** *Increased adoption of AM positively correlates with a rise in reshoring activities, driven by the rebundling of production processes.*

3. Data and empirical strategy

3.1. Data sources

Our study aims to investigate the relationship between the reshoring phenomenon and the adoption of I40 technologies. In so doing, the empirical analysis relies on three main sources of the data. Firstly, to investigate at the macro-level reshoring activities, we use country-sectoral data on transactions of intermediate goods for manufacturing sectors from the OECD Inter-Country Input-Output (ICIO) tables (2021 edition)[9]. One of the primary advantages of the OECD 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 "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 from 1995 to 2018 (see Appendix A for the description of the ICIO's structure). 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 of our independent variables related to AIRs, AM and IIoT technologies[10] from Eurostat's Comext database. Comext offers in-depth statistics on international trade in goods collected electronically through customs when goods transit EU28's borders, ensuring comprehensive coverage of trade data for the EU28. It captures trade both within the EU and between EU Member States and

[9] Data available at https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm.
[10] Data available at https://ec.europa.eu/eurostat/comext/newxtweb/.

non-EU countries. Goods in Comext are classified using the Combined Nomenclature (CN) system, an extension of the 6-digit Harmonised Commodity Description and Coding System (HS). The CN classification, build on the HS, offers 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].

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 et al. [2021][11]. 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:

$$Reshoring = R_t = (\frac{DI_t}{FI_t}) - (\frac{DI_{t-1}}{FI_{t-1}}) \qquad (3)$$

where *DI* and *FI* represent domestic and foreign inputs for a specific sector and country in year *t*. Building on this formula, the R_t index can assume either negative or positive values; a necessary condition for reshoring is a positive input differential, that is $R_t > 0$. Negative values, however, do not infer offshoring but merely denote the nonoccurrence of reshoring [Krenz and Strulik, 2021]. Conversely, positive values explicitly indicate reshoring activities. To isolate the impact of reshoring, we follow the authors' approach and normalized negative values to zero. However, positive 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 such pitfall, we modify implement additional conditions that controls for production fluctuations, both downward and upward, over time. Specifically, this narrow reshoring measure [Krenz et al., 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 Eq. 3, yielding:

$$\Delta R_t = ln(\frac{DI_t}{FI_t}) - ln(\frac{DI_{t-1}}{FI_{t-1}}) \qquad (4)$$

The final form of our reshoring dependent variable—formally corresponding to a growth rate—will adopt the values from Eq. 4, when the three above mentioned conditions are met.

[11] Differently from us, use data from the WIOD data.

In our empirical analysis, we extend this approach originally proposed by Krenz and Strulik [2021] by distinguishing between supply reshoring and production reshoring. Our extension is based on the approach is grounded in the seminal work of Feenstra and Hanson [1999], who firstly introduced the concepts of broad (i.e., *supply*) and narrow (i.e., *production*) offshoring. Therefore, our study adopts two distinct reshoring measures. The first measure provides a comprehensive view, capturing aggregate intermediate inputs that each manufacturing sector sources from all other manufacturing sectors. In contrast, the second measure adopts a narrower lens, focusing solely on intermediate imports sourced from the same industry. The first version, defined as *supply* reshoring, is calculated as:

$$\Delta R_t^S = ln(\frac{DI_t^S}{FI_t^S}) - ln(\frac{DI_{t-1}^S}{FI_{t-1}^S}) \qquad (5)$$

where DI^S and FI^S denote the domestic and foreign intermediate goods, respectively, imported by the focal sector from all other industries. The second version, defined as *production* reshoring is calculated as:

$$\Delta R_t^P = ln(\frac{DI_t^P}{FI_t^P}) - ln(\frac{DI_{t-1}^P}{FI_{t-1}^P}) \qquad (6)$$

where DI^P and FI^P represent the domestic and foreign intermediate goods sourced from the same industry, respectively.

The rationale for differentiating between the *supply* and *production* versions depends on the scope of inputs a firm purchases. The *supply* version represents a comprehensive set of inputs, encompassing those intermediates that firms might not have the capacity or inclination to produce in-house. This broader measure reveals patterns of sourcing inputs but might not elucidate how trade variations influence a firm's task composition, as highlighted by [Hummels et al., 2018]. Conversely, Feenstra and Hanson [1999] advocate for a more restrictive approach, focusing solely on inputs falling within the same industrial classification. The underlying *production* version stems from the challenge in discerning a firm's in-house production capabilities. This approach enables us to capture the essence of reshoring in production, as it reflects the return to the home country of those production activities that firms could potentially carry out in-house but have previously chosen to offshore.

Figure 1 shows the distribution of the logarithmic change of reshoring intensity for all country-sector-year observations in our data set, for both the supply and production variations. The plots on the left panel of the figure show that our data follows approximately a normal distribution. For both supply and production measures, 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 right-hand side graphs the distribution of the corrected measures (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 weakly negative correlation, with a of -0.0936, between reshoring offshoring growth rates. Consequently, to enhance the robustness of our analysis, we incorporate the offshoring measure into our framework. Drawing upon the approach outlined by Feenstra and Hanson [1996b], we compute the offshoring measure as the logarithmic change in the share of imported manufacturing intermediate inputs relative to the total manufacturing intermediate inputs[12]:

$$\Delta Off_t = ln(\frac{FI_t}{DI_t+FI_t}) - ln(\frac{FI_{t-1}}{DI_{t-1}+FI_{t-1}}) \qquad (7)$$

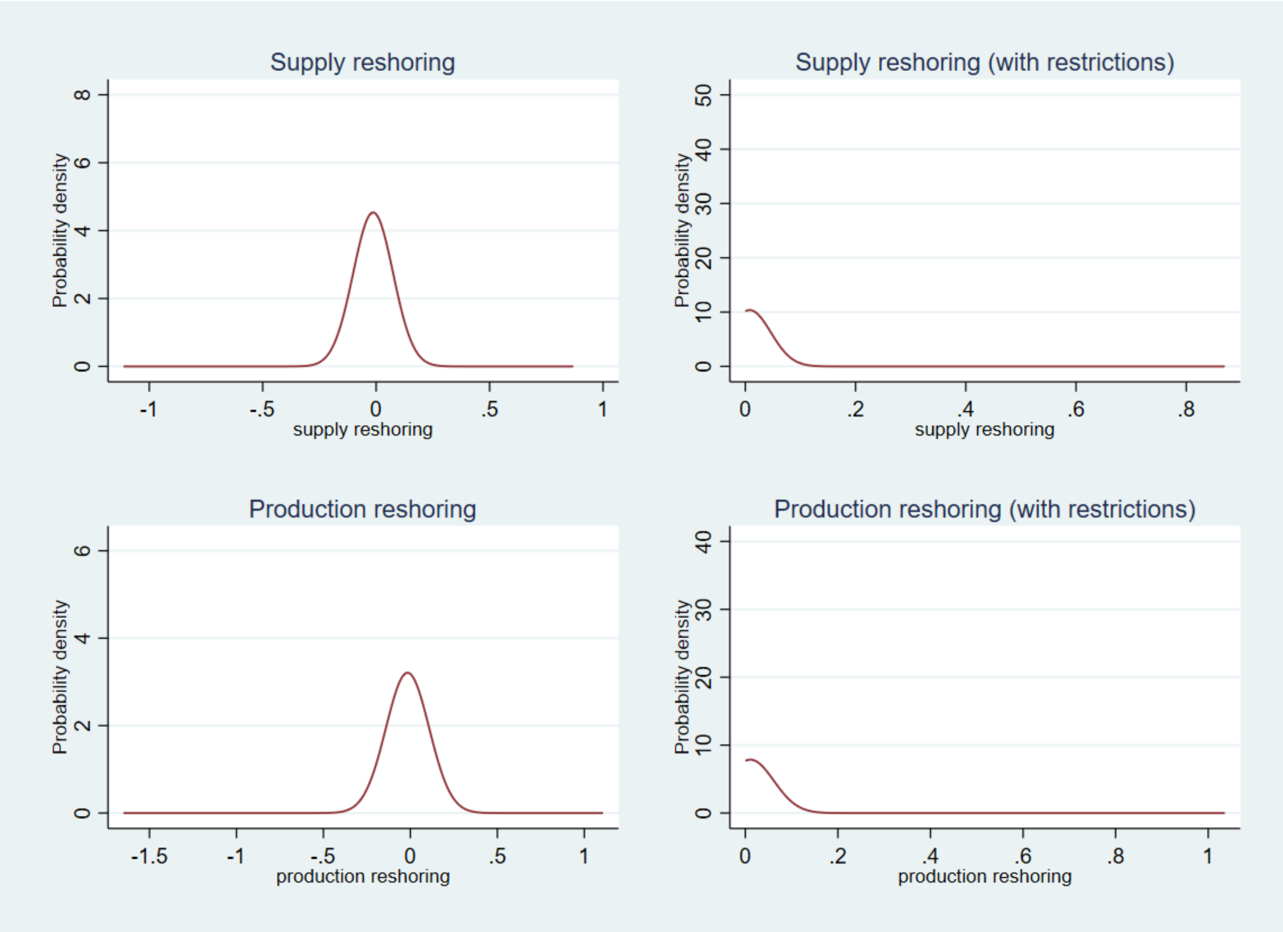
where *DI* and *FI* represent domestic and foreign inputs for a specific sector and country in year *t*. Analogous to our reshoring metric, we formulate two distinct variants of the offshoring measure: supply offshoring (ΔOff_t^S) and production offshoring (ΔOff_t^P). We compute reshoring and offshoring measures for the EU27 and the United Kingdom (UK)[13] and 10 manufacturing industries[14], spanning over the period 2009–2018.

