Automation Adoption and Reshoring: Using input-output table

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Abstract

The introduction of technologies such as computers and ICTs to better coordinate production organization and the opening of lower labour cost countries have contributed to an international fragmentation of production in the 1990s and 2000s. However, the recent rise of new automation technology in production and service has raised concerns about disrupting global value chains. In this paper, we examine the role of automation adoption as a driver of reshoring in the period 2008-2019, using a new measure that takes into account both intermediate and final imports, considers reshoring as a flow process, and includes direct and indirect effects. We find a negative relationship between automation adoption and reshoring, indicating that automation adoption reduces reshoring. We also find that this negative relationship is more pronounced for high-income and lower-middle-income countries, and for adoption of ICT and 3D printing technologies. We examine different time periods and find that the negative relationship between automation adoption and reshoring was strongest in the period 2008-2013, with a magnitude of around 0.28 percent if automation adoption increased by 1 percent. We find that automation adoption reduces reshoring in both manufacturing and service sector, but service sector drives this relationship. Our results suggest that he view that automation technology can replace offshore tasks and promote reshoring is not yet complete.

Keywords: Automation adoption, Reshoring, Global value chains

1 Introduction

As technology continues to evolve, the integration of computers and information and communication technologies (ICTs) has facilitated more effective coordination of production organization, while the rise of lower labor-cost countries has led to a "thick web of exchanges" between East and West, thus contributing to the global fragmentation of production (Los et al., 2015; Pegoraro et al., 2020). Although these developments have undoubtedly brought about numerous benefits, they also come with significant costs and risks.

One of the primary risks associated with the increasing fragmentation of production is the displacement of low-skilled workers in labor-intensive industries in developed countries to offshoring (Ebenstein et al., 2014). Additionally, external shocks, which are often outside of a firm's control, can disrupt supply chains and lead to significant production delays and losses (Novy and Taylor, 2020). To mitigate these risks, firms have been increasingly rethinking their manufacturing strategies, moving from offshoring to reshoring back to their home country, in an effort to avoid the risks associated with fragmentation of production.

The recent development of new automation technologies in production may help to enhance this initiative, as with these new technologies, it is expected that they could substitute low-skilled workers in offshoring countries and it is now more feasible for firms to produce products domestically, rather than relying on low-income countries. Furthermore, these new technologies provide advanced countries with opportunities to shift from mass-production to mass-customized production, where innovation and timely delivery are key comparative advantages (Brettel et al., 2014; Rodrik, 2018b).

Despite the potential benefits of automation and reshoring, it remains an empirical question as to whether these initiatives will be effective. Recent research has highlighted the resilience of supply chains in the face of disruption, particularly under the context of Industry 4.0 (Bürgel et al., 2023; Papadopoulos et al., 2017; Qader et al., 2022).

From this observation, this paper addresses the question of the link between automation and reshoring to the home country at the macro level (country level). In the literature of automation impact, the focus is mainly on employment in the local labor market (Acemoglu and Restrepo, 2020; Frey and Osborne, 2017; Graetz and Michaels, 2018; Nedelkoska and Quintini, 2018). Though informative, the above-mentioned research still ignores the interaction and amplifying effects through trade of automation technologies (Within this paper, we refer both automation technologies and 4IR as the same concept and we use them interchangeably). Since most economies are interdependent and participate in global value chains, the effects

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of automation in one country may spill over to others through trade. Countries offshore parts of their production or even innovation (R&D). Assuming that Germany innovates, files for patents in robots, and eventually adopt robots to replace some of the tasks that are offshored, so the effects of automation technologies do not stop in Germany alone, but also in the countries that Germany was offshoring parts of their production/innovation to.

On the other hand, automation has been increasingly invented and adopted in emerging countries. Some examples include Singapore, Taiwan, South Korea, and Hong Kong, since the 2000s; China since 2015, Thailand, Malaysia, Indonesia and other developing countries recently (Ing and Zhang, 2022). Automation in emerging countries has been seen to be a complement to the employment of production workers (Ing and Zhang, 2022), and a complement to country's upgrading through improving exports' quality (DeStefano and Timmis, 2021). Further, "rise of the South" (Programme, 2013) and the growing important role of China in the global value chain network makes the focus only on the North-South trade not complete.

This paper seeks to bring the discussion in the relationship between automation and reshoring into the table but in macro evidence. We investigate the role of automation adoption in reshoring by testing econometrically whether automation adoption has an effect on reshoring in a set of 60 countries and 35 industries from 2008 to 2019. The proposition to be tested is that automation adoption has a negative effect on reshoring (or increase the supply chain resilience). Further, we investigate whether the role of automation adoption in reshoring has changed over time, thus answer the question whether this effect is more of a recent period, rather than a long duration due to the development and diffusiton of automation.

There are three notable differences between our approach and the prior literature on automation and trade. First, we propose a new measure for computing reshoring at a macro level by utilizing data from regional input-output tables. By considering reshoring as a "flow" process that includes both intermediate inputs and final products, we measure reshoring at both country- and industry-country level. We compare our method with previous and mainly used in the literature, including famously knowned offshoring from Feenstra and Hanson (1996) and the recently proposal from Krenz and Strulik (2021). Second, rather looking solely at the impact of robots on reshoring like prior research (Faber, 2020; Krenz et al., 2021; Kugler et al., 2020), we will expand to all Industry 4.0 technologies. Papers focusing on robots are likely to only provide a partial picture of the impact of automation because robots tend to be concentrated in only some specific sectors. For example, French firms in motor vehicle sector accounts for almost 60% of robot adoption in France (Aghion et al., 2020).

To preview our results, our findings support the prior literature that associating automation with increasing offshoring, and contradict to the literature that support the view of increasing reshoring due to automation. We find an evidence of automation adoption reduces reshoring, however, the impact is limited. In particular, in high-income and lower middle-income countries, the effect of automation is stronger. We do not find a meaningful interaction between automation adoption and labour productivity, and between automation adoption and automation innovation. Furthermore, out results suggest that the reducing reshoring trend is driven by the service sector, while for the manufacturing sector, the impact is more limited. We acknowledge that the causality of our results may be questioned, but we attempt to mitigate these concerns through our econometric model.

The paper is structured as follows. The theoretical arguments for the causes of reshoring hypothesis and reviews of some of the recent literature are summarized in Section 2. Section 3 details our precise definition and measure for reshoring. Section 4 gives a glimpse on our data. Section 5 reports our empirical strategy while section 6 presents our results and discusses stories behind our results, and section 7 concludes the paper with some implications for policy and future research.

2 Theoretical and Empirical Evidence on the relationship between Automation and Reshoring

2.1 The rise of international fragmentation

The rise of international fragmentation in the era of globalization has fundamentally reshaped the organization and geographical distribution of production and trade. This transformation can be understood through the concepts of the first and second unbundling, as explained by Baldwin (2006). The first unbundling, driven by significant reductions in transportation costs, allowed production and consumption to be geographically separated, leading to the industrialization of the North (Western Europe and the US) and the deindustrialization of the South (India and China). This period also saw a substantial increase in international trade and a marked divergence in income levels between the industrializing North and the stagnating South.

The second unbundling, which began in the mid-1980s, was facilitated by advancements in communication and coordination technologies. This phase enabled the geographical separation of different stages of production within industries, giving rise to offshoring and the formation of global production networks. Unlike the first unbundling, which impacted entire firms and sectors, the second unbundling affects individual tasks within firms, making the impact of globalization more unpredictable and sudden. Tasks that were previously considered non-tradable, such as certain service sector jobs, are now subject to international competition, leading to a reorganization of labor markets based on the tradability of tasks rather than skill levels or sectors. Ali-Yrkkö et al. (2011) further illustrates this phenomenon by examining the economic consequences of the global dispersion of production processes. They found that while the Nokia N95 was assembled in both Finland and China, Europe captured a significant share of the value added. Even when assembled in China and sold in the US, Europe captured 51% of the value added, highlighting that value capture is largely detached from the flow of physical goods. Services and intangible aspects dominate the value added, with final assembly commanding only 2% of the total value. Other efforts to measure this international fragmentation at a more aggregated level by estimating the domestic value-added content of a unit bundles of exports, or vertical specialization in trade by Costinot et al. (2013); Feenstra and Hanson (1999); Grossman and Rossi-Hansberg (2008); Los et al. (2015); Timmer et al. (2021). The impact of the second unbundling is extensively discussed in the literature[1]. For example, offshoring was responsible for a significant portion of the increase in the relative demand for skilled labor in the manufacturing sector during the 1980s in the US because firms offshored labor-intensive stages of production and the remaining tasks in the home country required relatively more skilled labor (Feenstra and Hanson, 1999). Using Danish matched employer-employee data, Hummels et al. (2014) show that offshoring firms were able to increase their productivity by reallocating resources to more complex and skill-intensive tasks, thereby boosting wages for their employees.

Despite the benefits in terms of employment, wages, and productivity for skilled labor and firms, international fragmentation expose firms to significant risks. These include supply and demand shocks as well as transportation disruptions. Supply shocks, such as natural disasters, labor strikes, and bankruptcies of suppliers, can cause severe disruptions in production processes (Miroudot, 2020). For example, the 2011 Tohoku earthquake in Japan and the flooding in Thailand had far-reaching effects on global electronics and automotive supply chains (Carvalho et al., 2021). On the other hand, demand shocks can arise from factors like damage to product reputation, customer bankruptcies, and the entry of new competitors, leading to sudden drops in demand and financial instability for firms[2].

