Automation and off(re)shoring: a meta-regression analysis

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The ongoing debate on the effects of automation on off(re)shoring movements has gained growing attention. On the one hand, a relevant branch of related literature advocates that automation may facilitate the return of production to origin countries, thereby contributing to the increase of the reshoring movements. On the other hand, another branch of the literature argues that such increases are not directly related to automation and that the process of robotization may even contribute to increase offshoring.

In face of these apparently contradictory results, we conduct a meta-analysis on the empirical literature that estimates the impact of automation on
of automation on reshoring is positive and significant, both in developed and developing countries. We also find that the heterogeneity in the reported effects is explained by differences in the studies’ methodological characteristics.

**Keywords:** Offshoring; Reshoring; Automation; Meta-Analysis.

**JEL classification:** F23, F63, O24, O33

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In face of these apparently contradictory results, we conduct a meta-analysis on the empirical literature that estimates the impact of automation on off(re)shoring. After correcting for publication bias, we find that the overall effect of automation on reshoring is positive and significant, both in developed
and developing countries. We also find that the heterogeneity in the reported effects is explained by differences in the studies’ methodological characteristics.

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1. Introduction

For many decades offshoring was a term used to characterize much of the globalization phenomenon. Driven by the development of Information and Communication Technologies (ICTs) and naturally identified as the relocation of activities to locations where the cost of production is lower (Johanson & Olhager, 2018), offshoring has translated into an increase in the fragmentation of production in favor of Global Value Chains (GVCs), in the context of an increasingly interdependent world economy.

GVCs and offshoring stand out for their importance in the 1990s and 2000s. However, since the world crisis of 2008 the patterns of production international dispersion have changed considerably. This change has been based, on the one hand, on the global crises experienced in recent years and, on the other, on the increasing use of automation, which has posed new challenges and opportunities to multinational firms (UNCTAD, 2020).

Automation is an increasingly common phenomenon in some productive sectors. It allows for improve labor efficiency and productivity, as well as higher flexibility and quality at reduced costs (Krenz et al., 2021). From the vast theoretical framework that exists, automation is mirrored in a set of devices that alter the need for labor to perform tasks, potentially eroding the specific advantages gained in offshore countries. Thus, with the increasing implementation of automation we can question whether such development may affect the well-known offshoring in favor of a new trend of
reshoring/backshoring or nearshoring, generally characterized by the return to "home" or close location of previously offshored activities (Wiesmann et al., 2017).

A significant body of empirical literature has shown that automation has in fact contributed to reshoring (e.g., Faber, 2020; Krenz et al, 2021; Krenz & Strulik, 2021). However, other studies have presented a less clear picture, arguing that the effect of automation on reshoring has been overestimated, as automation technologies cannot per se facilitate the reshoring process (De Backer et al., 2016) and may even boost offshoring (Bergmann & Stapleton, 2020; Stapleton & Webb, 2020). Nevertheless, and despite these somewhat contradictory results, the scientific community seems to agree on the fact that reshoring movements have significant impacts on labor markets, which are not perfectly symmetric to those previously observed when firms first relocated (Krenz et al., 2021).

Following the apparent lack of consensus on the effects of automation on off(re)shoring, we develop a meta-analysis of the empirical literature on this topic. Meta-analysis is a quantitative literature review that allows summarizing and comparing the results of different studies on the same topic, identify patterns among them, and explain some conflictual results (Forza and Di Nuzzo, 1998). Our meta-analysis can thus contribute to have a better understanding of the automation-off(re)shoring link and to the broadening of
the related empirical literature, thereby providing insights on the new trends that are observed in the world economy and in international movements.

Our meta-data set is composed by 24 primary studies, from which we collect 330 estimates of the effect of automation on reshoring. A preliminary analysis of these estimates suggests the presence of publication bias, which makes the reported effects stronger in magnitude than they really are. After correcting for this bias, we find that the average effect of automation on reshoring is still positive, and equally strong in developed and developing countries. We also find that the heterogeneity in the effect sizes reported by the primary studies is explained by differences in the way offshoring is measured, the structure of the data, the estimation techniques, the unit of analysis, and the type and year of publication.

This paper is structured as follows. After this Introduction (Section 1), a review of the related literature is conducted (Section 2). Section 3 presents the methodology and the criteria used for the inclusion of primary studies in the meta-analysis. Section 4 reports the results of the meta-analysis and Section 5 concludes.

2. Literature Review

2.1. Offshoring, reshoring and their motivations

a) Offshoring

Offshoring is a complex phenomenon related to the globalization and
internationalization of firms, which gained prominence in Western Europe in the 1980s with the development of some emerging countries (Piatanesi & Arauzo-Carod, 2019). Subsequently, the phenomenon spread to other countries, reaching its peak in the 1990s.

Boosted by the ICT revolution, the development of transportation, and the reduction of tariffs associated with trade that allowed for the fragmentation of production (Gereffi et al., 2001), offshoring began to be implemented with a view to maintaining the competitiveness of firms in the global market. In this line of thought, firms began to relocate their factories to gain destination-specific advantages, usually to developing countries, crystallizing cost reduction through lower wages and less stringent environmental requirements (Piatanesi & Arauzo-Carod, 2019).

Although there is not a unique definition of offshoring (Aspelund & Butsko, 2010), it is widely accepted that it implies the transfer of productive and/or business processes to other countries, where costs are lower, while maintaining ownership and control in the country of origin (Arlbjorn & Mikkelsen, 2014; Johansson & Olhager, 2018). The literature highlights two types of offshoring: (i) captive offshoring, when the firm relocates its own factories or subsidiaries, and (ii) offshore outsourcing, when functions are operated by suppliers external to the firm (Kedia & Mukherjee, 2009; Piatanesi & Arauzo-Carod, 2019; Roza et al., 2011).

Although in the beginning offshoring was carried out by the desire of
reducing costs (Dachs et al., 2006; Kinkel & Maloca, 2009), over the years its motivations have moved to the need to hold skilled labor, have access to raw materials, proximity to new markets, FDI forgiving policies or better production facilities in the destination countries (Ellram et al., 2013; Joubioux & Vanpoucke, 2016; Piatanesi & Arauzo-Carod, 2019). Offshoring is more common in medium-large firms, given their capacity to absorb sunk costs (Kinkel & Maloca, 2009; Piatanesi & Arauzo-Carod, 2019), and in standardized and codified products and processes, which are more easily to relocate.

To understand firms' decisions to offshore, it is essential to refer to some internationalization theories. First, the Transaction Cost Economics (TCE), which focuses on the decision of firms between "make or buy", calls attention to the balance between transaction costs, specific investments, and consequent associated risks. This theory supports the view that firms tend to move away from regions where costs and opportunism are high (Williamson, 2008). In the same line, we can identify the Internalization Theory, from which it results that firms will choose to internalize processes when it proves to be more efficient than market transactions (Coase, 1937). This decision will depend positively on the costs, benefits and value added that firms incur with production (Dunning, 1998). Transaction costs tend to increase with the degree of uncertainty involved in relocation and decrease due to digitalization, thus allowing access to cheap labor in offshore countries (Coase, 1937).