[12] Feenstra and Hanson [1996b] labeled this metric as outsourcing. However, its essence more accurately measures offshoring, given it captures firms' source of intermediate goods and services. While the authors encompassed both goods and services as intermediates, our focus is exclusively on manufacturing intermediates.

[13] 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.

[14] 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 nonmetallic 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).

Figure 1: Reshoring probability density function



Notes: restrictions require 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.

Source: own elaboration using ICIO data.

3.3. Measuring adoption of advanced manufacturing technologies

To measure the adoption of the three I40 technologies central to our study (i.e., AM, IoT, and AIRs), we employ import data from the Comext database. As previously mentioned, this database provides detailed information for 8-digit product codes, which enable an accurate assessment of the adoption of the technologies under study. To identify the product codes in the CN that specifically capture imports of I40 technologies, we follow the approach developed by Castellani et al. [2022][15].

We acknowledge that I40 encompasses a broad spectrum of technologies, including Artificial Intelligence, Cloud Computing and Big Data Analytics. However, our analysis specifically targets AM, the IoT, and AIRs since these are hardware technologies, enabling their adoption to be proxied by trade data [Lamperti et al., 2023], while the other I40 technologies mentioned are mainly software-related and therefore hardly traceable if not via other data sources such as patents or survey data.

[15] See Table 8 in the Appendix B for the product codes related to I40 technologies.

We measure import flows of products and machinery that embody these technologies, hence that require the physical installation of specialised capital goods[16]. This approach is consistent with well-established methods in the literature [e.g., Acemoglu et al., 2020; Domini et al., 2021]. Specifically, we follow the measurement methodology delineated by Lamperti et al. [2023], which is similar to the adoption measurement used in related research [e.g., Acemoglu and Restrepo, 2020; Felice et al., 2022]. In order to measure the adoption of I40 technologies, we first aggregate import values for each product code related to each individual technology at the country-year level. Then, given the absence of granular sectoral import data, Lamperti et al. [2023] suggest using intermediates-weighted proportions of imports. This is achieved by: (a) analysing the fraction of a country's I40-relevant imports relative to its total imports originating from sectors producing each I40 technology; and (b) incorporating cross-national and cross-sectoral data on imported intermediate goods sourced from sectors producing each technology and used by all other manufacturing sectors[17]. We mathematically formalise the computation process in Appendix C.

In our regression analysis, we normalise our variables measuring the stock of AIRs, AM, and IoT imports per 1,000 workers. We source the number of persons engaged, encompassing both employees and the self-employed, at the country-sector level from the EU KLEMS database's 2023 revision. Table 1 presents summary statistics for our dependent and independent variables.

Table 1: Summary statistics of the main variables

						Correlation		
	Mean	SD	Min	Max	Obs	AM	IoT	$AIRs$
ΔR^S	0.0	0.0	0.0	0.9	5320	-0.007	-0.035	-0.140
ΔR^P	0.0	0.1	0.0	1.0	5320	0.011	0.008	-0.102
ΔOff^S	0.0	0.1	-0.9	1.1	5040	-0.014	0.033	0.082
ΔOff^P	0.0	0.1	-1.1	1.6	5040	-0.010	0.024	0.057
$AM = ln(\frac{K^{AM}}{1{,}000emp})$	-8.0	1.6	-13.4	-3.0	2620	1.000	0.382	0.298
$IoT = ln(\frac{K^{IoT}}{1{,}000emp})$	-0.5	2.3	-7.7	9.0	2705		1.000	0.504
$AIRs = ln(\frac{K^{AIRs}}{1{,}000emp})$	-9.1	2.4	-17.9	-3.5	2666			1.000

Notes: ΔR^S= reshoring supply; ΔR^P = reshoring production. Both reshoring measures require 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. ΔOff^S= offshoring supply; ΔOff^P = offshoring production; AM = additive manufacturing; IoT = internet-of-things; AIRs = advanced industrial robots.

[16] Castellani et al. [2022] develop two proxies to measure the adoption of I40 technologies. The first proxy is based on the import of I40 capital goods. The second, termed *net consumption*, is calculated using the formula: net consumption = (production + import - export). This approach allows them to consider both domestic and foreign sources of capital investments in I40 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 I40 technologies in some countries and for some product codes. Consequently, they use this measure primarily to validate the import-based proxies for I40 technology adoption, documenting a strong correlation between the import and net consumption measures, with pairwise correlation coefficients of 0.83 for AIR, 0.78 for AM, and 0.66 for IIoT.

[17] Sourced from the WIOD dataset [Timmer et al., 2015].

4. Descriptive evidence on reshoring

In Section 2, we already discussed the existing anecdotal evidence pointing at an increasing trend in reshoring and its possible link with a future potential shift towards deglobalisation [Antràs, 2020]. Here, we move on such discussion by turning to the data. Figure 2 and Figure 3 present a full-scale view of the trends in reshoring and offshoring[18]. In Figure 2, we plot the 5-period moving average of our supply (Eq. 5) and production reshoring (Eq. 6) measures. Similarly, Figure 3 plots the 5-period moving average of the supply and production offshoring measures (Eq. 7). At first glance, changes in reshoring and offshoring trends appear to exhibit an inverse relationship. The early 2000s period, leading up to the 2008's financial crisis—a period often characterized as one of hyper-globalisation—featured a noticeable and steady increase in offshoring across Europe, paired with a decline in reshoring. This trend underscores the prevailing economic dynamic of those years, characterised by a surge in global integration and production fragmentation. Conversely, observing trends for the post-2008's financial crisis period, two key insights emerge. First, this period features a slight increase in domestic production across European countries (i.e., rising reshoring). These years also correspond to the launch of most I40 industrial policy initiatives [Mariani and Borghi, 2019] and rising adoption of I40 technologies [Castellani et al., 2022]. However, this surge rapidly expires and reshoring rapidly drops after 2010, settling down in 2018 at about half of its average pre-2008 value. Second, despite offshoring trend has not returned to its pre-crisis levels (excluding the spike observed in 2011), it experienced a consistent recovery, going back to its early 2000's value. Notably, despite the downward trend observed for reshoring and the more constant one for offshoring, absolute values score consistently higher for the former.

Table 2 presents the top ten countries in terms of reshoring and offshoring activities for both production and supply, with the data representing mean values over the 2000-2018 period. Over this period, Greece exhibited the highest domestic foreign input differential in production, with a mean of 0.099 percentage points (p.p.). Other countries that have shown significant reshoring in production include Croatia, Lithuania, Romania, and Latvia. Regarding supply reshoring, Bulgaria exhibits the highest rate with a mean of 0.047 p.p. The table reveals that several countries listed under production reshoring also demonstrate reshoring trends in supply. Interestingly, a majority of the countries highlighted in the reshoring lists are from Central and Eastern Europe (CEE). At first glance, this may appear counterintuitive given that these nations are traditionally viewed as offshoring destinations. Nonetheless, the growing integration of these countries into global value chains (GSCs) has made it more conducive for Western companies to reshore or increase their production closer to home, specifically in Central and Eastern Europe. Additionally, while certain nations are popular offshoring destinations for more advanced economies, they can simultaneously engage in offshoring activities to, or reshore from, other economically less developed nations [Krenz and Strulik, 2021]. Examining the offshoring metrics, it's evident that Western European countries, such as the Netherlands, Austria, and Germany,

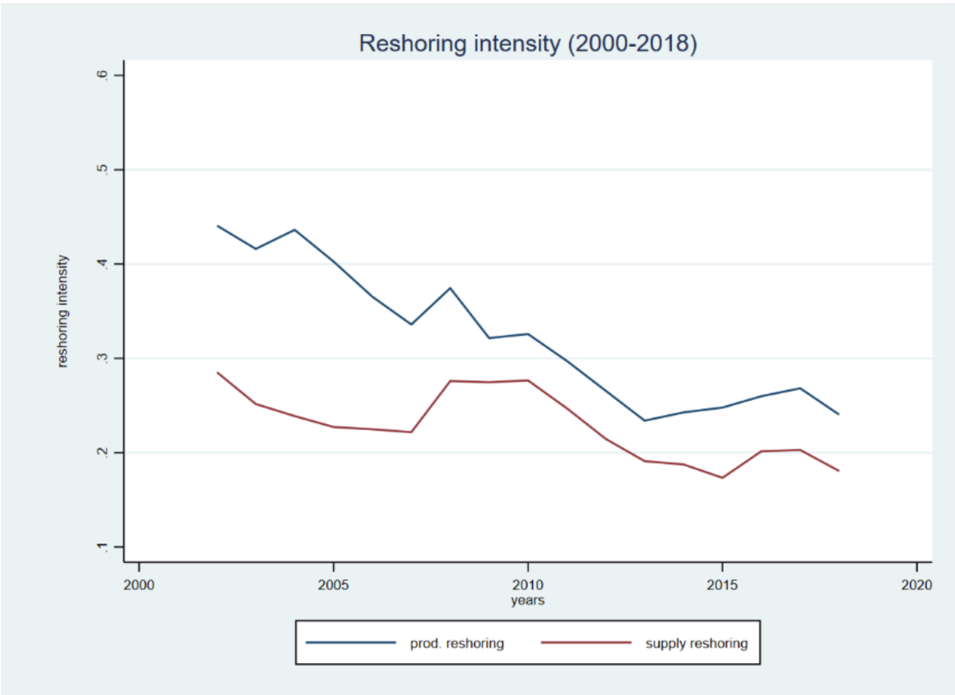
[18] See Appendix D for additional figures graphically illustrating the evolution of the reshoring measure over time for selected countries.

predominantly drive the list. The Netherlands takes the lead in both offshoring variants. However, Romania notably stands out in terms of production offshoring.