Recent trends in technology, including automation, robotics, and 3D printing, may help firms cope with these potential risks and further reshape the landscape of international fragmentation. The next section will discuss some initial theoretical insights and evidence on how automation could further transform this map.

[1]See the discussion paper by Hummels et al. (2018).

[2]See the discussion paper for associated risks by Baldwin and Freeman (2022).

2.2 Initial theoretical and evidence of automation adoption and reshoring

Recent advancements in production technology, such as automation, robotics, and 3D printing, present significant challenges for developing countries. While the second unbundling refers to the geographical separation of different stages of production within industries, giving rise to offshoring, new production technologies are primarily labor-saving and reduce the demand for unskilled labor, which is abundant in low-income countries. For example, the ability to produce shoes cheaply using 3D printing reduces the incentive for major brands to offshore production to countries with cheap labor, leading to reshoring (Rodrik, 2018a).

Empirical evidence on labor-saving technologies, particularly robots, mainly focuses on their impact on employment within advanced economies. The results are mixed and vary depending on the country. Graetz and Michaels (2018) found that robot adoption in various industries across seventeen countries from 1993 to 2007 did not significantly reduce overall employment but decreased the employment share of low-skilled workers. In the U.S., (Acemoglu and Restrepo, 2020) found negative effects of robots on employment and wages across commuting zones. Similarly, Dauth et al. (2021) found that robot exposure led to displacement effects in German manufacturing, which were fully offset by the creation of new jobs in the service sector. Using an event study and propensity score matching methodology to examine French data, Aghion et al. (2023) and Domini et al. (2021) found that automation technologies, not just robots, increased employment in commuting zones and firms that adopted them. This is consistent with findings in developing countries like China and Indonesia, where firm-level data by (Wang et al., 2024) and Ing and Zhang (2022) also show a positive relationship between robot adoption, and automation imports on employment. Therefore, whether robots or automation technologies, in general, are labor-saving depend on many factors, involving both displacement and reinstatement effects. Acemoglu and Restrepo (2019) developed a task-based framework to explain this: automation allows capital to replace labor in various tasks (displacement effect) but also creates new tasks that leverage labor's comparative advantage (reinstatement effect).

The argument for positive relationship between automation adoption and reshoring stems from the idea that automation technologies can replace labor in various manual and unskilled tasks, which are the main comparative advantage of developing countries. If automation can handle these tasks, firms may adopt these technologies and reshore activities back to their home countries. Initial empirical evidence supports this view. For example, De Backer et al. (2018) found that robot adoption in developed countries reduces offshoring, particularly in labor-intensive sectors. Using data from Mexican local labour market between 1990 and 2015, Faber (2020) showed that U.S. robots negatively impacted Mexican employment, exports, and export-producing plants, indicating reshoring. Similarly, Kugler et al. (2020) found that U.S. robot adoption negatively impacted Colombian employment and earnings, while Krenz et al. (2021) found a positive relationship between robot adoption and reshoring using the World Input-Output Dataset.

However, while it may seem reasonable to expect that automation will enhance reshoring, the decision to reshore is more complex. The next section will discuss why more evidence is needed to fully understand this relationship and provide new arguments in this relationship.

2.3 New explanations and empirical evidence of the relationship between automation adoption and reshoring

First, we argue that the productivity effects from automation adoption may offset the displacement effects brought by automation technologies. Artuc et al. (2023) develop a Ricardian trade model allowing robots to take over tasks previously done by humans, similar to the framework discussed by Acemoglu and Restrepo (2019). This model includes two layers of competition: between robots and workers in factor markets, and between countries in product markets. This framework is crucial for examining the impact of automation on reshoring and trade. Their key findings include a trade pattern shift from the North to the South. When the price of robots falls, robotization occurs primarily in the North, where labor costs are higher, leading to lower production costs and increased exports to the South. The effect on imports from the South is ambiguous; while Northern producers become more competitive, reducing some imports, the overall production expansion increases demand for Southern inputs. Automation may not necessarily enhance reshoring but instead promote more trade between the North and the South due to productivity effects from automation adoption. Their analysis using industry-country data from 1995-2015 confirms that increased robot intensity in production increases imports from less developed countries and even greater increases in exports to those countries. Supporting this view, Freund et al. (2022) observes a significant surge of approximately 80% in the exportation of hearing aids following the adoption of 3D printing technology. Similarly, Stapleton and Webb (2020) and Cilekoglu et al. (2021) and the number of affiliates in, lower-income countries, suggesting a decrease in reshoring and an increase in trade by importing intermediate inputs. Koch et al. (2021) also finds that robot adoption boosts productivity and exports. Some may argue using the modern Solow paradox that productivity effects of automation technologies are overstated. However, Capello et al. (2022) supports the view that new technologies boost productivity in sectors where they are adopted, though the overall positive impact at a more aggregated level may be dampened by employment shifts towards less productive sectors.

Second, the characteristics and adoption rate of current automation technologies are important for understanding potential displacement effects. Despite initial high expectations, the adoption rate of automation technologies remains limited, confined to specific sectors and driven by a small number of firms. These technologies appear to be continuous improvements of previous models rather than disruptive innovations (Fernández-Macías et al., 2021) Thus far, the capabilities and adoption of robots and other automation technologies enhance human work rather than replace it. The low adoption rate may point to the threshold effect discussed by Capello et al. (2022), which suggests that low adoption rates lead to negligible labor productivity gains. We also test this explanation in our model and argue that threshold effects exist in the relationship between automation adoption and reshoring.

Third, although we discussed some potential risks associated with increasing fragmentation in section 2.1, reshoring decisions are complex due to sunk costs. Many fixed costs associated with offshoring, such as information gathering, investments in physical assets, and relational capital, are sunk costs and cannot be recovered. When production involves multiple stages, reshoring decisions become more complex due to the need to co-locate production stages to minimize costs, making it challenging to reshore specific stages while keeping others offshored (Antràs, 2020). Firms face significant barriers to changing suppliers due to switching costs, as evidenced by nearly half of U.S. importers retaining their Chinese partners over time (Monarch, 2022).

Finally, measurement matters. Reshoring is a relatively new phenomenon, making it essential to identify and measure it accurately to understand its relevance. We will discuss this point further in the next section, addressing current limitations in the literature and proposing a new measure for reshoring to properly identify this concept in the data.

3 Definition and Measurement of Reshoring

3.1 Measurement from Literature

Reshoring is defined as the decision to relocate activities (values) back to the home country of the parent company (Foster-McGregor et al. (2019); Fratocchi et al. (2014). While the concept of reshoring is straightforward, there is no consistent and universally accepted way to measure it. The prevailing approach is to gauge reshoring based on offshoring, which is typically determined using imported intermediates as a metric, as previously established by Feenstra and Hanson (1999). This methodology, however, has been criticized for excluding final goods that are assembled abroad (Fort, 2017; Johnson, 2018). De Backer et al. (2018) address this issue by employing an indicator that considers both intermediates and final products to calculate the proportion of domestic demand served by foreign products. Nonetheless, this measure has limitations as reshoring pertains to not only domestic demand but also foreign demand.

To measure offshoring and reshoring, both firm-level and industry-country level data are employed. Firm-level data helps us comprehend the reasoning behind firms' decisions on when, why, and how they choose to locate their manufacturing activities, whereas industry-country level data aids in understanding whether a specific factor can impact the entire country. Previous research on offshoring has predominantly focused on macro-level analysis, but recent work has utilized firm-level data on importing and the number of affiliates for each firm in the host country (Stapleton and Webb, 2020). Bems and Kikkawa (2021) measure trade in value-added based on firm-level cross-border trade and domestic firm-to-firm sales without relying on sectoral aggregation. Other studies have focused solely on affiliate activities of multinational firms (Harrison and McMillan, 2011; Kovak et al., 2021), while others have relied on survey data from firms regarding their reshoring decisions (Fort, 2017). While these datasets provide detailed firm-level information, they only cover a subset of firms and limited years.

At the macro level, the typical approach to measure reshoring is to view it as the opposite of offshoring. However, Krenz and Strulik (2021) contend that a decline in foreign input shares in value-added may be due to a decrease in production and that this can be a misleading indicator of reshoring. Bailey et al. (2018) and Shingal and Agarwal (2020) similarly argue and propose that reshoring should be measured as an increase in domestic insourcing and a decrease in foreign outsourcing. However, this approach does not include both imports from intermediate inputs and final goods, and does not consider reshoring as a flow process, as discussed in Krenz and Strulik (2021).

Given the incomplete nature of existing measures of reshoring, we propose a novel approach that encompasses several improvements: (1) it is specifically designed to measure reshoring rather than relying on offshoring; (2) it describes reshoring as a flow process rather than a stock of a specific year to fully capture the moving process stated in the definition of reshoring; (3) it considers both intermediate inputs and final goods to capture final goods assembled abroad; (4) it takes into account both domestic and foreign demand and (5) it covers both direct and indirect supply chain relationships. To cover all these improvements, we utilize macro-level data at the cross-country and cross-sector-country level. The following section will explain our approach to computing this new mesure of reshoring.