Dunning (1988, 1998) highlights three advantages that explain
internationalization of production: (P) ownership advantages over assets that competitors do not own; (L) location advantages, with ownership allowing for greater efficiency in added value; and (I) internalization advantages, closely linked to the TCE, in which ownership exploited abroad is more efficient than market transactions. This set of advantages (PLI) justifies Foreign Direct Investment (FDI). In the case of offshoring, emphasis should be put in (I) and (L), the main reasons for relocating to countries whose wages are lower.

Finally, the Uppsala model of Johanson and Vahlne (1977) explains that firms begin their internationalization in countries that are culturally and physically "close," and subsequently invest in more "distant" markets. Thus, internationalization is as a process in which involvement and commitment abroad is slow and gradual. Kinkel and Maloca (2009) argue that firms with an intensive exporting propensity are more active in offshoring movements, as they gain knowledge and experience at the international level (Aspelund and Butsko, 2010).

Thus, as summarized in Roza et al. (2011), the drivers of offshoring can be grouped into three categories: (i) cost drivers: TCE and ownership advantages; (ii) resource drivers: resources that allow maintaining and improving the competitive position; and (iii) entrepreneurial drivers, based on a growth strategy and access to new markets.

However, it is important to note that offshoring can often have underestimated risks associated with quality control difficulties and
coordination efforts (Kandil et al., 2020; Piatanesi & Arauzo-Carod, 2019).

Today there is a relative consensus on the idea that the gains of offshoring were especially important until 2007, when the world entered a major global recession. From that moment on, the tendency was to reduce offshoring due to the economic instability experienced in that period, and the risks linked to high transportation costs, high dependence on suppliers and the consequent disruptions of GVCs began to be considered as a priority (Hurley et al., 2017 and Piatanesi & Arauzo-Carod, 2019).

b) **Reshoring**

Lately firms have been reconsidering offshore movements, paying an increasing attention to reshoring (Mcivor & Bals, 2021). Broadly speaking, reshoring refers to a change of firm location or production from the previous offshore country (Ancarani & Di Mauro, 2018; Ellram et al., 2013; Fratocchi et al., 2016; Johansson & Olhager, 2018; Kinkel, 2014). Two processes can be distinguished: backshoring, which concerns the relocation of production from an offshore location to the home country (Arlbjorn & Mikkelsen, 2014; Johansson & Olhager, 2018); and nearshoring, which refers to the relocation of production from an offshore location to a country close to the home country (Piatanesi & Arauzo-Carod, 2019; Kandil et al., 2020).

In general, the term reshoring is associated with the inversion of the offshoring phenomenon (Fratocchi et al., 2014) and there is a multitude of
other terms alluding to such movements: back-sourcing; de-internationalization; international divestment; onshoring; home-shoring (Fratocchi et al., 2014; Giuseppina & Michel, 2018).

Although reshoring is often associated with corrections regarding previous offshoring decisions (Kinkel & Maloca, 2009; Kinkel, 2014), the literature points to other drivers that explain the rise of this phenomenon. According to Ancarani & Di Mauro (2018), reshoring can be based on three strategies: (i) cost-oriented, referring to offshoring costs associated with physical distance, such as the price of fuel, transportation, and wages (Ancarani & Di Mauro, 2018; Foerstl et al., 2016; Kandil et al., 2020), or even the difficulty in transferring knowledge; the reshoring of activities can also be associated with the technological progress (automation) that allows a less labor-intensive production, favoring reshoring through a reduction in costs (Foerstl et al., 2016); (ii) flexibility-oriented, related to the loss of flexibility arising from a higher complexity of offshoring movements, which can refer to the dependence on suppliers or coordination and monitoring difficulties (Dachs & Kinkel, 2013; Foerstl et al., 2016; Fratocchi et al., 2016); (iii) quality-oriented, referring to the availability of high-quality labor and products, often non-existent in the host country, the need for fast delivery times, and risks of GVCs disruptions (Ancarani & Di Mauro, 2018; Dachs & Kinkel, 2013; Kandil et al., 2020). In the last decade, aspects of customer value perception (Fratocchi et al., 2016) and environmental concerns have also been mentioned.
as important determinants of reshoring (Sirilertsuwan et al., 2018).

According to Wiesmann et al. (2017), the above referred strategies can be associated with factors related to: global economic competitiveness; the specific characteristics of the offshoring destination market; the characteristics of the firm’s country of origin; the specificities and complexity of the value chain; the specificities, resources, and decisions of the firms, that may change the specific advantages.

To further understand reshoring decisions, it is also important to refer to some theories of internationalization. Although they served at first to explain the international expansion of the firm, the theories presented below have in recent years been applied to international reshoring (Fratocchi et al., 2016).

First, the EER used for "make or buy" decisions provides valuable insight into the exercise of ownership costs. Thus, if firms usually tend to relocate production to low-cost countries, the associated cultural, physical, and psychological distances, as well as limited intellectual property protection (opportunism) and increasing coordination costs, may decrease the attractiveness of reshoring countries (Foerstl et al., 2016; Fratocchi et al., 2016; Kinkel & Maloca, 2009; Martínez-Mora & Merino, 2014; Mclvor & Bals, 2021). In the same line, we can introduce the Internalization Theory, with Martínez-Mora & Merino (2014) stating that reshoring can occur due to changes in the location or properties of factors in host countries. These
variations translate into a decrease in the efficiency of the firm and the
distribution chain, increasing transaction costs.

Next, the Resource-Based View (RBV) can also explain international
restructuring, indicating that firms will invest in their key areas of activity and
outs source the remaining tasks (Wiesmann et al., 2017). Therefore, reshoring
decisions may be due to the firms lack of ability to develop assets essential
to maintaining competitive advantage in host countries (Teece et al., 1997),
and reshoring may allow for greater quality and flexibility in production
(Mclvor & Bals, 2021).

Finally, reference can be made to Dunning’s Eclectic Paradigm, which
has been applied to explain reshoring, in the sense that this phenomenon is
due to the loss, deterioration, or underestimation of one or several of the
advantages that firms may have in the host country (Dachs & Kinkel, 2013).
Thus, Dunning (2001) refers to a set of three categories capable of altering
location advantages: (i) infrastructure (communication, production, or
transportation capabilities), (ii) country risk (economic and political factors);
and, (iii) government policy ((dis)-incentives to locate). These constraints can
therefore alter the firm’s specific advantages in an offshore location, providing
repatriation of activities.

To conclude, it is important to note that, although reshoring has been
increasing in recent years, its intensity remains lower than that of offshoring,
indicating that both phenomena will continue to coexist on the international
2.2. Automation, Robotics and Industry 4.0

This section analyzes the concepts of automation, robotics, and Industry 4.0 (I4.0), since the first two are generally used interchangeably or complementarily with I4.0, forming an integral part of it (Haleem & Javaid, 2019).