Table 3 and Table 4 present the rankings based on mean values for reshoring and offshoring across industries over the period 2000-2018. Table 3 shows that the industries with the highest reshoring values are highly heterogeneous. For reshoring production, the manufacture of furniture sector (traditionally, a labour-intensive sectors) stands out with a mean value of 0.071 p.p. This is closely followed by the manufacture of wood, paper, and printing (a capital-intensive sector), and by the manufacture of computer, electronic, optical products (a high-tech, capital-intensive sector). Looking at reshoring supply, reshoring trends seem to follow different logics: the manufacture of furniture is among the sectors with lower values, while the manufacture of basic metals and fabricated metals (all labour-intensive industries) exhibits more substantial reshoring activity.

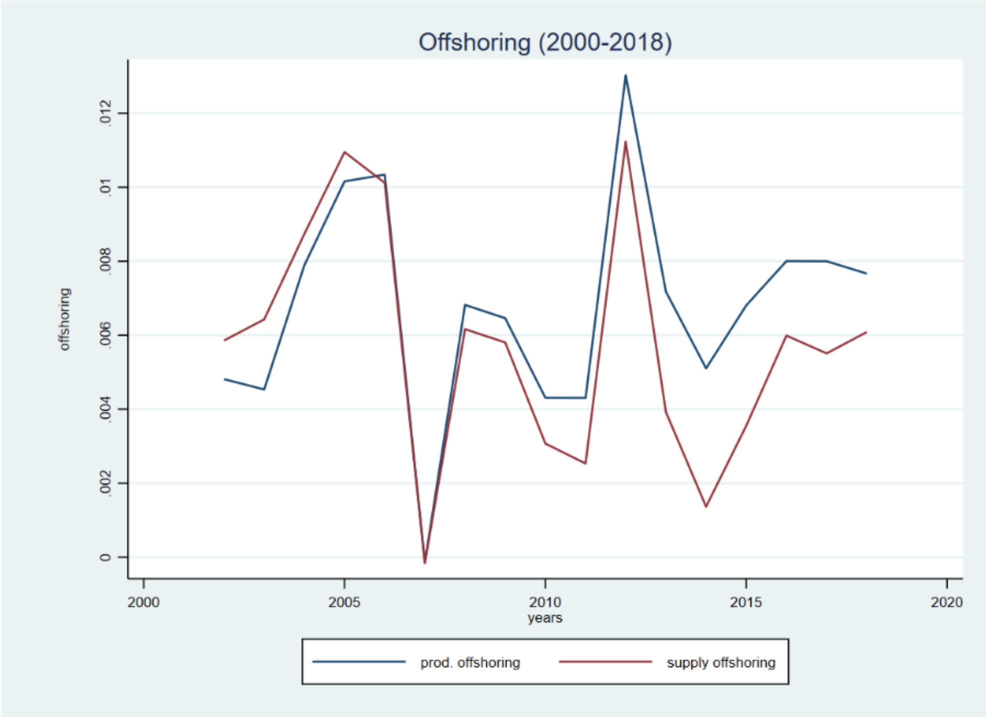
Concerning offshoring trends in Table 4, capital-intensive industries predominantly lead the list, with the notable exception the textile, apparel and leather sector (predominantly labour-intensive). It is also worth noting the magnitude of the values in Tables 2, 3 and 4: while reshoring values are higher, offshoring values are lower, suggesting a deceleration in the growth of offshoring activities.

Figure 2: Reshoring trends



Notes: 5-period moving average of ΔR_t^S and ΔR_t^P. It is subjected to the constraints 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.

Figure 3: Offshoring trends



Notes: 5-period moving of ΔOff_t^S *and* ΔOff_t^S.

Table 2: Top 10 reshoring and offshoring countries

Reshoring Production	mean (p.p.)	Reshoring Supply	mean (p.p.)	Offshoring Production	mean (p.p.)	Offshoring Supply	mean (p.p.)
Greece	0.099	Bulgaria	0.047	Netherlands	0.018	Netherlands	0.016
Croatia	0.048	Greece	0.045	Sweden	0.012	Austria	0.011
Lithuania	0.044	Croatia	0.033	Romania	0.012	France	0.010
Romania	0.040	United Kingdom	0.031	Germany	0.011	Germany	0.010
Latvia	0.039	Lithuania	0.023	Austria	0.011	Greece	0.009
Bulgaria	0.036	Latvia	0.023	Lithuania	0.011	Czechia	0.008
United Kingdom	0.035	Slovakia	0.012	France	0.009	Spain	0.008
Estonia	0.031	Romania	0.011	Spain	0.009	Romania	0.008
Belgium	0.030	Finland	0.011	Czechia	0.009	Portugal	0.007
Finland	0.029	Denmark	0.009	Latvia	0.008	Lithuania	0.007
Total EU	0.029	Total EU	0.018	Total EU	0.006	Total EU	0.004

Notes: reshoring is calculated as the average, over the period 2000-2018, of ΔR_t^S *and* ΔR_t^P. *It is subjected to the constraints* $R_t > 0$ *and the changes in* $DI_t - DI_{t-1}$ *and* $FI_t - FI_{t-1}$ *are not simultaneously positive, negative, or zero. Offshoring is determined as the average for the period 2000-2018 of* ΔOff_t^S *and* ΔOff_t^P.

Table 3: Reshoring trends by industry

Reshoring Production	mean (p.p.)	Reshoring Supply	mean (p.p.)
Manufacture of furniture	0.071	Manufacture of food products	0.021
Manufacture of wood, paper, printing and reproduction	0.034	Manufacture of wood, paper, printing and reproduction	0.021
Computer, electronic, optical products	0.023	Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.021
Manufacture of food products	0.023	Computer, electronic, optical products	0.019
Manufacture of textiles, wearing apparel, leather and related products	0.022	Manufacture of textiles, wearing apparel, leather and related products	0.018
Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.022	Coke and refined petroleum products and Chemicals	0.015
Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	0.021	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	0.014
Coke and refined petroleum products and Chemicals	0.019	Manufacture of machinery and equipment n.e.c.	0.013
Manufacture of machinery and equipment n.e.c.	0.017	Manufacture of furniture	0.013
Manufacture of rubber and plastic products and other non-metallic mineral products	0.016	Manufacture of rubber and plastic products and other non-metallic mineral products	0.012
Total EU	0.027	Total EU	0.017

Notes: reshoring is calculated as the average, over the period 2000-2018, of ΔR_t^S and ΔR_t^P. It is subjected to the constraints Rt >0 and the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

Table 4: Offshoring trends by industry

Offshoring Production	mean (p.p.)	Offshoring Supply	mean (p.p.)
Coke and refined petroleum products and Chemicals	0.011	Coke and refined petroleum products and Chemicals	0.008
Manufacture of textiles, wearing apparel, leather and related products	0.011	Manufacture of textiles, wearing apparel, leather and related products	0.008
Manufacture of food products	0.008	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	0.007
Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	0.007	Manufacture of food products	0.006
Manufacture of rubber and plastic products and other non-metallic mineral products	0.006	Manufacture of furniture	0.006
Manufacture of furniture	0.006	Manufacture of rubber and plastic products and other non-metallic mineral products	0.006
Computer, electronic, optical products	0.005	Manufacture of machinery and equipment n.e.c.	0.004
Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.004	Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.004
Manufacture of machinery and equipment n.e.c.	0.004	Manufacture of wood, paper, printing and reproduction	0.004
Manufacture of wood, paper, printing and reproduction	0.004	Computer, electronic, optical products	0.004
Total EU	0.006	Total EU	0.006

Notes: Offshoring is determined as the average for the period 2000-2018 of ΔOff_t^S *and* ΔOff_t^P.