3.2 Our measurement

3.2.1 Reshoring measure

Krenz et al. (2021) use World Input-Output Tables (WIOD) to compute the reshoring measure, in which they have:

Broad measure of reshoring

$Reshoring_t = (DI_t/FI_t) - (DI_{t-1}/FI_{t-1})$

with the restriction that $reshoring > 0$. DI_t denotes to domestic input at time t and FI_t denotes to foreign input at time t. The reshoring measure shows by how much domestic inputs increased relative to foreign inputs compared to the previous year. This broad measure may overestimate reshoring when there is none. For example, when both domestic and foreign inputs decline but foreign inputs decline by more. Therefore, they have **narrow measure** which requires that the changes $DI_t - DI_{t-1}$ and $FI_t - FI_{t-1}$ are neither both positive nor both negative or equal to 0.

However, Krenz et al. (2021) only consider intermediate inputs in their measure, without considering the final products when calculating reshoring. Therefore, we expand the methodology from Krenz et al. (2021) and we have:

$Reshoring_t = (DVA_t/FVA_t) - (DVA_{t-1}/FVA_{t-1})$

DVA_t is domestic value added at time t, and FVA_t is foreign value added at time t. We will not limit $reshoring > 0$ as we say that if $reshoring < 0$, it means reshoring decreases. We will also use both the term narrow and broad reshoring, but our definition in narrow and broad is different than Krenz et al. (2021). Narrow reshoring is when we only take into account domestic value added served domestic demand, and broad reshoring is when we consider domestic value added served both domestic and final demand. We will use numerical examples to illustrate our reshoring measure in the next section.

3.2.2 Numerical examples

Supposedly we have 3 countries participating in the global value chains, and we are talking about reshoring of country A. We divide into two cases. In the first case, the final demand for country B and country C are zeros and country A does not provide inputs to country B and country C, while in the second case, the final demand for country B and country C are different from 0 and country A also provides input to country B and country C. We have the beginning period (which is referred as period 1), in which the domestic input (DI) is 3, foreign input (FI) is 6, domestic input + foreign input $(DI + FI)$ equal 6, final demand $(F) equals 9, total output$(Y) is 12 (equals sum of domestic input and foreign demand). The illustration of the numerical examples can be accessed here.

In the first case, where the demand for country B and country C are zeros and country A does not provide inputs to country B and country C, we have domestic value added $(DVA = F - (DI + FI)$ equals 3, domestic value added over final demand (DVA/F) equals $3/9 = 0.33$, foreign value added over final demand $(FVA/F) = (F - DVA)/F$ equals 0.67, and we have domestic value added over foreign value added $(DVA/FVA) = DVA/(F - DVA)$ equals 0.5.

The period from 2-39 illustrates different cases in which we adjust for the change in final demand, domestic input, foreign input, and total output. From period 2 on wards, we have four other columns named input difference ($ID = \frac{DI_t}{FI_t} - \frac{DI_{t-1}}{FI_{t-1}}$), reshoring intensity (R equals maximum value of 0 and ID), and value added difference ($VAD = \frac{DVA_t}{FVA_t} - \frac{DVA_{t-1}}{FVA_{t-1}}$).

For example, in period 2, we have the case: "No change in F, DI increase, FI decrease, Y increase (compared to period 1)", so we have F is still 9, DI increases from 3 to 4, FI decreases from 6 to 5, and Y increases from 12 to 13. We have $DVA = 4$, $DVA/F = 0.44$, $FVA/F = 0.56$, $DVA/FVA = 0.8$. Therefore, we have $ID = (4/5) - (3/6) = 0.3$, $R = 0.3$, and $VAD = (4/5) - (3/6) = 0.3$. In this period, we have $ID = VAD$.

We conduct similarly for 37 more cases, and the yellow highlight in the table are the ones in which we have the contradicting values for input difference and value added difference. For example, in the period 3, we have $ID = 0.07$, which indicates there is a reshoring in the case, however, the VAD puts us in a different position where $VAD = -0.21$ which means the domestic value added decreases relative to foreign value added compared to period 1. The period 3 illustrates the case in which there is no change in F, DI increase, FI no chanage and Y increase. Normally, according to our perception and understanding from the reshoring measure of Krenz et al. (2021), we would interpret this case as reshoring. However, this may only reflect a part of the big picture where there is an increase of domestic input relative to foreign input, but country A actually captures smaller domestic value added over final demand.

In the second case, where the demand for country B and country C are different from 0 and country A also provides input to country B and country C, we will have a more general case to calculate DVA and FVA, as explained in the below section in matrix form. Similarly, the ones in yellow highlight are have contradicting values between ID and VAD (similar to the first case). The ones in orange highlight have different values compared to the first case, either in the case they have contradicting values but in the first case, there seems to have no contradiction; or in the case they do not show the contradicting values between ID and VAD but the first case shows there is a contradiction.

3.2.3 Matrix

We follow the standard input-output matrix to generalize our calculation for DVA and FVA. We denote $\boldsymbol{A}$ as a matrix of intermediate inputs technical coefficients. We also have $\boldsymbol{V}$ as a matrix of value added coefficients where elements $v_i = va_i/y_i$ or value added over total output on the diagonal and zeros otherwise. The inverse Leontief matrix as $\boldsymbol{L} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}$ with $\boldsymbol{I}$ is the identity matrix. We also introduce the matrix $\boldsymbol{F}$ as a diagonal matrix of final demands. We have the matrix of domestic and value added as matrix $\boldsymbol{S}$, where:

$$\boldsymbol{S} = \boldsymbol{VLF}$$

Along the rows, this matrix shows the distribution of value-added from one country-sector to all country-sectors' final goods production (final demand). Along the columns, this matrix $\boldsymbol{S}$ displays the contribution of value-added of all source country-sectors in the production of a specific country-sectors' final goods production (final demand). In other words, sum of columns of matrix $\boldsymbol{S}$ shows final demand of each country-sector and sum of rows of matrix $\boldsymbol{S}$ displays total value added of that country-sector.

Therefore, in our measure, we will focus on the column side of the matrix $\boldsymbol{S}$ to calculate DVA and FVA to the production of final goods and services of a country-sector. However, in a broad measure of DVA, we also take into account the DVA to the production of final goods and services of all country-sectors (sum of that country-sector row).

3.3 Comparison with other measures

3.3.1 Offshoring index

Krenz and Strulik (2021) explain in their article why using reverse offshoring is an imprecise measure of reshoring. They mention that Feenstra and Hanson (1996)'s measure of offshoring focus on a stock variable while reshoring is a dynamic activity in which we should take into account flow variable. Because we have the definition of reshoring as "moving production back home" or we need to have a baseline period to compare how the change in domestic and foreign input intensity is. Therefore, the current measure of offshoring could not capture this dynamic nature of reshoring.

3.3.2 The new GVC Participation index

Wang et al. (2017) propose the new GVC participation indexes include: domestic value added generated from a country-sector's GVC activities through downstream firms as share of that country's total value added and a second participation index measures the percentage of a country-sector's total production of final goods and services that represent the value added that is involved in GVC activities through upstream firms. Basically, their new measures are explained through the figure 1 and 2.

They have two GVC participation index as follows:
$GVCP_{t_f} = \frac{V_{GVC}}{Va'} = \frac{V_{GVCS}}{Va'} + \frac{V_{GVCC}}{Va'}$
$GVCP_{t_B} = \frac{Y_{GVC}}{Y'} = \frac{Y_{GVCS}}{Y'} + \frac{Y_{GVCC}}{Y'}$
The first equation $GVCP_{t_f}$ describes the domestic value added generated from a country-sector's GVC activities through downstream firms, as explained in figure 1. The second equation $GVCP_{t_B}$ measures the value added that is involved in GVC activities through upstream firms and explained in figure 2.

All of their decomposition comes from the matrix $\hat{V}B\hat{Y}$ where $\hat{V}$ is a diagonal matrix with the direct value-added

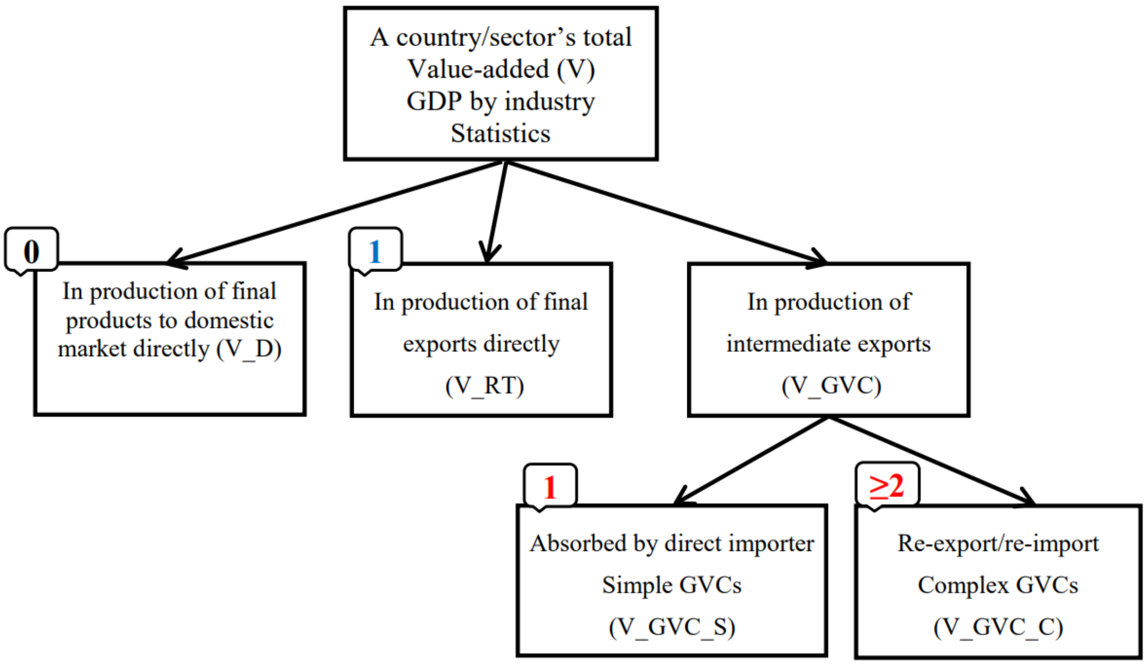

Figure 1: Decomposition of GDP by industry - Which types of production and trade are Global Value Chain activities?. Source: Wang et al. (2017)