According to the retrospectives outlined by Haleem & Javaid, (2019) and Oztemel & Gursev (2020), the evolution of Industry is divided into four stages. The First Revolution, in the mid-18th century, with the introduction of mechanized production, allowed for the reduction of human effort. This was followed by the Second Revolution, in 1870, characterized by the division of labor and electrification, which enabled greater production speed. A century later, in 1970, the Third Revolution, boosted by advances in ICT and electronic processes, facilitated the automation and robotization of production processes. The Fourth Revolution (I4.0) is characterized by a fusion between mechanical autonomy (automation and robotics) and the digitalization of production. This set of technologies, machines, and robots allow the substitution of labor, makes processes more autonomous and efficient, brings more flexibility and productivity, and can change the geography of production activity.
a) Automation

Automation can be defined as the progress and use of technologies - machines or industrial robots - that allow some, or all, of the labor required to perform tasks to be replaced (Acemoglu & Restrepo, 2019; Prettner, 2019). In fact, automation has changed the definition and distribution of work over the years and, as technological development occurs, has led to the substitution of labor by robots and other state-of-the-art machines (Acemoglu & Restrepo, 2019; Prettner, 2019).

This effect is mainly due to the search for optimization of production processes, quality, and efficiency of a given production structure (Goldberg, 2012; Stein & Scholz, 2020), undertaken through remote control by computers, use of Artificial Intelligence, or industrial robots (Acemoglu & Restrepo, 2019).

Currently, we are experiencing a period of rapid and sophisticated automation, which spreads beyond the production process, and the emergence of mixed work teams composed of humans and robots is frequent (Stein & Scholz, 2020). It is also important to highlight that, while automation was at first mostly used in the automotive industry, it is now widespread and applied to several branches and sectors (Acemoglu & Restrepo, 2019; Frohm et al., 2008; Prettner, 2019).

b) Robotics

The genesis of the industrial robot dates to 1961, with the appearance of the
first programmed device (Dhillon, et al., 2002). Since then, machines have expanded and gained importance, both in the productive activity and in the day-to-day life of population (Dhillon et al., 2002; Ghobakhloo, 2018).

Robots started to be defined as autonomous machines, capable of being programmed and performing several tasks (Acemoglu & Restrepo, 2020), through sequential and repetitive processes of high accuracy. Considering the skills of robots, their increasing use is due, on the one hand, to the need for flexibility, speed, efficiency and high quality production and, on the other hand, to the need to reducing environmental impact and waste, increasing human safety in performing certain tasks, and space optimization (Esmaeilian et al., 2016).

c) Industry 4.0

The technological developments experienced in recent decades have enabled a modernization of the way people and firms act and interact, revolutionizing the organization of production processes (Hirsch-Kreinsen, 2016).

The concept of I4.0, first used in 2011 in Germany, by Kagermann (Ejsmont et al., 2020), has been subject to debate. Although the most common designations are automation and mechanization (Dachs et al., 2019), the term I4.0 seems to gain scope within the European Union. Contrasting with previous definitions, Leyh et al. (2017) highlight that I4.0 allows the transition from centralized production to flexible and self-controlled production, whose stages are digitized and interconnected to fluidify information. Therefore, we
are witnessing a transformation from machine-dominated production to digital-dominated production (Oztemel & Gursev, 2020).

From the studies of Dachs *et al.* (2019) and Ejsmont *et al.* (2020) it is evident that I4.0, when compared with previous approaches, shows a revolutionary level, especially regarding automated processes, allowing to idealize new business models and productive forms (Haleem & Javaid, 2019). The transformation is carried out along 10 pillars/technologies that form the basis of I4.0: cloud, augmented reality, simulation, big data, internet of things, additive manufacturing, autonomous robots, horizontally and vertically integrated system, cybersecurity of Rüßmann *et al.* (2015), and "the other technologies", which, albeit vague, refer to innovations of limited use in the ecological branch (e.g., Büchi *et al.*, 2020).

Thus, we can conclude that I4.0 develops along the pillars constituting the Cyber Physical Systems defined by Berger *et al.* (2016) as embedded systems that through software allow an integration in networks and a transversal communication. Thus, the fusion between the digital and the physical components is reinforced, in a system that facilitates access to information, immediate feedback of events, and optimization of routines (Hirsch-Kreinsen, 2016; Lasi *et al.*, 2014; Oztemel & Gursev, 2020).

As mentioned before, this revolution has led to the emergence of a new business model called Smart factories, which aims to optimize production by making it more autonomous, interconnected, efficient, and digitized (Haleem
& Javaid, 2019; Lasi et al., 2014; Oztemel & Gursev, 2020). These smart factories are supported by low-cost autonomous robots, storage software, among others, which allow for integrated automation of production processes and the reduction of labor use (Acemoglu & Restrepo, 2019; Ancarani & Di Mauro, 2018), making it easier to reconfigure production.

2.3. Automation and Off(re)shoring

It is commonly accepted that automation and other technologies rooted in I4.0 may lead more firms to perform reshoring (Butollo, 2021), thus converging with the need to shorten GVCs.

However, the topic of the relationship between automation and reshoring does not seem to bring unanimity in the scientific and academic community. On the one hand, some authors claim that automation changes the bases of labor costs and needs, productivity, and flexibility, favoring reshoring. On the other hand, other authors have shown that automation has no strength per se to bring activities back home and that it can even boost offshoring.

The first major conclusion drawn from the literature relates to the cost advantage and need of labor. De Backer et al. (2018) argue that, from an economic perspective, automation can be seen as a substitute for low-skilled labor and complementary to skilled labor, decreasing the proportion of labor needed. This effect allows companies to offset the labor cost advantages of
offshoring locations through a blurring of prices, promoting a productive reconfiguration of the firm. Thus, this approach predicts a reduction of the location advantages previously obtained in low-cost countries (Ancarani et al., 2019; Carbonero et al., 2020; Dachs & Seric, 2019; Dachs et al., 2019; Fratocchi & Di Stefano, 2019, 2020). Consequently, developed countries tend to become relatively more attractive, which discourages offshoring and favors reshoring (De Backer & Di Stefano, 2021; De Backer et al., 2018).

Cost advantages seem to be increasingly blurred, as wage increases have been registered in offshore countries. In China, for example, wages have increased since 2008 by an average of 13% to 15%, compared to only 1 to 3% registered in countries like France or the USA (Huygevelde et al., n.d.). Thus, while wages in China were previously 20 times lower than in France, in 2017 they were only 5 times lower, and by 2022 they are expected to be only 2 times lower (Kandil et al., 2020).

In a complementary way, it is important to analyze the effects of automation on productivity. The literature points out that technological developments allow a higher productivity of robots, which, combined with the increase in their stocks, contributes positively to the reshoring of factories as a viable alternative to the localization of production. In fact, over the years an increase in the stock of robots in developed economies has been registered, in simultaneous with a reduction in their price (the average price of robots has dropped from 99.23K $ and 112.09K $ in 1990 to 49.65K $ and 52.81K $ in
2019, in Germany and the USA, respectively - Klump et al., 2021). Through robotic manufacturing, reshoring firms are thus able to avoid the tariffs and transportation costs associated with relocation and to benefit from wage savings through reduced labor requirements. Thus, as the productivity of industrial robots rises and their price drops, the incentive for reshoring increases because firms with high productivity in automation can produce more efficiently domestically with the help of robots (De Backer et al., 2016; Dachs et al., 2019; Krenz et al., 2021; Krenz & Strulik, 2021).