5. Econometric strategy

Our analysis sets out to investigate the distinct effects of the adoption of AIRs, AM, and the IIoT on reshoring and offshoring phenomena spanning the years 2009 to 2018, for the (former) EU28 countries. The initial phase of our examination focuses on the broad impacts at the aggregate level. For this purpose, we set up the following baseline reduced-form equation:

$$Y_{i,j,t} = \beta_0 + \beta_1 AM_{i,j,t-1} + \beta_2 IoT_{i,j,t-1} + \beta_3 AIRs_{i,j,t-1} + \gamma_{i,s} + FE_{i,j,t} + u_{i,j,t} \qquad (8)$$

where $Y_{i,j,t}$ is our dependent variable for industry *j* in country *i* at time *t*. Since we have four dependent variables—namely, $\Delta R^S_{i,j,t}$, $\Delta R^P_{i,j,t}$, $\Delta Off^S_{i,j,t}$ and $\Delta Off^P_{i,j,t}$—we estimate four different regressions; $AM_{i,j,t-1}$, $IOT_{i,j,t-1}$, $AIRs_{i,j,t-1}$, are our log-transformed explanatory variables, normalised by 1,000 persons employed in the same country-sector at time *t*. Our identification strategy is based on the use of the within estimator (i.e., we include country-sector fixed effects $\gamma_{i,j}$ in each of our specifications) to account for the potential unobserved heterogeneity. We further incorporate additional fixed effects (i.e., $FE_{i,j,t}$) in our model[19]. Specifically, in some 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. Alternatively, we test specifications of our model in which we control for sector-specific time trends $\theta_{j,t}$ capturing unobserved factors that vary across sectors and over time, such as 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. This 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 on our results capturing 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 et al., 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, starting with the geographical locations of the intermediate inputs. Following our conceptualisation in Section 3.3.2, 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 3.5 and Figure 3.6 illustrate 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,

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[19] We use a linear model with high-dimensional fixed effects, using the *reghdfe* package in Stata implemented by Correia [2016].

post-financial crisis, this growth seems to stabilise. Furthermore, as Castellani et al. [2022] note, the year 2009 is usually recognized as the starting point of a global wave of technological innovation around I40. These considerations highlight the importance of focusing on Asia as a pivotal region for analysing the dynamics of offshoring and the potential for reshoring activities.

To measure reshoring from Asia, we employ the domestic–Asia input differential:

$$\Delta R_t^{Asia} = ln(\frac{DI_t}{FI_t^{Asia}}) - ln(\frac{DI_{t-1}}{FI_{t-1}^{Asia}}) \qquad (9)$$

Asia with the aggregate measure, we formulate the two variations supply ($\Delta R_t^{S,Asia}$) and production ($\Delta R_t^{P,Asia}$) reshoring from Asia. Further, for offshoring we compute the following variable:

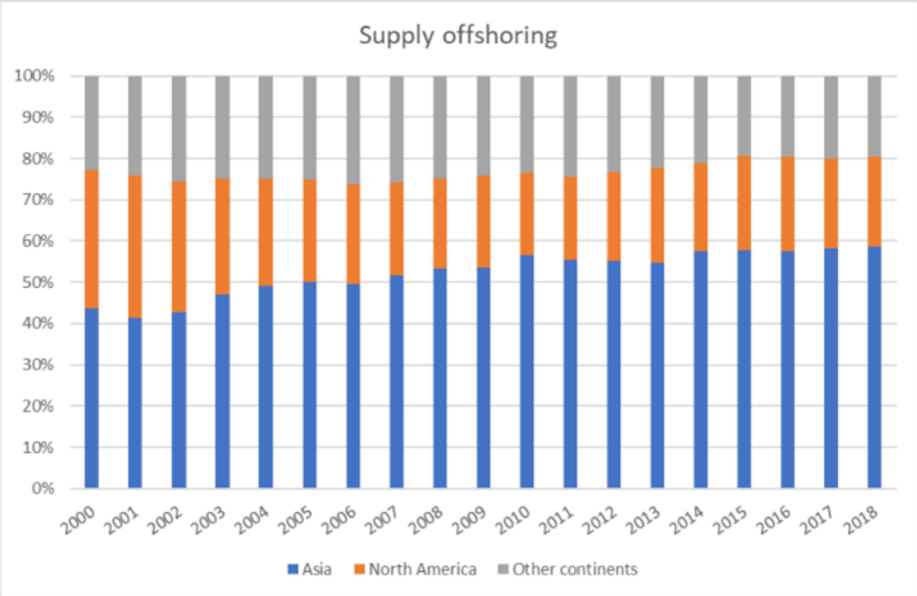
$$\Delta Off_t^{Asia} = ln(\frac{FI_t^{Asia}}{DI_t + FI_t}) - ln(\frac{FI_{t-1}^{Asia}}{DI_{t-1}+FI_{t-1}}) \qquad (10)$$

Again, this includes the two distinct variations of supply ($\Delta Off_t^{S,Asia}$) and production ($\Delta Off_t^{P,Asia}$).

To further understand the complexities of reshoring and offshoring trends, our research will highlight the geographical distinctions between developing and developed countries in Asia[20]. 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 labour 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 I40 technology adoption, could lead to divergent decisions regarding the relocation of production back to European countries.

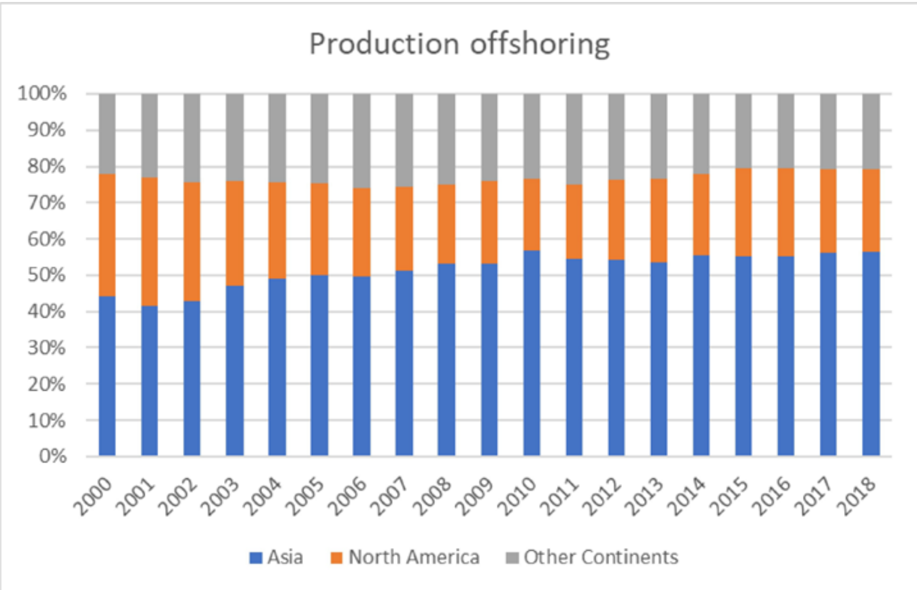
[20] As for UNCTAD classification, Asia developing includes the following countries: Brunei Darussalam, Cambodia, China, India, Hong Kong, Laos, Malaysia, Myanmar, Philippines, Singapore, Taiwan, Thailand, Viet Nam, Kazakhstan, and Indonesia. Asia developed includes: Japan, South Korea.

Figure 4. Supply offshoring toward Asia



Source: own elaboration using ICIO data

Figure 5. Production offshoring toward Asia



Source: own elaboration using ICIO data

6. Results

In this section, we present the findings from our econometric analysis. We first examine the influence of I40 technologies—specifically AM, IoT and AIRs—on overall trends in reshoring and offshoring. Then, we examine how these technologies influence the relocation of production back from Asian economies and toward them, with a particular focus on distinguishing between developed and developing nations within Asia. Before introducing our main findings, we assess the presence of unit roots in our data using Im, Pesaran, and Shin's

(2003) procedure (Table 9 in the Appendix E). Results confirms the stationarity of all variables within our models. Furthermore, to investigate the cointegrating relationship among the model's variables, we apply the panel test by Pedroni (2004) (Table 10 in the Appendix E). Our findings substantiate a significant long-run cointegrating relationship among the model variables, evidenced by residuals from both Phillips–Perron (PP) and Augmented Dickey–Fuller (ADF) tests, significant at the 1% confidence level.

6.1. The effect of I40 technologies on reshoring and offshoring

Table 5 presents the regression results for changes in reshoring and offshoring activities. Columns (1) and (2) assess the link between I40 technologies and our supply measure of reshoring, while columns (3) and (4) focus on the production measure[21]. In line with our hypotheses, we find that on average the adoption of AIRs positively correlates with an increase in reshoring supply (columns (1) and (2)) but not with production reshoring (columns (3) and (4)): a 1% increase in robots investment per 1,000 employees associates with about a 0.01 percentage points (p.p.) increase in ΔR_t (significant at the 1% level). This suggest H1 to be partially supported. Conversely, the adoption of IoT technology is negatively related to reshoring production only. The significant coefficients in columns (3) and (4) suggest that a 1% increase in IoT investment per 1,000 employees leads to a decrease in the growth rate of ΔR_t of about 0.008 p.p. As IoT adoption rises, reshoring tends to grow at a slower rate, suggesting H2 to be supported. For AM, we find no statistically significant results, indicating no clear average relationship with reshoring activities at the country-industry level, lending no support to H3.