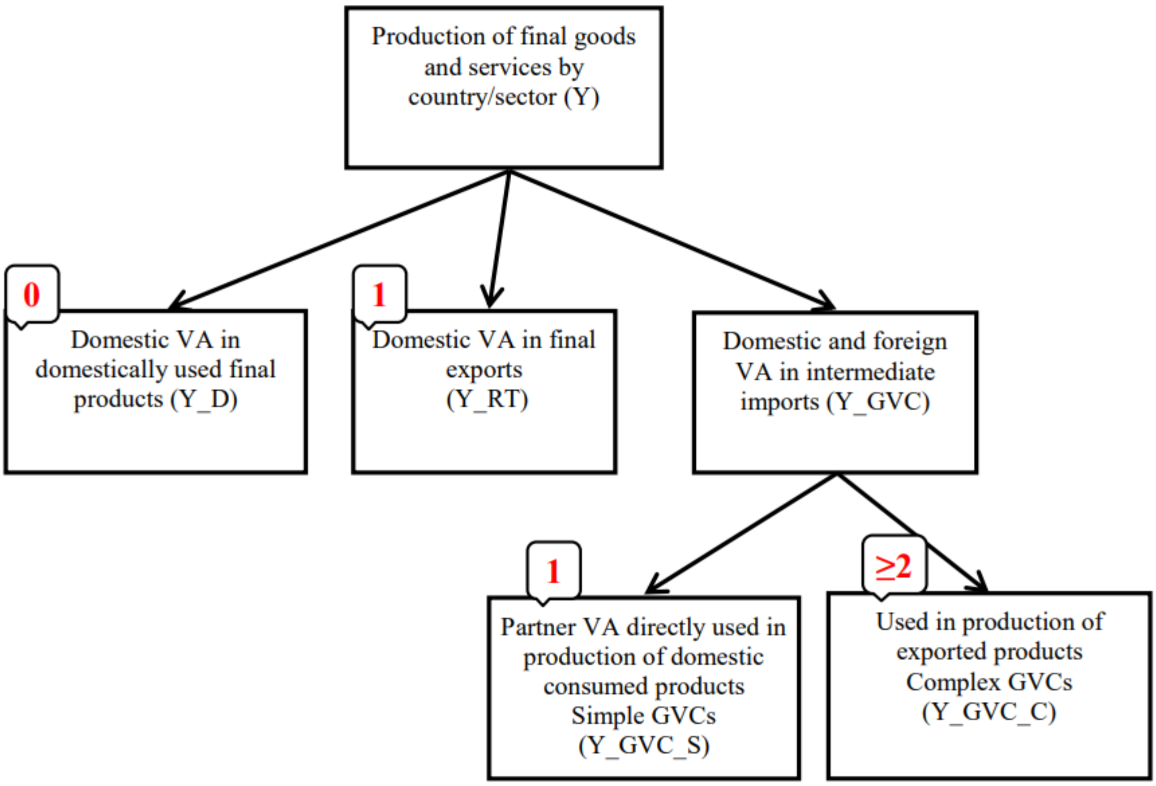

Figure 2: Decomposition final goods production by country/sector - Which part of final goods production and trade belong to GVCs?. Source: Wang et al. (2017)

coefficients in its diagonal, $\hat{Y}$ is a diagonal matrix with the final goods and service production in its diagonal, and $B = (I - A)^{-1}$ is the (global) Leontief inverse matrix. Therefore, our measure has the same originate form with the measure from Wang et al. (2017). However, their new GVC participation index focus more on the global value chains participation, which is through four ways (1) exporting its domestic value-added in intermediate exports used by a direct importing country to produce for domestic consumption; (2) exporting its domestic value-added in intermediate exports used by a direct importing country to produce products for a third country; (3) using other countries' value-added to produce its gross exports; and (4) using other countries' value-added to produce for domestic use.

Our measure for reshoring covers all four ways that they are mentioned, but we also include the use of domestic value added to that country's own consumption, and the way we measure reshoring will reflect a different idea than Wang et al. (2017). Our main motivation is to discover how much of domestic production increase/decrease relatively compared to foreign production over time, therefore, our measure describes flow, while Wang et al. (2017)'s measure is to decompose a country/sector's GDP and final goods production into pure domestic activities and GVC production activities. Hence, their measure is to describe stocks. Our measure can be illustrated as in the figure 3 and 4.

3.4 With data

In this section, we apply the new reshoring index into the ADB Multi Regional Input-Output table (ADB-MRIO).

3.4.1 The reshoring index from Krenz et al. (2021)

The reshoring index from Krenz et al. (2021) applying into WIOD is illustrated in the figures 5 and 6.

Figure 5 describes the trend for domestic-foreign input differential (their proposed reshoring index) for four countries, China, Great Britain, Spain and the U.S (the upper panel), and the trend for offshoring (as measured by FI/VA proposed by Feenstra and Hanson (1996) and widely used in the literature). The first panel shows both increasing and decreasing trends of reshoring index. In China and Great Britain, from 2005 on wards, there is an upward trend of reshoring and from then reshoring is always above zero, while in Spain an opposite trend shows where reshoring intensity declines over time, especially from 2005 on wards, the reshoring intensity is always below zero. For the US, there is not much of a clear trend in reshoring intensity where it is up and down along the years, but the reshoring intensity is always below zero. The second panel for offshoring shows a clearer trend where three out of four countries show an increasing offshoring trend, while for China, their offshoring decreases from 2010 on wards.

Figure 6 shows a reshoring and offshoring trend in food, textiles, minerals, and computer industry in China. The first panel similarly shows reshoring index, while the second panel shows offshoring index. The reshoring index increases over time in these four selected industries in China, however, their reshoring indices are always below zero. The offshoring indices in these four industries increase over time. The offshoring here describes offshoring from world to China.

3.4.2 Our proposed new reshoring index

We apply the new proposed reshoring index into ADB-MRIO. The figures below show the new proposed index, and illustrate the differences between our proposed new reshoring index with the reshoring index from Krenz and Strulik (2021).

Figure 7 uses the value added difference (new reshoring index) with the domestic value added not include the domestic value added to other countries' final demand. Figure 8 uses the value added difference with the domestic value added, also include the domestic value added to other countries' final demand. Our reshoring index shows a somewhat different trend than the proposed measure by Krenz and Strulik (2021). For all four countries, there is not a clear indication of increasing trend of reshoring. The reshoring fluctuates from 2008 to 2019. There is an increasing trend of reshoring from 2010 to 2015. But from 2008 to 2010, reshoring seems to decrease, and the trend is repeated again from 2015 to 2019 for all four countries. For China, there is an upward trends of reshoring until 2009, and drops in 2010, then increases from 2010 on wards before decreasing again from 2015 and later years. For Great Britain, our reshoring measure shows a more stable trend compared to China, however, it also follows a similar trend. Reshoring increases until 2009, then drops in 2010 and increases from 2010 on wards before dropping again in 2013 and 2015. The trend is different from the figure of Krenz and Strulik (2021). Spain's reshoring intensity seems to be more fluctuated during the earlier years and more stable the years later. Reshoring in Spain increases in the period 2008 - 2009, drops in 2010 before increases again until 2012. After having a drop in 2014, reshoring increases in 2015 and again drops in the later years. However, for Krenz et al. (2021), it has been in a decreasing trend. Reshoring in the United States follows a similar trend to China, however, the fluctuation between years is larger compared to China.

Figure 7 and 8 show the reshoring index at country level of four countries. I also attach reshoring figure for all countries included in the ADB-MRIO in Appendix **??** and **??**. Now I look into more depth at the industry-country level for China in Food, beverages and tobacco industry and Textiles and textile products industry.