Additionally, the increased investment in automation spreads the benefits of its applicability, bringing to production a higher quality and flexibility through precise and sophisticated processes with a low degree of error, as well as a great capacity for innovation at reduced costs, allowing the relocation of activities near, or in the domestic market (Ancarani et al., 2019; Dachs et al., 2019; Krenz & Strulik, 2021). Thus, I4.0 offers the possibility for firms to have faster responses in changing contexts and facilitates the delivery to customers if they are near reshoring zones (Fratocchi & Di Stefano, 2019). Embedded systems also allow for innovation in an efficient way, as they reduce the time to conceive the idea and bring the product to the market. They also allow for the customization of products in smaller volumes and with competitive prices (Dachs & Seric, 2019; De Backer et al., 2016).

Most of these theoretical mechanisms have been corroborated by the empirical evidence. Artuc et al. (2019), for example, identified that increased
exposure to U.S. robots causes a decrease in exports from Mexico to the USA, a finding consistent with the hypothesis that automation increases the pace of reshoring and/or decreases the pace of offshoring. Concomitantly, Faber (2020) showed that the use of robots reduces the demand for imports and export-producing factories in offshoring countries. Additionally, Kugler et al. (2020), found that the Colombian market has been facing a large loss of employment, mainly in sectors where there were previously large volumes of exports to the US. The authors argue that through increased US automation, multinationals have a great sophistication of robots domestically, which allows them to achieve more competitive production than offshoring (Colombian) production, leading to repatriation of production. Finally, De Backer et al. (2016) found a negative association between the growth of Multinational Corporations (MNCs) on domestic soil and their investment abroad.

Thus, the application of these technologies seems to improve ownership advantages on domestic soil through more capital-intensive production, allowing to slow down the future evolution of GVCs, making them shorter and more regional (Dachs & Seric, 2019; Dachs et al., 2019; De Backer et al., 2018).

However, some authors have called attention to the possibility that reshoring movements may not be caused by the increasing use of automation systems, as these can even favor offshoring.
First, the international business literature tends to see ICT as tools that help firms expand their geographic scope and reduce network coordination costs. Ancarani & Di Mauro (2018) and Butollo (2021), state that different I4.0 technologies can have different impacts on the location of manufacturing activities, by favoring the remote coordination of activities, potentially making offshoring locations attractive again. Furthermore, they find that increasing automation cannot, per se, change the advantages of offshoring, unless technological superiority of Western countries’ innovation systems can be assumed in the medium term. In the same line, Dachs & Seric (2019) found that the attractiveness of these countries is not only based on low costs, but they are also considered increasingly sophisticated markets with an interesting basis for business expansion, which make it possible to obtain skilled labor and suppliers.

Complementarily, Hallward-Driemeier & Nayyar (2019) found that automation through increased robotization of production leads to an increase in offshoring, measured in FDI stock, from high-income countries to low- and middle-income countries. This study shows that at least so far, the threshold above which robots would cause reshoring happens only in 3% of the sample analyzed. In turn, Bergmann & Stapleton (2020), reinforced that the use of industrial robots in Denmark allowed an increase in offshoring, both for low- and middle-income countries, as well as for high-income countries. The authors explain that the increase in productivity generated by automation
allows firms to decrease costs and thus have more capital for investment, showing a higher productivity effect than offshoring. In the same line, and although the conclusions drawn are less pronounced, Stapleton & Webb (2020) argue that automation favored offshoring and international exchanges between the MNE and its affiliates, showing differences regarding the sequence of occurrence of the phenomena. For firms that had not yet performed offshoring, the adoption of robots led them to start doing it intensively, or even to open subsidiaries in those countries. In contrast, for firms that had already offshored production, the adoption of robots had no impact on offshoring, but decreased the share of imports, suggesting that automation, to some extent, drives economic activity away from low-income countries.

Additionally, and to prove the above statement, evidence of changes in bilateral trade in favor of increased offshoring has been found. First, Pacini & Sartorio (2017), through an analysis of bilateral trade between three of the largest robot holders in the most robotized sector, the automotive industry, investigated a possible decline in their relations with major partners and, therefore, a regression of offshoring and GVCs. However, and contradictory to the premise that automation would favor reshoring, the authors found an increase in trade in intermediate goods between China, the US and Germany and their major trading partners in auto parts. Thus, a complementarity effect could be observed between increased production due to the use of robots and
increased imports of intermediate goods, rather than their substitution. This study does not rule out, however, the possibility that this process is at an early stage and therefore no evidence of increased reshoring and/or decreased offshoring is yet noticeable.

Recently, Cilekoglu et al. (2021) analyzed how robots affect the international sourcing of Spanish manufacturing firms and concluded that there was an increase in the trade of intermediate goods and dispersion, contrary to reshoring. In fact, like Butollo (2021), this study points out that the decision to reshoring activities can be costly and not very beneficial from an economic point of view, leading the firm to incur in large costs and the need for additional investments for the reorganization of production and work, at the national level.

Thus, although it has been shown that the adoption of automation allows firms to become more productive, they may choose to use the economic benefits to increase their international presence (offshoring), as suggested by Bergmann & Stapleton (2020) and Cilekoglu et al., 2021. Therefore, the authors conclude that the effects of automation on reshoring movements have been overestimated and that their relationship is not as clear and linear as it seems, since some studies do not point to import substitution.

In short, the theoretical and empirical literature offers a fragmented picture, and it is difficult to assess the repercussions of automation on reshoring. It will therefore be central to further analyze the different
considerations of each study in the following sections, with a view to understanding whether or not automation causes reshoring.

Nevertheless, and despite the lack of consensus regarding the effects of automation on *reshoring*, the academic world seems to converge on the idea that, if automation succeeds in bringing production back home, it will not be able to repatriate all the work that was previously delocalized. Thus, there will be little noticeable labor benefits in reshoring countries, in that the repatriated jobs will not be similar in number, nor in skills, to those previously offshored (Dachs & Seric, 2019; De Backer *et al.*, 2016 and Krenz *et al.*, 2021).

3. Methodology and studies’ selection

This section contextualizes the methodology to be employed by introducing the concept and procedures of meta-analysis. Then, the selection criteria for the empirical studies to be used in the meta-analysis will be clarified and applied.

3.1. Meta-analysis

Meta-analysis is described as a quantitative literature review through which comparisons are made and conclusions are drawn from the analysis of several independent empirical studies whose research question is similar, using statistical procedures (Stanley & Jarrell, 1989).

Initially introduced in the mid-20th century in the fields of archeology and psychology (Forza & Di Nuzzo, 1998), meta-analysis gained prominence
in the field of psychotherapy in 1977 through the research developed by Smith and Glass, who coined the term "meta-analysis" as a statistical regrouping of independent results from the empirical literature (Cook et al., 1992). In the fields of economics and management, it has gained increasingly importance over the last two decades. In comparison with traditional literature review, meta-analysis has the advantage of identifying more objectively patterns and sources of disagreement in the empirical literature, avoiding the repetition of errors, and reducing subjectivity and misinterpretations (Gorg & Strobl, 2001).

Typically, conducting a meta-analysis involves the following steps: formulation of the problem; collection and selection of studies to be included; data assessment; data analysis; and data presentation (Cook et al., 1992 and Forza & Di Nuzzo, 1998).