Columns (5)-(8) in Table 5 extend our investigation to the effects of I40 technologies on offshoring activities. Across the models, the coefficients for AM and AIRs are consistently negative, although not statistically significant. Conversely, a positive and significant (at the 10% level) relationship emerges between the IoT and offshoring activities on the supply side, further supporting H2. Specifically, an increment of 1% in IoT capital per worker is associated with around 0.012 p.p. increase in the growth rate of supply offshoring, as evidenced in columns (5) and (6) respectively. However, this relationship does not persist on the production side, where the coefficients for IoT are negative and not statistically significant.

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. All in all, our findings lend empirical support to our theoretical expectations and suggest that the adoption of I40 technologies could be reshaping the geography of production in ways that are consistent with our initial predictions.

[21] We note that reported coefficients can be interpreted as semi-elasticities.

Table 5: I40 technology and effects on reshoring and offshoring

	Reshoring				Offshoring			
	Supply (ΔR_t^s)		Production (ΔR_t^P)		Supply (ΔOff_t^s)		Production (ΔOff_t^P)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM	0.00175	0.00156	-0.00149	-0.00102	-0.00465	-0.00542	-0.00366	-0.00439
	(0.00180)	(0.00177)	(0.00275)	(0.00258)	(0.00517)	(0.00518)	(0.00879)	(0.00838)
IoT	-0.00432	-0.00449	-0.00809**	-0.00737**	0.0121*	0.0123*	-0.00291	-0.00422
	(0.00297)	(0.00323)	(0.00345)	(0.00361)	(0.00651)	(0.00668)	(0.0145)	(0.0142)
AIRs	0.00950***	0.00934***	0.00150	0.00268	-0.00598	-0.00680	-0.00895	-0.0131
	(0.00338)	(0.00338)	(0.00360)	(0.00375)	(0.00797)	(0.00795)	(0.00928)	(0.00934)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes		Yes		Yes		Yes	
Time-sector FE		Yes		Yes		Yes		Yes
N Obs.	2358	2358	2358	2358	2358	2358	2358	2358
R^2	0.141	0.158	0.139	0.169	0.192	0.212	0.118	0.155

*Notes: Robust standard errors 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.*

6.2. I40 technologies, reshoring and offshoring from and towards Asia

In recent decades, Asia has emerged 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 6 and Table 7 investigate the effects of I40 technologies on the restructuring of supply chains with Asia.

Table 6 shows that the coefficients for AIRs are positive and statistically significant across almost 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. Specifically, a 1% increase in AIRs adoption is correlated with a higher reshoring growth rate of about 0.03 p.p. (both in the case of supply and production), on average, for all Asian countries, from 0.023 (supply) to 0.032 p.p. (production) for developing Asian countries, and from 0.033 (supply) to 0.063 p.p. (production) for developed Asian countries.

Looking at IoT adoption, the analysis reveals that an increase related investment associates with a decrease in the growth rate reshoring, yet mostly across developing Asian countries. IoT coefficients are always negative and reach statistical significance at the 10% or 5% levels in models related to all Asian countries and developing ones, respectively. The larger magnitude of coefficients in the case of developing Asian economies indicates that results for Asia are primarily driven by developing countries. Specifically, a 1% increase in IoT adoption relates with a drop in the growth rate of reshoring by approximately 0.017 p.p. in the case of all Asian countries, and by approximately 0.02 p.p. for developing economies. This negative relationship only works in the case of supply reshoring (i.e., it is not statistically significant in the case of production measures). As for the aggregate investigation, AM coefficients are never statistically significant, suggesting that the technology has no clear effect on reshoring activities over the observation period and across the different regions examined.

Table 37 complements our examination by presenting the findings for offshoring variables. The data indicates that there is a negative average relationship between the adoption of AIRs and offshoring activities across all Asia, as well as when distinguishing between developing and developed countries within the region. In detail, a 1% increase in AIRs adoption is associated with a decrease in offshoring activities towards Asia by approximately 0.055 p.p., larger in magnitude (i.e., about -0.065 p.p.) in the case of developed countries in the region. Table 7 further shows that, although the sign of IoT adoption coefficients is consistent with our expectations—hence, suggesting 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 tides with other Western regions. Finally, our findings for AM mirror once more previous results on this technology, yet highlighting some heterogeneity in the sign of the coefficients when looking at different activities (supply vs production) and country groups in Asia (developed vs developing).

Table 6: I40 technology and effects on reshoring from Asia

	Asia				Asia developing				Asia developed			
	Supply		Production		Supply		Production		Supply		Production	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AM	0.00564	0.00398	-0.00613	-0.00697	0.00354	0.00217	-0.00417	-0.00570	0.00345	0.00328	-0.00798	-0.00717
	(0.00692)	(0.00686)	(0.0121)	(0.0112)	(0.00537)	(0.00545)	(0.0122)	(0.0118)	(0.0137)	(0.0133)	(0.0196)	(0.0186)
IoT	-0.0165*	-0.0174*	-0.0192	-0.0165	-0.0202**	-0.0203**	-0.0164	-0.0126	-0.00240	-0.00387	0.0124	0.00927
	(0.00895)	(0.00947)	(0.0130)	(0.0135)	(0.00914)	(0.00952)	(0.0140)	(0.0139)	(0.0172)	(0.0175)	(0.0219)	(0.0222)
AIRs	0.0296**	0.0289**	0.0307*	0.0336**	0.0234**	0.0229**	0.0297*	0.0321**	0.0335*	0.0329*	0.0583*	0.0639*
	(0.0123)	(0.0121)	(0.0156)	(0.0167)	(0.0112)	(0.0110)	(0.0160)	(0.0158)	(0.0175)	(0.0176)	(0.0316)	(0.0326)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes		Yes		Yes		Yes		Yes		Yes	
Time-sector FE		Yes		Yes		Yes		Yes		Yes		Yes
N Obs.	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358
R^2	0.145	0.169	0.166	0.203	0.140	0.162	0.153	0.190	0.157	0.178	0.166	0.217

*Notes: Robust standard errors 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 7: I40 technology and effects on offshoring towards Asia

	Asia				Asia developing				Asia developed			
	Supply		Production		Supply		Production		Supply		Production	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AM	-0.00360	-0.00236	0.00350	0.00543	-0.00883	-0.00844	-0.0141	-0.0130	0.0131	0.0162	0.0306	0.0332
	(0.0103)	(0.0101)	(0.0162)	(0.0148)	(0.00971)	(0.00961)	(0.0157)	(0.0145)	(0.0209)	(0.0207)	(0.0314)	(0.0292)
IoT	0.0108	0.0129	0.0132	0.0185	0.00547	0.00625	0.00306	0.00413	0.00590	0.0171	0.00628	0.0348
	(0.0132)	(0.0140)	(0.0211)	(0.0212)	(0.0135)	(0.0147)	(0.0198)	(0.0199)	(0.0261)	(0.0270)	(0.0435)	(0.0446)
AIRs	-0.0541***	-0.0573***	-0.0392*	-0.0470**	-0.0455***	-0.0501***	-0.0206	-0.0294	-0.0669**	-0.0642**	-0.0801*	-0.0841**
	(0.0170)	(0.0173)	(0.0224)	(0.0207)	(0.0175)	(0.0174)	(0.0253)	(0.0231)	(0.0261)	(0.0262)	(0.0424)	(0.0410)
Country-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes		Yes		Yes		Yes		Yes		Yes	
Time-sector FE		Yes		Yes		Yes		Yes		Yes		Yes
N Obs.	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358	2358
R^2	0.119	0.160	0.0929	0.193	0.112	0.160	0.0851	0.183	0.0916	0.121	0.0626	0.149

*Notes: Robust standard errors 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.*

7. Discussion and conclusions

In recent years, the dynamics of the global economy have undergone significant changes, sparking debates both within and outside academic circles about a potential shift toward deglobalisation and more resilient global value chains in the aftermath of global turmoil and economic shocks. Central to this discussion is the concept of reshoring—the process of moving previously offshored activities back (or closer) to a company's home country. This trend has gained momentum against the backdrop of the fourth industrial revolution, or Industry 4.0, characterized by advancements in AM, the IoT, and AIRs identified as the "game-changing" technologies in manufacturing [Eurofound, 2018].