Figure 9 shows reshoring values at industry level in China. Both reshoring index fluctuates over time. However, reshoring in Food, beverages and tobacco shows an increasing trend between 2008 and 2015. Then it has a huge drop between 2015 and 2017, and again increases after 2017. Our measure again shows a more fluctuated trend of reshoring compared to Krenz et al. (2021)'s

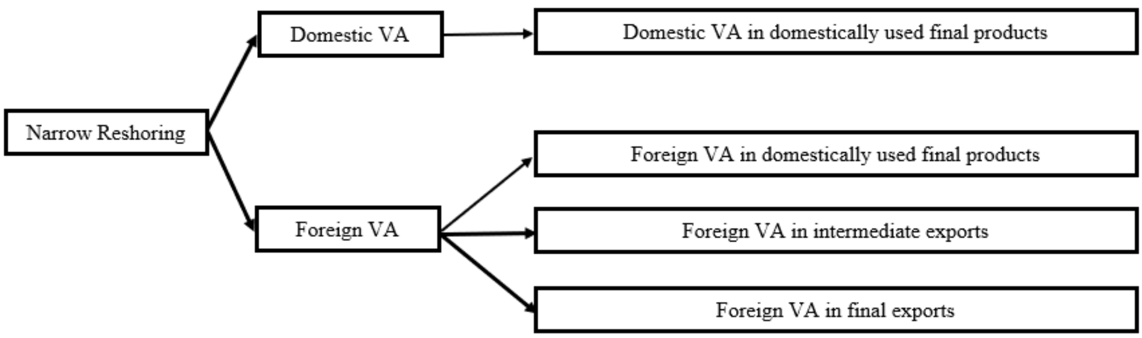

Figure 3: Narrow Reshoring Index Illustration

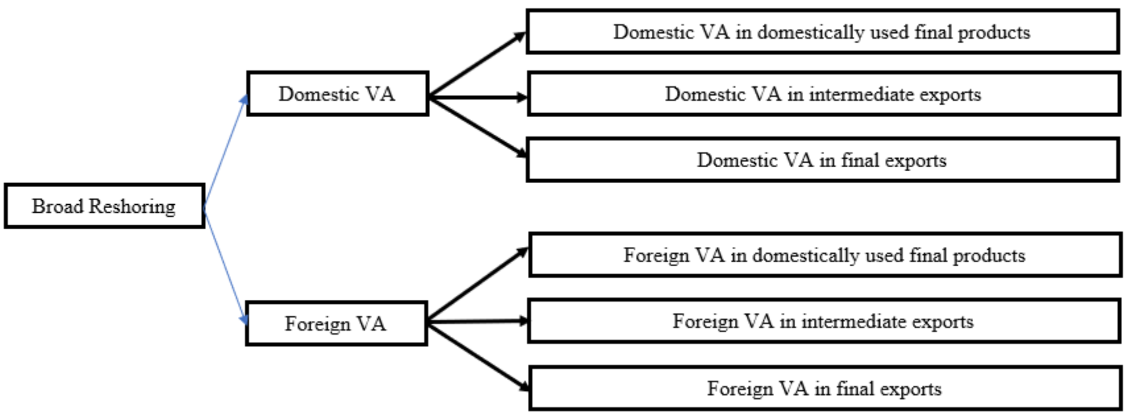

Figure 4: Broad Reshoring Index Illustration

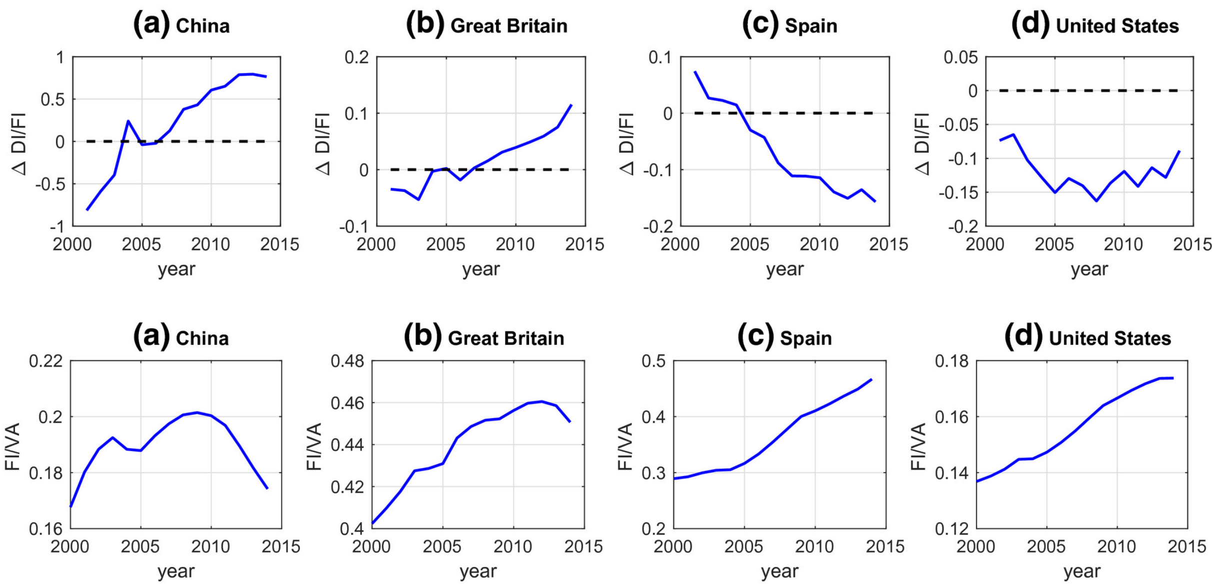

Figure 5: Reshoring index by Krenz et al. (2021) in China, Great Britain, Spain, and United States. Source: Krenz et al. (2021)

findings for textile and food industries.

4 Data

4.1 Data sources

The primary source of data comes from two different sources: Asian Development Bank Multiregional Input-

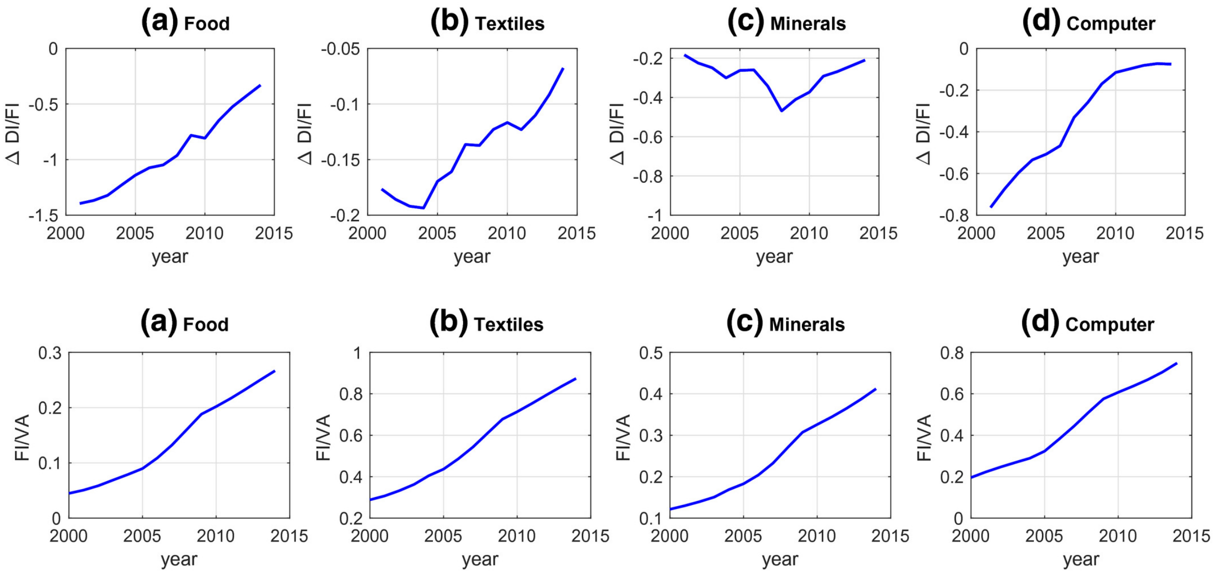

Figure 6: Reshoring index by Krenz et al. (2021) at industry level in China. Source: Krenz et al. (2021)

Figure 7: New reshoring index in China (PRC), Great Britain (UKG), Spain (SPA), and United States (USA)

Output Tables (ADB-MRIO) and ADB-ADBI Innovation and Structural Transformation Database.

The ADB-MRIO develops the World Input-Output Tables (Timmer et al. (2015)) by including 19 Asian economies for the years 2000, 2007 to 2019. The added countries include: Bangladesh, Bhutan, Brunei Darussalam, Cambodia, Fiji, Hong Kong, China, Kazakhstan, Kyrgyz Republic, Lao People's Democratic Republic,

Figure 8: New reshoring index with broad DVA in China (PRC), Great Britain (UKG), Spain (SPA), and United States (USA)

Malaysia, Maldives, Mongolia, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, and Vietnam. The WIOD combines information on demand, production and international trade for 43 countries (including all twenty-eight members of the European Union (as of July 1, 2013) and fifteen other major economies: Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Norway, Russia, South Korea, Switzerland, Taiwan, Turkey and the United States) (Timmer et al. (2015)). While the WIOD covers information for 56 sectors and products, the ADB-MRIO only covers 35 industries, at 2-digit ISIC revision 4 level due to adding more countries.

The ADB-ADBI Innovation and Structural Transformation Database is a collaboration between ADB Institute, ADB, and United Nations University - UNU-MERIT (Foster-McGregor et al. (2022). The database provides information about structural change, product complexity, innovation, and global value chains at country level. Within this paper, we will use their data on cover data on automation innovation and automation adoption.