3.2. Criteria for literature selection and collection

The collection and selection of the literature proves to be a capital step for the development of a meta-analysis. Having defined our problem of investigation – the impact of automation on reshoring – we relied on bibliometric procedures to identify and select the studies of interest.

The search was initiated in October 2021, extending until early February 2022 through the Scopus and Web Of Science databases, with the introduction of several sets of keywords, of which we highlight: "re(-)shoring AND automation"; "back(-)shoring AND..."
and their synonyms found throughout the literature. After analyzing the results obtained and to give consistency and diversity to our work, we extended our search to other databases, namely Google Academic, ECONPAPERS, Taylor & Francis, SPRINGER, SCIENCE DIRECT, SSRN, OECD Library, European Reshoring Monitor and CAIN.INFO.

Given that we were interested in collecting estimates of the effect of automation on reshoring movements, all theoretical articles already analyzed and presented in the sections above were removed from the potential sample. We therefore considered articles that: (i) report estimates of the effect of automation/robots or I4.0 on reshoring (but also on offshoring, when the authors interpret it as symmetric to reshoring); (ii) show changes in the level of exports of intermediate goods and/or inputs, as well as in the level of employment in selected countries after the introduction of robots, with such changes being interpreted by the authors as a decrease/increase in reshoring; (iii) are written in English, Portuguese, Spanish or French.

After analyzing the abstract, keywords and reported statistics of the 1657 articles and books obtained in the initial stage of collection, we were left with 62 potentially eligible articles or book chapters. Each of these was then analyzed in full and 38 documents were discarded for not containing the required information for the meta-analysis (namely, effect sizes and standard
errors) or for not estimating empirically the effects of automation on reshoring.

Consequently, and applying all the criteria described above, the final sample for the meta-analysis comprises 330 estimates collected from 24 studies published as articles in scientific journals or as working papers. These studies are listed in Table 1.

The studies differ among them in several aspects, one of them being the way of measuring off(re)shoring. While some studies use the traditional concepts of broad or narrow off(re)shoring, others use dummy variables to capture whether or not reshoring was implemented. In addition, some studies consider only the flows of intermediate goods, while others use a broader definition of international flows. The studies also differ according to the countries included in the sample, the unit of analysis, the estimation techniques, and the way of measuring automation.

Given the heterogeneity of the scales and metrics used in the studies, it is necessary to convert the estimates of the effects of automation on reshoring to a common metric. Following Ugur (2014), we use the partial correlation coefficient, which is our effect size. The partial correlation coefficient, $r$, and its standard error, $se$, are calculated as follows:

$$ r_i = \frac{t_i}{\sqrt{t^2_i + df_i}} \quad (1) $$

$$ se_i = \frac{\sqrt{1 - r^2_i}}{df_i} \quad (2) $$

In (1) and (2), variable $t_i$ represents the t-statistic of the coefficient of
each study associated with the effects of automation on reshoring and the variable $df$, represents the degrees of freedom of each of the reported estimates. Thus, applying these formulas and the consequent homogenization of the data, it is possible to compare the effect sizes of the different studies, since the partial correlation coefficients are independent of the technical specificities of each study (Ugur, 2014).

Inspection of the 330 estimates of our meta-analysis suggests that there is considerable variability in the studies’ results. The partial correlation coefficients, $r$, range from a minimum of -0.1385 (in Pacini & Sartorio, 2021) to a maximum of 0.6801 (in Faber, 2000). 252 of the 330 coefficients are positive, while the remaining 78 present negative values. Table 1 presents the means of the collected estimates of $r$ and $se$, for each study.

*Table 1* – Main characteristics of the studies included in the meta-analysis

<table>
<thead>
<tr>
<th>Study</th>
<th>Nr. of estimates</th>
<th>Mean of the coefficient estimates ($r$)</th>
<th>Mean of the SE of estimates ($se$)</th>
<th>Countries</th>
<th>Effect analyzed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Krenz &amp; Strulik</td>
<td>40</td>
<td>0.0322</td>
<td>0.0461</td>
<td>Reshoring to and Offshoring of 12 Eastern European countries with ROW;</td>
<td>Reshoring and Offshoring and Reshoring to 8 developing countries with ROW.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Reshoring from ROW to 48 selected countries; Reshoring to 8 selected European</td>
<td></td>
</tr>
<tr>
<td>Krenz <em>et al.</em></td>
<td>48</td>
<td>0.0720</td>
<td>0.0355</td>
<td>Reshoring from ROW to 48 selected countries; Reshoring to 8 selected European</td>
<td></td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Authors</th>
<th>Sample Size</th>
<th>Mean/Min.</th>
<th>Median/Min.</th>
<th>Country Type of Offshoring/Backshoring</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dachs B. <em>et al.</em> (2019)</td>
<td>3</td>
<td>0.0595</td>
<td>0.0247</td>
<td>Backshoring from the ROW to Germany, Austria and Switzerland</td>
</tr>
<tr>
<td>Stentoft &amp; Rajkumar (2020)</td>
<td>2</td>
<td>0.0605</td>
<td>0.0607</td>
<td>Backshoring to and Offshoring Backshoring and Offshoring from Denmark with the ROW</td>
</tr>
<tr>
<td>Carbonero F. <em>et al.</em> (2020)</td>
<td>4</td>
<td>0.0122</td>
<td>0.0524</td>
<td>Offshoring of selected developed countries with the ROW</td>
</tr>
<tr>
<td>De Backer <em>et al.</em> (2018.)</td>
<td>12</td>
<td>0.0091</td>
<td>0.0183</td>
<td>Offshoring of developed and developing countries with the ROW. Backshoring from the ROW to developed countries</td>
</tr>
<tr>
<td>De Backer &amp; De Stefano (2021)</td>
<td>6</td>
<td>0.0104</td>
<td>0.0082</td>
<td>Offshoring from and backshoring to developed countries with ROW</td>
</tr>
<tr>
<td>Bendermacher (2019)</td>
<td>32</td>
<td>0.0200</td>
<td>0.0344</td>
<td>Offshoring from 28 OECD countries + North America with ROW</td>
</tr>
<tr>
<td>Bonfiglioli <em>et al.</em> (2021)</td>
<td>6</td>
<td>0.2540</td>
<td>0.0271</td>
<td>Offshoring from the United States</td>
</tr>
<tr>
<td>Bergmann &amp; Stapleton (2020)</td>
<td>6</td>
<td>-0.0422</td>
<td>0.0133</td>
<td>Offshoring from Denmark to 22 high-, medium- and low-income countries</td>
</tr>
<tr>
<td>Jäger <em>et al.</em> (2015)</td>
<td>2</td>
<td>0.0550</td>
<td>0.0226</td>
<td>Offshoring from Austria, Denmark, France, Germany, the Netherlands, and Spain to non-European countries.</td>
</tr>
<tr>
<td>Nievas (2019)</td>
<td>78</td>
<td>0.0870</td>
<td>0.0383</td>
<td>Offshoring from a set of 71 countries selected for the ROW</td>
</tr>
<tr>
<td>Hallward-Driemeier &amp;</td>
<td>5</td>
<td>-0.0227</td>
<td>0.0277</td>
<td>Offshoring from and nearshoring to selected set of Nearshoring</td>
</tr>
<tr>
<td>Source</td>
<td>N.</td>
<td>p-value</td>
<td>p-value (0.05)</td>
<td>Offshoring/Reshoring from/To</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>----</td>
<td>---------</td>
<td>---------------</td>
<td>------------------------------</td>
</tr>
<tr>
<td>Nayyar (2019)</td>
<td></td>
<td></td>
<td></td>
<td>Offshoring from and</td>
</tr>
<tr>
<td>Dachs &amp; Seric (2019)</td>
<td>4</td>
<td>-0.0054</td>
<td>0.0217</td>
<td>Backshoring to Germany,</td>
</tr>
<tr>
<td>Faber (2020)</td>
<td>16</td>
<td>0.2221</td>
<td>0.0813</td>
<td>Offshoring from the USA to</td>
</tr>
<tr>
<td>Artuc et al. (2019)</td>
<td>2</td>
<td>0.0558</td>
<td>0.0263</td>
<td>Offshoring from the USA to</td>
</tr>
<tr>
<td>Cilekoglu et al. (2021)</td>
<td>6</td>
<td>-0.1250</td>
<td>0.0091</td>
<td>Offshoring from Spain to ROW</td>
</tr>
<tr>
<td>Pavez &amp; Martinez-Zarzoso (2021)</td>
<td>32</td>
<td>-0.0052</td>
<td>0.0170</td>
<td>Offshoring from and</td>
</tr>
<tr>
<td>Lampón &amp; González-Benedito</td>
<td>4</td>
<td>0.1332</td>
<td>0.0680</td>
<td>Backshoring from ROW to</td>
</tr>
<tr>
<td>Lampón &amp; Rivo-López (2022)</td>
<td>4</td>
<td>0.0942</td>
<td>0.0740</td>
<td>Backshoring from ROW to</td>
</tr>
<tr>
<td>Pacini &amp; Sartorio (2017)</td>
<td>4</td>
<td>-0.0768</td>
<td>0.0289</td>
<td>Offshoring from Germany,</td>
</tr>
<tr>
<td>Kugler et al. (2020)</td>
<td>7</td>
<td>0.0002</td>
<td>0.0001</td>
<td>Offshoring from the USA to</td>
</tr>
<tr>
<td>Kinkel (2020)</td>
<td>3</td>
<td>0.0664</td>
<td>0.0340</td>
<td>Backshoring from the ROW to</td>
</tr>
<tr>
<td>Denicolai et al. (2018)</td>
<td>4</td>
<td>0.0099</td>
<td>0.0707</td>
<td>Backshoring from ROW to</td>
</tr>
</tbody>
</table>