These technological innovations are increasingly recognised as drivers of reshoring [Javorcik, 2020], contributing to a burgeoning corpus of research investigating such connections [Buonafede et al., 2018; De Backer et al., 2018; Artuc et al., 2023; Stapleton and Webb, 2020; Krenz et al., 2021]. Notably, while there is a preponderance of studies examining the impact of robotics on reshoring and offshoring, there is a relative paucity of comprehensive analyses that consider the collective influence of multiple I40 technologies. This oversight is significant because, despite the transformative potential of AIRs, the real-world implications of the I40 transformation are complex and varied. Indeed, these technologies are distinct in their characteristics and functionalities, they operate on different stages of the production process and affect distinct aspects of manufacturing, thereby influencing global supply chains in diverse ways. 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 deglobalisation continues, it is essential to develop a nuanced understanding of how each I40 technological advancement contributes to the reshaping of GSCs. Therefore, our contribution provides a multi-faceted exploration of I40 technologies, offering a broader perspective on their implications for reshoring. By doing so, we fill the gap in the literature and provide a more holistic view of how the fourth industrial revolution is reshaping the landscape of global manufacturing and production.

Our results indicate a significant positive average relationship between robot adoption in European countries and overall reshoring of supply activities. As we articulate in Section 2, this finding may be attributed to the positive impact of AIRs on productivity and production costs: as companies benefit from enhanced efficiency and reduced costs due to robotic automation, they may become less concerned about the costs associated with sourcing supplies. Consequently, this could lead to an increase in the number of domestic suppliers, as the imperative for cost minimization diminishes in the face of improved operational efficiency. Conversely, AIRs seem not able to trigger consistent reshoring in production activities, as the sunk costs incurred by firms when deciding to relocate production activities may not yet break-even with the efficiency gains from automation [Antràs, 2020]. All in all, our findings corroborate the existing literature on robots, reshoring, offshoring and their broader impact on GSCs [Artuc et al., 2019; Carbonero et al., 2020; Faber, 2020; Krenz et al., 2021].

Regarding the impact of the IoT, to the best of our knowledge, we provide a first evidence supporting the notion that increased IoT adoption corresponds to a diminishing trend in reshoring of production activities and rising offshoring trend in supply activities. Following prior studies on ICTs, this is likely due to IoT's role in reducing coordination and transaction costs [Hallward-Driemeier and Nayyar, 2017]. Finally, despite substantial theoretical discussion and some preliminary evidence exist on the potential role of AM in reversing the fragmentation pattern characterising GSCs, we find no evidence of such influence on either reshoring or offshoring activities, over the last decade. Despite ever growing adoption and widespread technological maturity [Felice et al., 2022; Laplume et al., 2016], the effect this technology may exert on GSCs reconfiguration is still likely to be bounded to few, highly exposed, industries [Buonafede et al., 2018].

Our investigation further delves into the geographical heterogeneity of reshoring activities, with a particular 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 labour markets and favourable manufacturing environments. By exploring the distinct patterns that characterise developing and developed Asian nations, our study uncovers nuanced insights into how I40 technologies are influencing economic behaviours across diverse economic landscapes. Such findings suggest that the integration of AIRs within European industries may be incentivising 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, and is consistent across both supply and production measures. IoT investments seem to lower the growth rate of reshoring from the region, although this trend is confined to developing countries. Coherently with our expectations, the results highlight an inverse relationship between investments in robots and the propensity of European companies to offshore to Asian markets, suggesting that as automation spreads, companies tend to bring production processes closer to their operational base, reducing reliance on foreign manufacturing thanks to the improved efficiency and cost-effectiveness. Admittedly, our results on the role of IoT and AM in affecting reshoring and offshoring activities across Asia are inconclusive. While there is considerable speculation regarding the reconfiguration of global supply chains in the wake of the I40 revolution, it is essential to recognize that these technologies do not universally drive trends towards reshoring. Instead, as our analysis illustrates, the adoption of new digital technologies may incentivize movements in both directions, i.e. towards the consolidation of production domestically or towards enhanced fragmentation and offshoring. Each technology exerts distinct effects on these dynamics, in turn, implying a multifaceted—rather than unidirectional—on production geographies. Policymakers aiming to devise strategies to encourage reshoring must consider these differential effects. Tailored policies that recognize the specific influences of each technology will be crucial in effectively leveraging I40 to shape the desired outcomes in global production networks.

7.1. Limitations and future research

While our study provides valuable insights into the adoption of different technologies and their association with the reconfiguration of GSCs, it has its own drawbacks. Firstly, our analysis is concentrated on the reconfiguration of GSCs within the EU context. This focus offers a detailed view of trends characterizing Europe but does not account for heterogeneity within member states or compare these trends with other major economic players such as the US. Future studies could provide valuable insights by investigating intra-EU variations and by drawing comparisons with the supply chain dynamics in the US, which may exhibit different patterns due to distinct regulatory environments, labour market conditions, and technology adoption rates. Secondly, while our study investigates the impact of AM, the IoT, and AIRs on reshoring activities, it does not encompass the broader spectrum of supply chain reconfigurations, such as diversification and regionalization strategies. Future work is needed to provide a more comprehensive analysis considering whether these technologies also drive other forms of GSC restructuring. Moreover, understanding how these potential effects coexist with reshoring could elucidate the complex interplay between technological advancements and GSC strategies, offering a holistic view of the I40 era's impact on global trade patterns.

Appendix A: Global Inter-Country Input-Output Tables structure

Figure 6 illustrates the ICIO table, encompassing *n* countries, with each country having *m* sectors. We focus on the $m \times m$ matrix *Z*, which details the intermediate inputs from country *c* to country *i*. More precisely, we consider the intermediate goods produced by sector *s* in country *c* and used by sector *j* in country *i*. This specific interaction is represented by the element z_{sj}^{ci} within the matrix. For our analysis we consider inputs from 2-digit sectors 10 to 33 of every country other than the home country to gauge foreign inputs, whereas inputs within the home country were used to measure domestic inputs. Given z_{sj}^{ci}, we can express the domestic and foreign inputs for sector j in country i as follows:

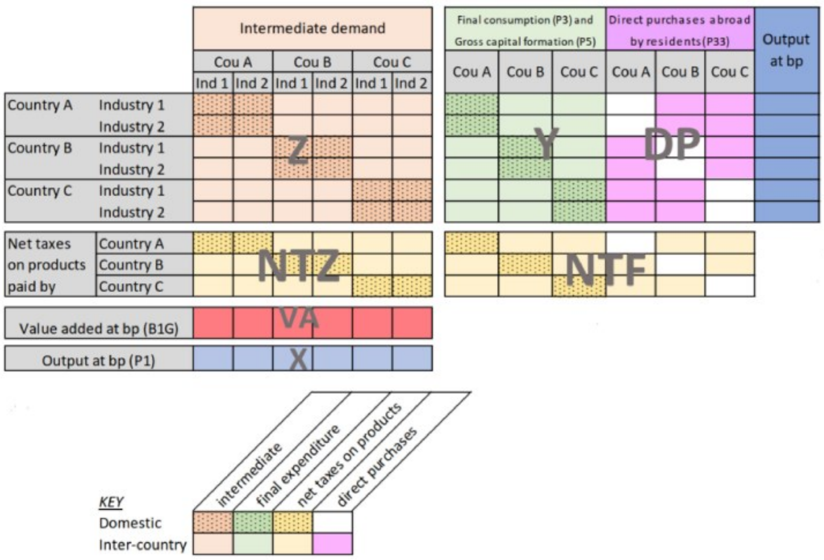
$$DI_j^i = \sum_{s=1}^{m} z_{sj}^{ii} \qquad (1)$$

where DI_j^i represents the total value of intermediate goods used by sector *j* in country *i* that are also produced within the same country. Mathematically, it is the sum of all intermediate inputs from sectors 1 to *m* within country *i* itself.

$$FI_j^i = \sum_{c=1,c\neq 1}^{n} z_{sj}^{ii} \sum_{i=1}^{m} z_{sj}^{ci} \qquad (2)$$

FI_j^i captures the total value of intermediate goods used by sector *j* in country *i* that originate from all other countries except *i*. That is, aggregates the total foreign input for sector *j* in country *i*, summed across all sectors *s* from each foreign country *c*, excluding inputs from the home country *i*.

Figure 6. The OECD Inter-Country Input-Output (ICIO) table



Source: OECD presentation for the launch of the 2021 OECD Inter-Country Input-Output (ICIO) and Trade in Value-Added (TiVA) Databases on 17 November 2021.

Appendix B: I40-related product code

Table 8. List of initially identified CN product codes related to I40 technologies

4-digits HS product codes, 8-digits CN product codes and CN product descriptions		
Advanced Industrial Robots		
8479	Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter	
	84795000	Industrial robots, not elsewhere specified or included
Additive Manufacturing		
8463	Other machine tools for working metal or cermets, without removing material	
	84639000	Other machine tools for working metal or cermets, without removing material; Other
8477	Machinery for working rubber or plastics or for the manufacture of products from these materials, not specified or included elsewhere in this chapter	
	84778011	Machines for the manufacture of foam products; Machines for processing reactive resins
	84778019	Machines for the manufacture of foam products; Others
	84778099	Other machinery; Other; Other
Industrial Internet of Things		
8471	Automatic data-processing machines and units thereof; magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included	
	84718000	Other units of automatic data-processing machines
	84719000	Other
8517	Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network (such as a local or wide area network), other than transmission or reception apparatus of heading 8443, 8525, 8527 or 8528	
	85176200	Machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus
8526	Radar apparatus, radio navigational aid apparatus and radio remote control apparatus	
	85269120	Radio navigational aid apparatus; Radio navigational receivers
	85269200	Radio remote control apparatus
8542	Electronic integrated circuits	
	85423111	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)
	85423119	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Other
	85423190	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Other
	85423911	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)
	85423919	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Other
	85423990	Other; Other
9032	Automatic regulating or controlling instruments and apparatus	
	90321020	Thermostats; Electronic
	90321080	Thermostats; Other
	90322000	Manostats
	90328100	Other instruments and apparatus; Hydraulic or pneumatic
	90328900	Other instruments and apparatus; Other

Notes: The reference CN classification is the 2017 version.