For automation adoption, we use their data on 4IR technologies. They use a classification of export products based on Foster-McGregor et al. (2019) and Acemoglu and Restrepo (2022). They cover six types of sub-fields related to 4IR, including CAD-CAM, Robots, Automated welding, 3D printing, Regulating instruments, and ICT. The detailed product codes are in Appendix ??. Though they try to cover details on 4IR technologies, due to an overlap between third industrial revolution technologies and 4IR and an imperfect HS code system, they admit they may cover third industrial revolution technologies into their data. However, a majority of the classifications belongs to 4IR.

For automation innovation, they have two indicators related to automation innovation. Their original database to construct patent indicators based on PATSTAT. Their method to identify 4IR patents based on a method proposed by the European Patent office. They use the 10-year cumulative numbers and have indicators for total number of patents and the 4IR subfields. We will use total number of 4IR patents to refer as automation innovation at country level. Figure ?? shows automation innovation over time by country covered in ADB-MRIO table.

Our paper also exploits country - industry level data, so an indicator for patents at industry level is essential for us. However, in the ADB-ADBI Innovation and Structural Transformation Database, they do not have a direct measure of number of patents at industry level. We also notice that they have patent indicators in the context of global value chains, which include *patent content of value*

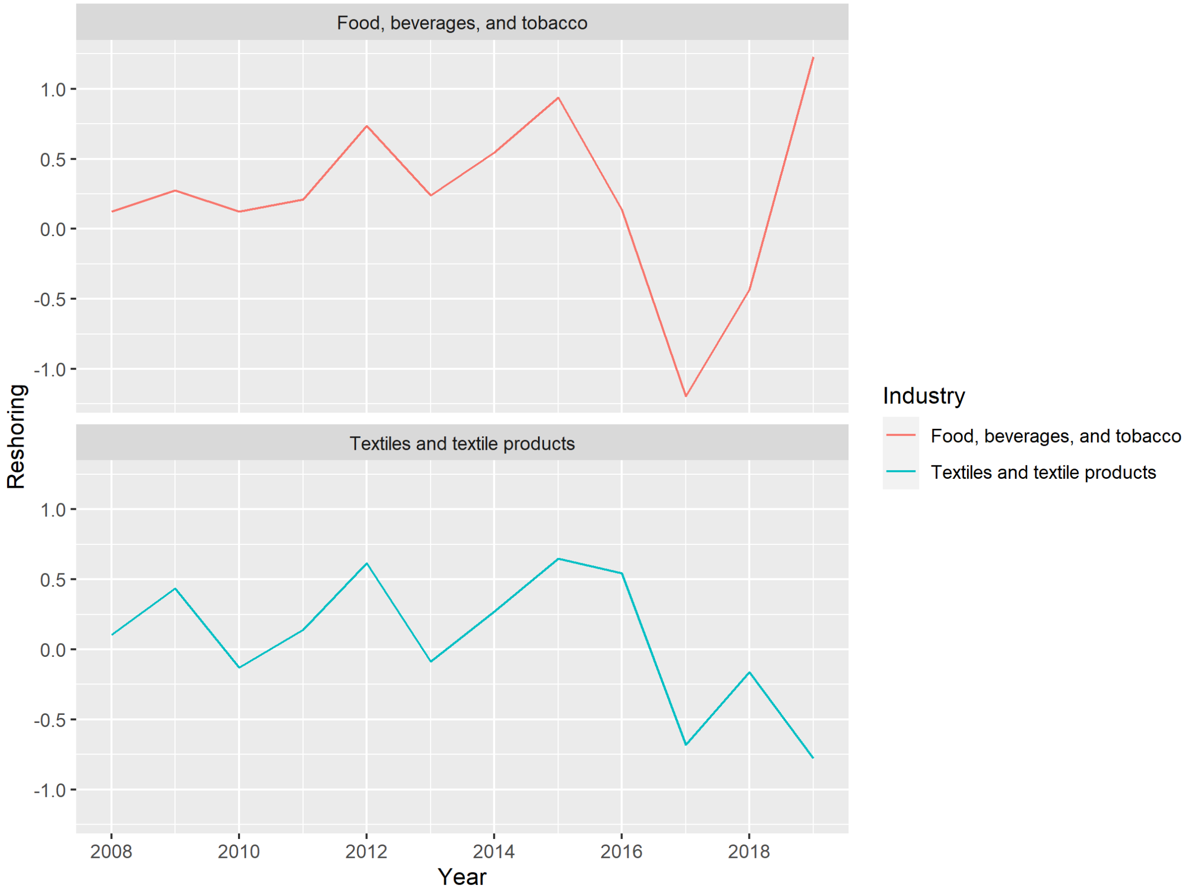

Figure 9: New reshoring index at industry level in China in Food and Textiles industry

added at the level of sectors in economies: $Q_j = Pat_j/VA_j$ where Qj is the patent content of value added in sector j, VAj is value added in the sector, and $Patj$ is the number of patent families assigned to the sector. From this, we can calculate the number of patent families assigned to the sector by getting the Qj multiply by VAj. This is exactly what we did to get the total number of patents at industry level.

Another data source is labour productivity downloaded from Our World in Data (as a control variable) - which is published by Feenstra et al. (2015).

4.2 Descriptive statistics

Table 1 summarises our data in terms of mean, standard deviation, minimum, maximum value, and number of observations. The mean of reshoring variable (narrow) computed at country level is -0.0194. LGAUTO is the logarit form in the total automation weighted by population. The logarit form in number of patents with 10 years cumulative weighted by population (LGPAT) has a mean of 0.017. and LGLBPROD is the logarit form of labour productivity.

5 Empirical Strategy

We examine the impact of automation adoption on reshoring in two levels, beginning with cross-country level and finding the different impacts with our base model, adding interaction terms, level of incomes in the home country, different types of technology, and different time period varying by 5-year period from 2008 to 2019. Then we continue to the sector-country level to distangle the impacts between manufacturing and service sectors.

5.1 At cross-country level

5.1.1 Baseline Model

We present our core estimation strategy at country level as follows:

$$\begin{aligned} RES_{ct} = \beta_0 + \beta_1 LGAUTO_{ct} + \beta_2 LGPAT_{ct} \\ + \beta_3 LGLBPROD_{ct} + \mathbf{C}_c \\ + \mathbf{T}_t + \varepsilon_{ct} \qquad (1) \end{aligned}$$

where c is country, t is time period and ε_{ct} is the error term. RES_{ct} is reshoring variable in country c at

Table 1: Summary statistics

	Mean	SD	Min	Max	N
Main dependent variable					
RES	-0.0194	0.5257	-4.9364	4.026	744
Automation Adoption variables					
LGAUTO	8	2	3	11.512	744
LGAUTO_CADCAM	2	1	0	3.921	744
LGAUTO_ICT	5	2	0	9.513	744
LGAUTO_REGINSTR	2.158	1.272	0.000	4.926	744
LGAUTO_ROBOTS	2.459	1.318	0.000	6.433	744
LGAUTO_WELDING	0.747	0.617	0.000	3.123	744
LGAUTO_3D	1.999	1.068	0.000	5.604	744
Other control variables					
LGPAT	0.017	0.033	0.000	0.187	744
LGLBPROD	3.295	0.846	1.188	4.911	744
LGDIST	4.992	1.194	1.871	7.349	744
LANDLOCKED	0.194	0.395	0.000	1.000	744
LGTEMP	3.473	0.286	2.528	3.863	720

time t, measured both at narrow and broad definition; $LGAUTO_{ct}$ is the logarit form for total automation imports value at country c at time t; $LGPAT_{ct}$ is the logarit form for number of patents for 10 years cumulation in country c at time t; $LGLBPROD_{ct}$ is the logarit form for labour productivity at country c at time t. In the base line model, time periods cover from 2008 to 2019, as the reshoring variable describes the flow and we have the data from ADB-MRIO from 2007 onwards, so the reshoring variable can be constructed from 2008 to 2019. Our main independent variable is $LGAUTO$. We also have automation innovation at country c at time t and labour productivity at country c at time t as our control variables. We have automation innovation and automation adoption weighted by national population. We add country fixed effects as $\mathbf{C}_c$. These may include potential cross-country differences in the measurement of reshoring. The country fixed effects also pick up effects due to country-size differences, since larger countries may have more domestic resources and motivations to bring production back home. We add year fixed effects to account for time differences. We can interpet the coefficient of interest as follows: a significant positive coefficient on the innovation variable indicates a higher domestic value added compared to foreign value added of the previous year, or a sign of reshoring.

Although we try to solve omitted variable bias, we have to emphasize that the relationship between reshoring and automation adoption that we try to measure here is an association rather than causal effects. In particular, this set up may suffer from reverse causality. Reshoring may affect adoption as some literature already describes the relationship between trade and adoption and innovation (Bloom et al., 2016; Branstetter et al., 2021), when import competition serves as a drive or hindrance for innovation. We try to address this issue by using the lag variable of automation adoption and using automation innovation as 10-year cumulative data. We use automation innovation as 10-year cumulative data also because the innovation usually needs several years to come into practice and have real effects on other economic outcomes.

5.1.2 Interaction Terms

We introduce a new interaction term $LGAUTOLBPROD$ in table **??**. $LGAUTOLBPROD$ is equal to $LGAUTO$ times $LGLBPROD$. We introduce this interaction term to study whether the effect of automation adoption depends on how much labour productivity of that country is. We expect that the reshoring effects are stronger where countries have lower labour productivity and this pattern may be more related to the "upgrading" concept.