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In the next section we compute the average effect of $r_i$, test for the presence of publication bias, and explore the main factors behind the heterogeneity in the studies’ results.

4. Estimation Strategies and Results

We start by presenting the results of the estimation of the average effect of automation on reshoring using the two most common estimators: the fixed effects estimator and the random effects estimator. This analysis will then be supplemented with the assessment of the possible presence of publication bias through visual inspection of a funnel plot and the estimation of a PET/FAT regression. Finally, a multivariate meta-regression will be estimated to identify the factors that contribute to the heterogeneity of the results reported in the primary studies.

4.1. Average effect estimation and Publication Bias

Taking as a starting point the homogenized data from the previous section, we first compute the average effect size, $r_i$, using the fixed effects and the random effects estimators. The fixed effects estimator assumes that there is only one true average effect, common to all studies, and that the variability observed in the reported estimates comes only from sampling variation. It is a weighted average of all estimates of the effect reported in the primary
studies, with weights given by the inverse of their variance, $1/se^2$. The random effects estimator accounts for the presence of heterogeneity in true effect sizes, as it considers that each study has its own average effect, with the observed differences coming not only from sampling error (intra-study variation) but also from differences in the true effect among studies (inter-study variations). Like the fixed effects estimator, the random effects estimator is a weighted average of the estimates reported in the primary studies, but the weights are now given by $1/(se^2+\theta^2)$, where $se^2$ is a measure of intra-study variation and $\theta^2$ a measure of inter-study variation (Hedges & Olkin, 1985; Dominicis et al., 2008).

The average effect of automation on reshoring was calculated for our meta-sample. We obtained values of 0.0002 and 0.0326 for the fixed effects and random effects estimators, respectively. These results are positive, albeit not similar in magnitude, which suggests that, overall, automation contributes to reshoring.

Nevertheless, even if these results are positive and we admit that weighted averages are more credible than simple averages, it is possible that they may be distorted by publication bias. Publication bias is a recurrent phenomenon in the empirical literature that refers to the tendency for studies with statistically significant results to have a greater preference for publication than studies reporting non-significant result. This may lead to a
truncated pool of published studies, making empirical effects seem larger than they are (Doucouliagos, 2005; Sequeira & Neves, 2020).

Several instruments have been developed to test for the presence of publication bias. One of the most used is funnel plot, developed by Egger et al. (1997). It is a scatter diagram that compares the effect sizes collected from the primary studies $r_i$ with their precision, defined as the inverse of the standard errors, $1/se_i$. If there is no publication bias, the diagram will present the shape of an inverted funnel plot, with the estimates symmetrically distributed along the mean. However, in the presence of publication bias the estimates will be skewed in a certain direction, giving the plot an asymmetric appearance, especially in its lower part. This occurs because studies with lower precision will produce higher effect sizes to get higher t-statistics (Stanley, 2005; Sequeira & Neves, 2020).

Figure 1 displays the funnel plot for our meta-dataset. The plot seems to be asymmetric, as most observations are concentrated in the right side of the mean. This suggests the presence of publication bias towards reporting positive effects.

The funnel plot can be formally tested using the PET/FAT (Precision Effect Test / Funnel Asymmetry Test), which consists of running the following regression:

$$ r_i = \alpha_0 + \alpha_1 se_i + \mu $$

(3)
In equation (3), $r_i$ represents the partial correlation coefficient associated with the reported estimate in each primary study, and $se_i$ represents the respective standard error. If there is no publication bias, the estimates are expected to vary around the average effect ($\alpha_0$) regardless of the value of the standard error; that is, there is no correlation between $r_i$ and $se_i$ and $\alpha_1 = 0$. In the presence of publication bias, when authors face high standard errors they will tend to seek to achieve higher estimates and therefore inflate the coefficients to obtain statistically significant results. In this case, $r_i$ and $se_i$ will be correlated and $\alpha_1 \neq 0$. Given these assumptions, it is possible to use equation (3) to test both the existence of publication bias (through the Funnel Asymmetry Test, FAT), i.e., test for $\alpha_1 = 0$, and the
existence of a significant average effect (through the Precision Effect Test, PET), i.e., test for $\alpha_0 = 0$ (Eger et al., 1997; Ugur et al., 2016).

However, the estimation of equation (3) by OLS in a meta-analysis has two econometric problems: (a) heteroscedasticity and (b) autocorrelation. The first problem occurs because the standard errors are not constant across the sample, as each estimate taken from the primary studies has its own standard error. This problem can be solved by dividing both sides of equation (3) by the standard error (Stanley, 2005), which yields:

$$t_i = \alpha_0 \text{precision}_i + \alpha_1 + \nu_i$$

(4)

In equation (4) we have the t-statistic associated with $r_i$ regressed on precision. The coefficients are now reversed, with the constant standing for the coefficient of publication bias and the slope standing for the average effect size beyond publication bias.