Source: Castellani et al. [2022].

Appendix C: Mathematical calculation of I40 variables

The proxy measures for the adoption of Industry 4.0 technologies for every country i, sector j, and year t are computed by assessing the imports of our specific technologies, namely Advanced Industrial Robots (AIRs), Additive Manufacturing (AM), and the Internet-of-Things (IoT). The imports of each technology are adjusted by the proportion of technology-linked intermediate goods sourced by sector j of country i from technology-producing sectors across all other countries, relative to the total intermediate goods consumed by sector j in country i. Formally, the import measures for each technology and sector are calculated as follows:

$$M_{i,j,t}^{AIRs} = (M_{i,t}^{AIRs} \times \sigma_i^{AIRs} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}}) \qquad (11)$$

$$M_{i,j,t}^{AM} = (M_{i,t}^{AM} \times \sigma_i^{AM} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}}) \qquad (12)$$

$$M_{i,j,t}^{IoT} = (M_{i,t}^{IoT} \times \sigma_i^{IoT} \times \frac{\sum_c int_{i,j}^{c,26}}{\sum_c \sum_s int_{i,j}^{c,s}}) \qquad (13)$$

where i and j denote the country and the sector buying intermediates; c and s denote the country and the sector selling intermediates (i.e., the source); $\sigma_i^{AIRs}= M_i^{AIRs}/M_i^{28}$ denotes, in each country i, the share of AIR imports in all imports of goods produced by sector 28; $\sigma_i^{AM}= M_i^{AM}/M_i^{28}$ denotes the same share for AM; $\sigma_i^{IoT}= M_i^{IoT}/M_i^{26}$ denotes the same share of IoT imports in all imports of goods produced by sector 26. The final term of each formula (e.g., the ratio $\frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}}$) represents, for each country i and sector j, the share of intermediates produced by specific technology-producing sector and imported from any other country in all imported intermediates from any country and sector. Predetermined weights for year 2008 are used in order to mitigate potential reverse causality bias.

To clarify, for every country i, sector j, and year t, the I40 related imports (i.e., M^{AIRs}, M^{AM} and M^{IoT}) are computed by adjusting (i.e., weighting) for the proportion of I40-linked intermediate goods sourced by sector j of country i from tech-specialised sectors across all other countries (i.e., $\sigma_i^{AIRs} \times \sum_c int_{i,j}^{c,28}$, $\sigma_i^{AM} \times \sum_c int_{i,j}^{c,28}$ and $\sigma_i^{IoT} \times \sum_c int_{i,j}^{c,26}$), relative to the total intermediate goods consumed by sector j in country i (i.e., $\sum_c \sum_s int_{i,j}^{c,s}$).

Finally, we compute the stock of sectoral imports for each technology, following the perpetual inventory method and assuming a constant depreciation rate δ of 15% (as commonly done in the automation literature), as:

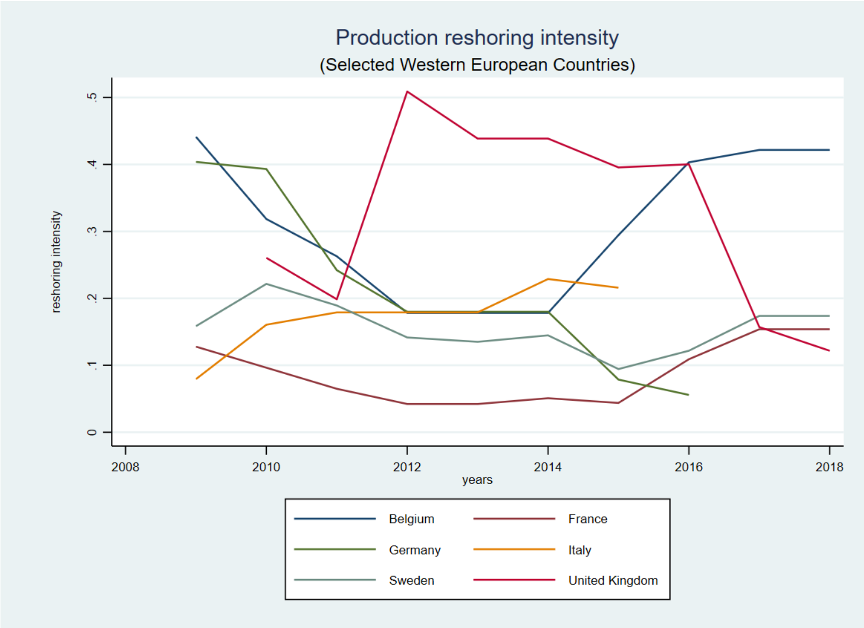
$$K_{i,j,t}^{AIRs} = M_{i,j,t}^{AIRs} + (1 - \delta) \times M_{i,j,t-1}^{AIRs} \qquad (14)$$

$$K_{i,j,t}^{AM} = M_{i,j,t}^{AM} + (1 - \delta) \times M_{i,j,t-1}^{AM} \qquad (15)$$

$$K_{i,j,t}^{IoT} = M_{i,j,t}^{IoT} + (1 - \delta) \times M_{i,j,t-1}^{IoT} \qquad (16)$$

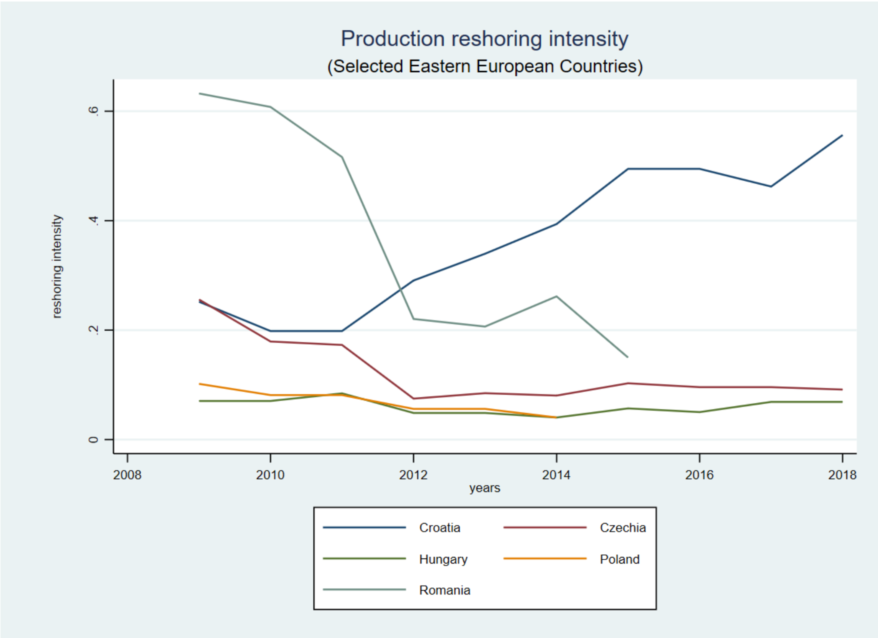
Appendix D: Additional Figures

Figure 7: Production reshoring trends for selected Western European countries



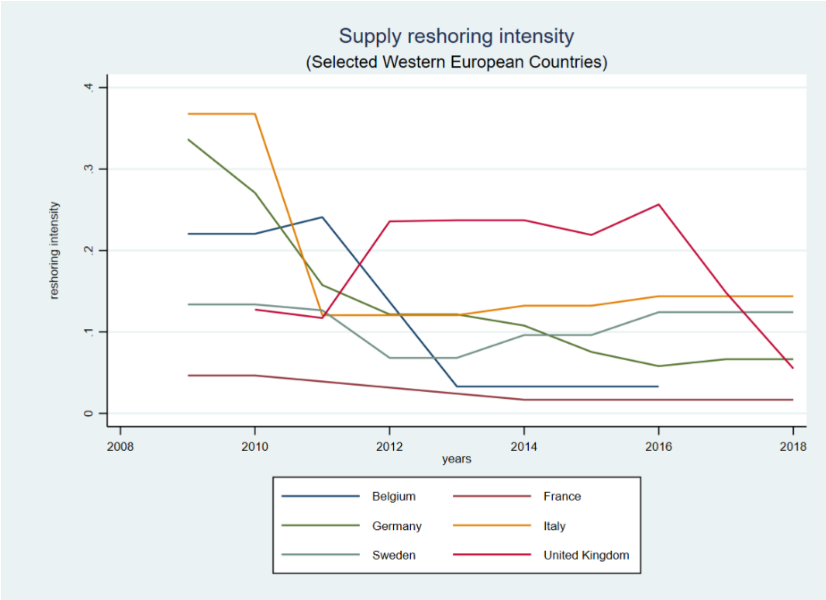
Notes: 5-period moving average of ΔR_t^P for selected Western European countries. It is subjected to the constraints Rt >0 and the changes in $DI_t - DI_{t-1}$and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