We base our theoretical argument to include this interaction term on the argument of upgrading. Zhou et al. (2022) argue that inward-sourcing capability for emerging countries is the ability to implement the transition in GVCs from foreign sourcing to local sourcing. They argue that "catching up" does not just happen for emerging countries but they have to build the absorptive capability. In the first stage, firms in emerging countries use foreign sourcing due to lower cost, efficiency improvement and knowledge spillovers. However, in the second stage, firms in emerging countries may prefer to bring production and innovation together, replace old foreign sourcing to new local sources (Zhou et al. (2022)).

The $LGAUTO$ times $LGLBPROD$ captures the idea that reshoring/offshoring tends to be larger when countries increase automation adoption at lower levels of labour productivity. If the impact of automation adoption is larger in countries where having lower labour productivity (developing countries), we expect that the sign of the coefficient on $LGAUTO$ times $LGLBPROD$ will be negative, and the coefficient on LGAUTO will be negative.

We also include an interaction term between $LGAUTO$ times $LGPAT$. The notion behind this interaction term is reshoring tends to be larger in countries where having lower level of innovation. We expect that the sign of the coefficient on $LGAUTO$ times $LGPAT$ will be negative, and the coefficient on LGAUTO will be negative.

With an addition of the new interaction model, our new model is expressed as follows:

$$\begin{aligned} RES_{ct} = \beta_0 &+ \beta_1 LGAUTO_{ct} + \beta_2 LGPAT_{ct} \\ &+ \beta_3 LGLBPROD_{ct} + \beta_4 LGAUTOLGLBPROD_{ct} \\ &+ \beta_5 LGAUTOLGPAT_{ct} + \mathbf{C}_c + \mathbf{T}_t + \varepsilon_{ct} \end{aligned} \tag{2}$$

5.2 At sector-country level

The effects of automation adoption on reshoring may be affected by sector characteristics as well as how automation adoption characteristics are different across sectors. Manufacturing with the more intensity of robots applications and robots patents might drive reshoring more, while in service, the driving force of automation adoption mostly on facilitating the cross-border trade, rather than to replace low-skilled workers. For example, in assessing the innovation-employment nexus, focusing instead on services, Evangelista and Savona (2003) find that innovative strategies are focused on the introduction of new services and the internal generation of knowledge. Sectoral patterns and technological regimes are important when assessing the impact of innovation on employment (Calvino and Virgillito (2018)).

The cross-country regression models described in the previous sections use 10-year cumulative data to adjust for endogeneity of our independent variable – innovation. However, as explained above, this strategy do not fully solve the problem of endogeneity and our interested coefficient is still biased. As an alternative approach, we apply a country-sector regression model. The model to estimate the role of automation innovation in explaining reshoring at the country-sector level is given by:

$$\begin{aligned} RES_{ict} = \beta_0 &+ \beta_1 LGAUTO_{ict} + \beta_2 LGPAT_{ict} \\ &+ \beta_3 LGLBPROD_{ct} + \mathbf{IC}_{ic} + \mathbf{T}_t + \varepsilon_{ict} \end{aligned} \tag{3}$$

where i is industry, c is country, t is time period and ε_{ict} is the error term.RES_{ict} is reshoring variable in industry i and country c at time t, measured both at narrow and broad definition; $LGPAT_{ict}$ is the logarit form for number of patents for 10 years cumulation in industry i and country c at time t; $LGAUTO_{ct}$ is the logarit form for total automation imports value at country c at time t;$LGLBPROD_{ct}$ is the logarit form for labour productivity at country c at time t. LGPAT and LGAUTO are weighted by national population. We use sector-country fixed effect to predict the relationships about within-country differences between sectors. We add year fixed effects to account for time differences.

The sector-country model helps to mititgate the endogeneity problems that arise in cross-country regressions by assuming that it is unlikely that strong sectoral reshoring causes changes in the country-level determinants.

6 Results

6.1 At cross-country level

6.1.1 Baseline Results

We present our results for our base model in table **??**. The dependent variable is reshoring measured as narrow at country level. In the first column with basic OLS regression, the coefficient for LGAUTO is -0.032, not statistically significant. However, with country fixed effects in column (2), the coefficient for LGAUTO increases to -0.511 and becomes statistically significant. Column (3) only adds year fixed effects into the model. The coefficient for LGAUTO is still negative but decreases to -0.020 and statistically insignificant. With both country and year fixed effects in column (4), the coefficient becomes statistically significant at 1 % and the magnitude is -0.314. When we change our model to random effects in column (5), the coefficient for LGAUTO decreases to the level of OLS regression in column 1, and is still statistically significant . When we include other control variables including distance, geography (landlocked or not) and climate (temperature), the coefficient in column (6) has similar magnitude and sign to column (4) and statistically significant at 1 % with both country and year fixed effects, but becomes statistically insignificant in column (7) when we only have year fixed effects which is similar to column (3). The point estimate in column (4) suggests that in countries that adopt an extra of 1 percent more reduces reshoring by 0.31 percent.

This finding is opposite to the previous findings mainly used with aggregate data (Faber (2020); Krenz and Strulik (2021); Kugler et al. (2020)). Krenz et al. (2021) find that coefficients of the impacts of robots on reshoring range from 0.0161 to 0.0341 and statistically significant at 10%. They refer that an increase of robots (per 1000 workers) by one unit is correlated with an increase of reshoring by 1.6%. Our opposite results may be from some reasons. First, our automation adoption and innovation is measured with all technologies and fields together, unlike

Table 2: The impact of automation adoption on reshoring (narrow measure)

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LGAUTO	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-stage							
Rep × *GDPpc* × *GAS*							
						(0.001)	(0.001)
LGAUTO × *LGLBPROD*					0.003***		0.003***
					(0.001)		(0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Krenz et al. (2021) who focus only on robots. The effects of automation on trade or labor market is unclear compared to robots. Second, automation technologies, such as robots which are used widely in manufacturing today, are argued as the continuation of previous industrial automation technologies which have existed for a while and not yet being so disruptive as predicted (Fernández-Macías et al. (2021)). Finally, automation technologies have been invented in quite a few countries (as described in figure ??), and the adopting process have not been yet widespread, focused only on big firms (Acemoglu et al. (2020). Therefore, our results seem to be in agreement with the recent literature argued the "not so disruptive yet" characteristics of automation technologies.

These initial results suggests a negative relationship between automation adoption and reshoring. The sign of the coefficients suggests that automation adoption reduces reshoring. Our model so far describes a log-linear relationship between automation and reshoring, which means an increase in adoption of automation has the same effects for countries with lower labour productivity (developing countries) and countries with higher labour productivity (developed countries). To capture this different effect, we next will try to add interaction effects between our automation adoption variable (LGPAT) and labour productivity (LGLBPROD), and our automation innovation variable (LGPAT) and automation adoption variable (LGAUTO).

6.1.2 Interaction Terms

The results are reported in table ??. The first column added LGPATxLGAUTO interaction and used both time and country fixed effects. The second column added LGAUTOxLGLBPROD interaction and used both time and country fixed effects. The third column added both LGPATxLGAUTO and LGAUTOxLGLBPROD while used both time and country fixed effects in the model. When adding interaction terms, the coefficient for interaction terms of LGAUTOxLGLBPROD are statistically insignificant in all of our models. Therefore, the interaction term between LGAUTOxLGPAT seems to have no meaningful interpretation into the model and the sign of the interaction term LGAUTOXLGPAT aligns with our expectation. We find a similar result with the interaction term LGAUTOxLGLBPROD. Interestingly, the sign of the interaction term LGAUTOXLGLBPROD is opposite to our expectation. Furthermore, to understand and capture fully the interaction effect, we will use graphics to illustrate our results.

It is important to understand the full picture of adding interaction terms into our model, therefore, we use figures to illustrate the marginal effects of LGAUTO and LGLBPROD depending on LGPAT in figure ??. The horizontal axis is LGLBPROD in figure ??, and LGAUTO in figure 12. We use the results in column (2) for figure ?? and column (1) for figure 12. The picture describes that the level of reshoring increases with the level of labour productivity when LGPAT is small. However, the relationship becomes more negative when LGPAT is greater (for example, in the figure ?? when LGPAT equals -4). The slope is also greater when the LGPAT is small which agrees with our expectation.