As for problem (b), autocorrelation can arise because estimates taken from the same study share similar samples, specifications, and estimation techniques, which makes them to be correlated (Balima & Sokolova, 2021). This problem can be addressed in several ways. The first is selecting only one estimate from each study. However, this is not the best option, since in our case we would have only 24 observations to perform the meta-analysis and, in addition, the criteria for the choice of the estimate of each study may be subjective. Alternative methods to deal with the problem of statistical dependence within articles are: (1) estimation by OLS with clustered standard
errors; (2) estimation by OLS with bootstrapped standard errors; (3) hierarchical models (Doucouliagos & Laroche, 2009; Nelson & Kennedy, 2009).

In alternative (1) the coefficients are estimated by OLS using clustered standard errors, with each study representing a cluster. Alternative (2) is more adequate when the number of clusters is relatively small (Sokolova & Sorensen, 2021). Alternative (3) allows for the regression coefficients to vary randomly across studies, considering that observations (estimates) are nested into groups (studies) with different characteristics. Thus, each regression coefficient has a fixed part, common to all studies, and a random part, representing variation between studies (Ugur et al., 2016; Cardoso et al., 2021).

In Table we present the results of the estimation of equation (4) using techniques (1), (2) and (3). The constant is positive and statistically different from 0 at 1% in column (2) and at 10% in column (1), although it is not significant in column (3). This suggests that there seems to be some evidence of publication bias in favor of positive results, which confirms the conclusions of the visual analysis of the funnel plot. Variable Precision is statistically significant at 1% in all three estimations and its coefficient is positive, showing that the average effect size is strong and positive. We can thus conclude that, even after correcting for publication bias, automation has on average significantly contributed to reshoring.
For robustness analysis, we perform three additional estimations of equation (4). First, we address the problem of outliers by winsorizing the dependent variable at 5% and 95%. Second, we give each study the same weight by weighting each observation by the inverse of the number of estimates taken from the respective primary study. Third, following Havranek & Sokolova (2020) and Sokolova & Sorensen (2018), we address the problem of potential endogeneity of the reported standard errors by using the square root of the number of observations as instrument for $se$. The estimation results (presented in Table 3) are similar to those obtained using techniques (1), (2) and (3), which makes our conclusions regarding publication bias and the average effect robust.

Table 2. Results of the estimation of equation (4)

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS with Clusters SE</th>
<th>(2) OLS with Bootstrapped SE</th>
<th>(3) Hierarchical Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>0.00014 ***</td>
<td>0.00014 ***</td>
<td>0.00015 **</td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
<td>(0.00003)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.01808 *</td>
<td>1.01808 ***</td>
<td>0.44632</td>
</tr>
<tr>
<td></td>
<td>(0.50482)</td>
<td>(0.13783)</td>
<td>(0.79693)</td>
</tr>
<tr>
<td>Number of observations (studies)</td>
<td>330 (24)</td>
<td>330 (24)</td>
<td>330 (24)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0108</td>
<td>0.0108</td>
<td>-</td>
</tr>
<tr>
<td>F-stat / Wald</td>
<td>18.31***</td>
<td>21.54***</td>
<td>5.28**</td>
</tr>
</tbody>
</table>

Notes. Dependent variable: $t$. Standard errors reported in parentheses. Significance levels: *** for $p$-value < 0.01; ** for $p$-value < 0.05; * for $p$-value < 0.1.

Table 3. Estimation of equation (4) – robustness

Notes. Dependent variable: $t$. Standard errors reported in parentheses. Significance levels: *** for $p$-value < 0.01; ** for $p$-value < 0.05; * for $p$-value < 0.1.
4.2. Multivariate meta-regression

To complement the previous analysis, we estimate a multivariate meta-regression in order to assess how the differences in studies’ methodological characteristics explain the heterogeneity in the reported effect sizes.

The differences in studies’ methodological characteristics are captured by dummy variables. Based on the literature review and the considerations of Section 3, we consider dummies for the: structure of the data; estimation methods; types and number of countries analyzed; measurement of reshoring; measurement of automation; level or unit of analysis; and type of publication. We also consider two quantitative variables reflecting the year of publication and the number of citations that the study has got. Table 4 lists and describes the moderator variables and Table 5 presents the results of the estimation of the multivariate meta-regression using (1) OLS with clustered standard errors, (2) OLS with bootstrapped standard errors and (3) hierarchical models.

Table 4. Moderating variables of the effect of automation on reshoring
<table>
<thead>
<tr>
<th>Variable</th>
<th>Type of variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel</td>
<td>Dummy</td>
<td>1 if the article uses panel data; 0 otherwise.</td>
</tr>
<tr>
<td>FE</td>
<td>Dummy</td>
<td>1 if fixed effects (FE) is used as estimation method; 0 otherwise.</td>
</tr>
<tr>
<td>IV</td>
<td>Dummy</td>
<td>1 if instrumental variables (IV) are used to account for endogeneity; 0 otherwise.</td>
</tr>
<tr>
<td>Developed</td>
<td>Dummy</td>
<td>1 if the study uses only developed countries in the sample; 0 otherwise.</td>
</tr>
<tr>
<td>Developing</td>
<td>Dummy</td>
<td>1 if the study uses only developing/emerging countries in the sample; 0 otherwise.</td>
</tr>
<tr>
<td>One country</td>
<td>Dummy</td>
<td>1 if the study focuses on only 1 country; 0 otherwise.</td>
</tr>
<tr>
<td>Inputs</td>
<td>Dummy</td>
<td>1 if reshoring/offshoring is captured through input/intermediate goods flows; 0 otherwise.</td>
</tr>
<tr>
<td>Broad</td>
<td>Dummy</td>
<td>1 if reshoring/offshoring is calculated by its Broad measure; 0 otherwise.</td>
</tr>
<tr>
<td>Narrow</td>
<td>Dummy</td>
<td>1 if reshoring/offshoring is calculated by its Narrow measure; 0 otherwise.</td>
</tr>
<tr>
<td>Robots</td>
<td>Dummy</td>
<td>1 if robots are used to measure the automation level; 0 otherwise.</td>
</tr>
<tr>
<td>Industry/Sector</td>
<td>Dummy</td>
<td>1 if the unit of analysis is sector or industry; 0 otherwise.</td>
</tr>
<tr>
<td>Firm</td>
<td>Dummy</td>
<td>1 if the unit of analysis in the study is firm; 0 otherwise.</td>
</tr>
<tr>
<td>Publication</td>
<td>Dummy</td>
<td>1 if the article has been published in a scientific journal; 0 otherwise.</td>
</tr>
<tr>
<td>Year</td>
<td>Quantitative</td>
<td>It assumes a value of 1 in 2015 (the year in which the first study was published); 2 in the following year (2016) and so on until the year 2022, where it assumes a value of 8.</td>
</tr>
<tr>
<td>No. of citations</td>
<td>Quantitative</td>
<td>Number of citations of each study as of April 1, 2022</td>
</tr>
</tbody>
</table>
Table 5. Results of the estimation of the multivariate meta-regression