Figure 8: Production reshoring trends for selected Eastern European countries



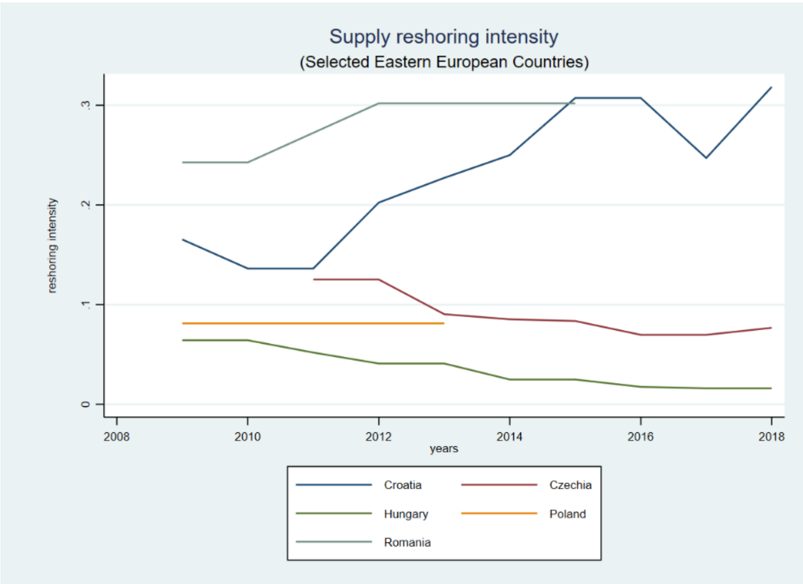
Notes: 5-period moving average of ΔR_t^P for selected Eastern European countries. It is subjected to the constraints Rt >0 and the changes in $DI_t - DI_{t-1}$and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

Figure 9: Supply reshoring trends for selected Western European countries



Notes: 5-period moving average of ΔR_t^S for selected Western European countries. It is subjected to the constraints $R_t > 0$ and the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

Figure 10: Supply reshoring trends for selected Eastern European countries



Notes: 5-period moving average of ΔR_t^S for selected Eastern European countries. It is subjected to the constraints $R_t > 0$ and the changes in $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are not simultaneously positive, negative, or zero.

Appendix E: Additional robustness check

Table 9. Panel unit root test.

	Im, Pesaran, and Shin (2003): Integration order I(1)		
Variables	t	Standardised t	p-value
AM	-3.1054	-15.4528	0.0000
IoT	-3.1319	-15.3312	0.0000
AIRs	-2.2351	-1.8375	0.0331
ΔR^{S} ($s$upply reshoring)	-4.5905	-23.6005	0.0000
$\Delta R^{S,Asia}$ (supply reshoring from Asia)	-4.1972	-23.0732	0.0000
$\Delta R^{S,AsiaDeveloping}$ ($s$upply reshoring from Asia developing)	-4.2991	-23.2137	0.0000
$\Delta R^{S,AsiaDeveloped}$ ($s$upply reshoring from Asia developed)	-3.7688	-22.2925	0.0000
ΔR^{P} (production reshoring)	-4.6726	-23.5876	0.0000
$\Delta R^{P,Asia}$ (production reshoring from Asia)	-4.1505	-22.9614	0.0000
$\Delta R^{P,AsiaDeveloping}$ (production reshoring from Asia developing)	-4.1902	-22.9695	0.0000
$\Delta R^{P,AsiaDeveloped}$ (production reshoring from Asia developed)	-3.9483	-22.4143	0.0000
ΔOff^{S} ($s$upply offshoring)	-4.5905	-23.6005	0.0000
$\Delta Off^{S,Asia}$ ($s$upply offshoring from Asia)	-4.1296	-23.0528	0.0000
$\Delta Off^{S,AsiaDeveloping}$ ($s$upply offshoring from Asia developing)	-4.2266	-23.0298	0.0000
$\Delta Off^{S,AsiaDeveloped}$ ($s$upply offshoring from Asia developed)	-3.734	-22.1627	0.0000
ΔOff^{P} ($production$ offshoring)	-4.6726	-23.5876	0.0000
$\Delta Off^{P,Asia}$ ($production$ offshoring to Asia)	-4.0436	-22.624	0.0000
$\Delta Off^{P,AsiaDeveloping}$ ($production$ offshoring to Asia developing)	-4.1672	-22.5323	0.0000
$\Delta Off^{P,AsiaDeveloped}$ ($production$ offshoring to Asia developed)	-3.8612	-22.2011	0.0000

*Notes: AR parameter is assumed to be panel-specific, panel means and time trend are included. Critical values for t are: −2.420 (1%), −2.340 (5%), −2.300 (10%). The null hypothesis is that all panels have a unit root. The alternative hypothesis is that the fraction of panels that are stationary is non-zero. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.*

Table 10. Panel cointegration test[22].

Pedroni (2004)	*t*	*p*-value
PP (ΔR^{S} $as\ dependent$)	-26.4143	0.0000
ADF (ΔR^{S} $as\ dependent$)	-33.8910	0.0000
PP ($\Delta R^{S,Asia}$ $as\ dependent$)	-28.7393	0.0000
ADF ($\Delta R^{S,Asia}$ $as\ dependent$)	-41.1261	0.0000
PP ($\Delta R^{S,AsiaDeveloping}$ $as\ dependent$)	-27.7986	0.0000
ADF ($\Delta R^{S,AsiaDeveloping}$ $as\ dependent$)	-41.6405	0.0000
PP ($\Delta R^{S,AsiaDeveloped}$ $as\ dependent$)	-33.7489	0.0000
ADF ($\Delta R^{S,AsiaDeveloped}$ $as\ dependent$)	-42.7527	0.0000
PP (ΔR^{P} $as\ dependent$)	-27.5610	0.0000
ADF (ΔR^{P} $as\ dependent$)	-34.0038	0.0000
PP ($\Delta R^{P,Asia}$ $as\ dependent$)	-33.0662	0.0000
ADF ($\Delta R^{P,Asia}$ $as\ dependent$)	-42.2481	0.0000
PP ($\Delta R^{P,AsiaDeveloping}$ $as\ dependent$)	-31.2599	0.0000
ADF ($\Delta R^{P,AsiaDeveloping}$ $as\ dependent$)	-41.1056	0.0000
PP ($\Delta R^{P,AsiaDeveloped}$ $as\ dependent$)	-40.3975	0.0000
ADF ($\Delta R^{P,AsiaDeveloped}$ $as\ dependent$)	-37.8118	0.0000
PP (ΔOff^{S} $as\ dependent$)	-26.4143	0.0000
ADF (ΔOff^{S} $as\ dependent$)	-33.8909	0.0000
PP ($\Delta Off^{S,Asia}$ $as\ dependent$)	-31.7636	0.0000
ADF ($\Delta Off^{S,Asia}$ $as\ dependent$)	-45.1097	0.0000
PP ($\Delta Off^{S,AsiaDeveloping}$ $as\ dependent$)	-30.9813	0.0000
ADF ($\Delta Off^{S,AsiaDeveloping}$ $as\ dependent$)	-42.9790	0.0000
PP ($\Delta Off^{S,AsiaDeveloped}$ $as\ dependent$)	-33.1729	0.0000
ADF ($\Delta Off^{S,AsiaDeveloped}$ $as\ dependent$)	-44.8216	0.0000
PP (ΔOff^{P} $as\ dependent$)	-27.5610	0.0000
ADF (ΔOff^{P} $as\ dependent$)	-34.0038	0.0000
PP ($\Delta Off^{P,Asia}$ $as\ dependent$)	-28.1927	0.0000
ADF ($\Delta Off^{P,Asia}$ $as\ dependent$)	-39.3056	0.0000
PP ($\Delta Off^{P,AsiaDeveloping}$ $as\ dependent$)	-27.5163	0.0000
ADF ($\Delta Off^{P,AsiaDeveloping}$ $as\ dependent$)	-37.7800	0.0000
PP ($\Delta Off^{P,AsiaDeveloped}$ $as\ dependent$)	-38.8249	0.0000
ADF ($\Delta Off^{P,AsiaDeveloped}$ $as\ dependent$)	-39.6750	0.0000

Notes: The null hypothesis is no cointegration. The alternative hypothesis is that the variables are cointegrated in all panels. PP= Phillips-Perron test. ADF= Augmented Dickey-Fuller test. Autoregressive parameter as panel-specific.

[22] Results for the panel cointegration test, specifying the autoregressive parameter as the same for all the panel, are available upon request.

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