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) OLS with Clustered SE</th>
<th>(2) OLS with Bootstrapped SE</th>
<th>(3) Hierarchical Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>-0.0142 (0.0757)</td>
<td>-0.0142 (0.0644)</td>
<td>-0.0441 (0.0867)</td>
</tr>
<tr>
<td>Panel</td>
<td>-0.0678 ** (0.0327)</td>
<td>-0.0678 *** (0.0233)</td>
<td>-0.0240 *** (0.0026)</td>
</tr>
<tr>
<td>FE</td>
<td>0.0188 (0.0111)</td>
<td>0.0188 * (0.0100)</td>
<td>0.0001 (0.0149)</td>
</tr>
<tr>
<td>IV</td>
<td>-0.0001 *** (0.0000)</td>
<td>-0.0001 (0.0092)</td>
<td>-0.0001 *** (0.0000)</td>
</tr>
<tr>
<td>Developed</td>
<td>-0.0130 (0.0151)</td>
<td>-0.0123 (0.0096)</td>
<td>-0.0020 (0.0187)</td>
</tr>
<tr>
<td>One country</td>
<td>-0.0421 (0.0354)</td>
<td>-0.0421 (0.0323)</td>
<td>0.0620 ** (0.0266)</td>
</tr>
<tr>
<td>Inputs</td>
<td>-0.0611 * (0.0347)</td>
<td>-0.0611 ** (0.0314)</td>
<td>-0.1224 *** (0.0287)</td>
</tr>
<tr>
<td>Broad</td>
<td>0.0631 ** (0.0231)</td>
<td>0.0631 *** (0.0136)</td>
<td>-0.0421 *** (0.0154)</td>
</tr>
<tr>
<td>Narrow</td>
<td>0.0720 *** (0.0187)</td>
<td>0.0720 *** (0.0151)</td>
<td>-0.0242 (0.0174)</td>
</tr>
<tr>
<td>Robots</td>
<td>0.0169 (0.0402)</td>
<td>0.0169 (0.0301)</td>
<td>-0.0048 (0.0609)</td>
</tr>
<tr>
<td>Industry and Sector</td>
<td>-0.0125 (0.0593)</td>
<td>-0.0125 (0.0599)</td>
<td>0.1865 *** (0.0325)</td>
</tr>
<tr>
<td>Firm</td>
<td>-0.0684 *** (0.0242)</td>
<td>-0.0684 ** (0.0284)</td>
<td>0.0573 ** (0.0287)</td>
</tr>
<tr>
<td>Publication</td>
<td>-0.0805 * (0.0417)</td>
<td>-0.0805 *** (0.0216)</td>
<td>0.0089 (0.0089)</td>
</tr>
<tr>
<td>Year</td>
<td>0.0167 * (0.0095)</td>
<td>0.0167 *** (0.0059)</td>
<td>0.0017 (0.0073)</td>
</tr>
<tr>
<td>Notes. Dependent variable: t. Standard errors reported in parentheses. Significance levels: *** for p-value &lt;0.01; ** for p-value &lt;0.05; * for p-value &lt;0.1.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Citations | 0.0005 * (0.0003) | 0.0005 *** (0.0001) | 0.0001 (0.0002) |

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The results of Table 5 show that the structure of the data and the estimation methods have a significant impact on effect sizes reported by the primary studies. Dummy Panel is statistically significant in the three columns, while dummy IV is significant at 5% in columns (1) and (3). Since the coefficients of these two variables are negative, we conclude that studies using panel data and employing instrumental variables estimation techniques tend to report lower effects of automation on reshoring.

Dummy Developed is not significant in any of the estimations, which shows that the effect size does not depend on countries’ development level. Keeping in mind the conclusion of the previous subsection that the overall average effect is positive, we conclude that the impact of automation on reshoring is equally strong in developed and developing countries. Dummy One country has also a low significance level, meaning that the estimates reported by studies that focus on one single country are not systematically different from those reported by studies that have more than one country in their samples.

Dummy Inputs is statistically significant at 10%, 5% and 1% in columns (1), (2) and (3), respectively. Its negative coefficient suggests that smaller effects are reported when off(re)shoring is captured through the import of...
intermediate goods (comparing to the cases in which it is captured by other types of goods or services). Dummies *Broad* and *Narrow* have also high levels of significance, meaning that studies’ results are sensitive to the way offshoring is measured. However, they are not sensitive to the measure used for automation, since *Robots* is not statistically significant in any of the estimations of the multivariate meta-regression. This conclusion may lead to questioning the claims of Ancarani & Di Mauro (2018) and Butollo (2021), since measuring the degree of automation using the quantity of robots, the amount of machines, or the level of Industry 4.0 does not seem to affect the effect sizes.

The results that concern the level of analysis also seem to be relevant in explaining the observed heterogeneity, as articles that use firms as the unit of analysis tend to report smaller effects than studies using other units of analysis, such as industries/sectors.

Furthermore, there is also some evidence that the number of citations and the type and year of publication are relevant in explaining the observed heterogeneity. Variables *Publication*, *Year* and *Citations* are all statistically significant at 1% in columns (2) and at 10% in column (1). The negative coefficient of *Publication* means that the effects reported in articles published in scientific journals tends to be smaller than the effects reported in other papers. As for the coefficients of variables *Year* and *Citations*, their positive values suggest that, on the one hand, the reported effects of automation on
reshoring are increasing in magnitude over the years and, on the other hand, more cited articles report higher effects.

5. Conclusion

In this paper we developed a meta-analysis of the effects of automation on reshoring. Motivated by the current context of uncertainty, the major technological developments of the last decades and the disruptions of GVCs arising from the pandemic scenario, many multinational firms have explored the possibility of returning their activities to the origin country.

The impact of automation on reshoring has been increasingly investigated in the literature, but there seems to be some divergence regarding its magnitude and even its direction. The meta-analysis shows that there are traces of publications in this empirical literature, which tends to make the reported effects stronger than they actually are. Nevertheless, after correcting for publication bias, we find that the average effect of automation on reshoring is still significant and positive, meaning that automation has in fact contributed to reshoring.

We also find that the heterogeneity of the effects reported by the primary studies is to a large extent explained by differences in methodological characteristics, such as the structure of the data, the estimation techniques, the measure of off(re)shoring, the unit of analysis, and the type and year of publication. The meta-analysis also suggests that the impact of automation
on reshoring is equally strong in developed and developing countries, as the
effect sizes reported by the primary studies are not significantly affect by the
development level of the countries included in the sample.

These conclusions highlight the importance that the development of
automation processes and technologies has played in shaping the patterns of
international flows and production locations. They also open avenues for
future research. In particular, they call attention to the need to explore in more
detail the transmission mechanisms through which automation influences
off(re)shoring. Moreover, given the impacts of both the automation process
and the reshoring movements on the labor markets, it would be relevant to
investigate in more detail how the interplay between automation and
reshoring impacts wages, job losses and job creations in both the origin and
host countries.

Data availability statement

The data that support the findings of this study are available from the
corresponding author upon reasonable request.

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