For LGPATxLGAUTO, the coefficients are negative in both column (1) and column (3) which are as expected. The coefficient is statistically significant in model (1) implies that countries with low level of automation innovation (LGAUTO) will have a relatively higher positive marginal effect of automation adoption of reshoring. The magnitude again depends on the exact parameter values. Figure 12 describes that when LGPAT is small, the relationship between automation adoption and reshoring tends to be positive. However, when LGPAT becomes greater, the relationship between automation adoption and

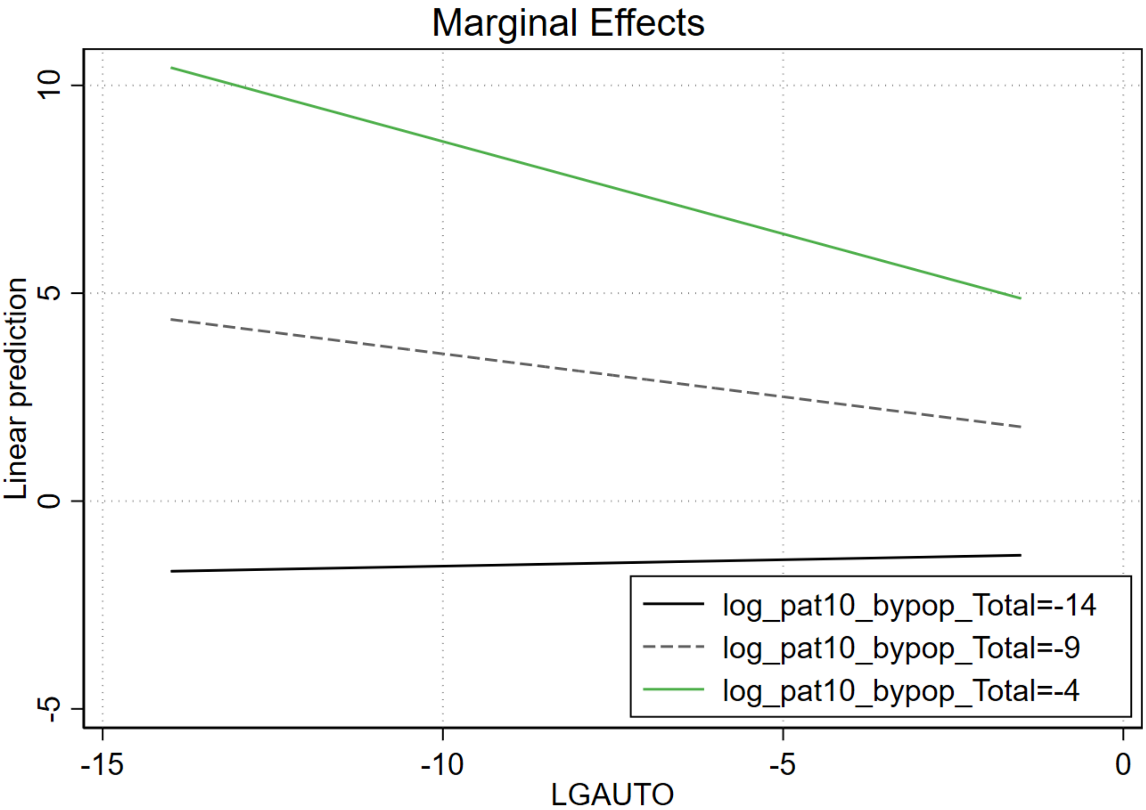

Figure 12: The marginal effect of LGAUTO on reshoring - keeping LGPAT constant

reshoring becomes negative, and the slope is greater when countries have higher innovation outputs.

6.2 At sector-country level

We report the results for sector-country level analysis in table **??**. Results for manufacturing sector are reported in column (1) and (3), while results for service sector are reported in column (2) and (4). We run the regression with the base model without the interaction terms and without the other control variables about geography, climate and distance in column (1) and (2) while for column (3) and (4), we add interaction terms.

The effects of automation adoption on reshoring in manufacturing and service are both negative and statistically significant in our result. The coefficients for LGAUTO is -0.069 in column (1) for manufacturing and -0.201 in column (2) for service. Therefore, if we look at these results, the effect of automation import on reducing reshoring might be more for service sector, than for manufacturing sector. We also have similar result if we compare the magnitude of the coefficients on automation imports in column (3) and (4). Therefore, our findings suggest that the impact of automation adoption might be more relevant in the service sector, which is still under-explored in current research.

6.3 Robustness Check

6.3.1 Using broad reshoring measure

6.3.2 Using long differences for reshoring - 3 years; 5 years; 10 years

6.3.3 Exclude China

6.3.4 Exclude 2008 and 2009 financial crisis

6.4 Heterogeneity

6.4.1 By region

The number of case studies and surveys for reshoring has been mainly in high-income countries. One of the main reasons is they have been the driver of offshoring trend in the last decades. It may be interesting to look at country heterogeneity in this case since we might expect the relationship between automation and reshoring are more prominent in high-income countries where they are both pioneer in automation and reshoring trend. The definition of high-income, middle-income, and lower middle-incomes countries follow the definition of World Bank. The list of countries are attached in the appendix **??**.

In table **??**, we report the results for our models without interaction terms from column (1) to (3), with interaction terms from (4) to (6) and our dependent variable

Table 3: The impact of automation adoption on reshoring (narrow measure) at sector-country level

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$LGAUTO_m$	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
First-stage							
$Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003*** (0.001)		0.003*** (0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

is narrow reshoring at country level. The estimate is negative for LGAUTO in column (1) with high-income countries and (3) and (6) with lower-middle income countries and statistically significant. The magnitude in the impacts of automation adoption on reshoring is also larger for high-income countries at -0.360. The interaction terms of LGAUTO with LGPAT and LGLBPROD are not statistically significant in column (4) and (5) but are statistically significant in column (6). We expect that because these countries do not have automation innovation, so it drives the result to be statistically significant, rather than the true impact is there. The results imply that for if we divide the countries into income effects, the relationship between automation adoption and reducing reshoring still holds in high-income countries and low-middle-income countries. Only in the case of high-middle-income countries, there seems to be no effects between automation adoption and reshoring.

The estimates in table **??** further emphasize that the impact of automation adoption on reshoring is not unified and homogeneous among countries. The negative relationship between automation adoption and reshoring are concentrated among high-income countries and lower middle-income countries, while for middle-income countries, there seem to be no effect. Therefore, to some extent, automation adoption may promote trade.

6.4.2 Threshold effects

6.4.3 By Technology

Our next set of empirical exercises considers the types of technology dimension of automation adoption. We expect the negative relationship between automation adoption and reducing reshoring to be most concentrated among technology that already widely adopted that relate more to the aspect of increasing productivity, reducing cost, and improving quality.

Our dataset gives us the options to explore the relationship between automation adoption on reshoring in 6 different fields, including: CAD-CAM, ICT, Reg Instruments, Robots, Welding, and 3D printing. We expect that the negative relationship between automation adoption and reshoring is more prominent in fields that are suggested in the literature that reducing cost, improving quality, and increasing productivity, such as 3D printing and ICT.

We report the results in table **??**, In column (1), we use our base model but with automation adoption in CAD-CAM technology. The main coefficien tof CAD-CAM technology is still negative, but it is not statistically significant. It means there seems to be no relationship between CAD-CAM technology and reshoring. In column (2), we use our base model with ICT technology adoption. The result agrees with previous research saying that ICT promotes trade as we find the coefficient for ICT adoption is negative and statistically significant at 5 %. We again do not find any effects for other technologies including reg instruments, welding machines, and suprisingly to us is we do not find any relationship between robots adoption and reshoring. We also find similar results to Freund et al. (2022) that 3D-printing adoption promotes trade. The coefficient of 3D printing is negative and statistically significant at 5%.

7 Conclusion

The introduction of technologies such as computers and ICTs to better coordinate production organization and the opening of lower labour cost countries have contributed to an international fragmentation of production in the 1990s and 2000s. However, the rise of new automation technology in production and service brings worries in disrupting global value chains. New automation technologies could

Table 4: The impact of automation on reshoring - threshold effects

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LGAUTO	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-stage								
$Rep \times GDPpc \times GAS$				0.003***	0.003***	0.003***	0.003***	0.003***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$LGAUTO \times LGLBPROD$			0.003***			0.003***		0.003***
			(0.001)			(0.001)		(0.001)
Threshold			0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Country fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations								
R-squared								
F-stat				119.20	119.20			

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(8) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

substitute workers; hence, it may be cheaper to produce their products in their home country rather than offshore to low-income countries.

We re-examine this view considering the role of automation adoption as a driver of reshoring in the period 2008-2019. We propose a new measure f reshoring to take into account both intermediate and final imports, consider reshoring as a flow process, and include both direct and indirect effects in the measure. We find a negative relationship between automation adoption and reshoring or in other words, automation adoption reduces reshoring. We do not find a meaningful interaction effect between automation adoption and labor productivity, and between automation adoption and automation innovation. Furthermore, our results point out that the negative relationship automation adoption and reshoring is more driven by high-income countries and lower- middle-income countries, while for upper middle-income countries, automation adoption does not have any effects on reshoring. Among types of technology, we only find a negative relationship between adoption in ICT as well as 3D printing and reshoring. We examine different time periods in our models and find a negative relationship between automation adoption and reshoring in the period 2008 - 2013 with the magnitude around 0.28 percent if increase automation adoption by 1 percent. We also find heterogeneity in the effects between manufacturing and sector. Both in manufacturing and service sector, automation adoption reduces reshoring, however service sector drives this relationship. Our results highlight the importance of examining automation adoption as a driver of reshoring and suggest that the popular notion that automation disrupts trade may not be accurate. Instead, our findings support the notion that automation adoption may reduce reshoring, promote offshoring, and increase productivity.

For the future work, we propose to remeasure our reshoring variable. Instead using year-to-year change, another interesting measure is to use greater than one-year change, for example, three-year change. The reason is the decision to reshore may happen in longer time period than one year. Another promising direction is to provide more sectoral details, in which not only differentiate between manufacturing and service sectors, but also within manufacturing, and within service sector with a more focus on service sector. Our findings have important policy implications for countries aiming to enhance their technological capabilities and more involve into global value chains.

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Appendix

A.1 Data sources

A.2 Variable definitions

This section provides a detailed description of the variables used in the econometric analysis.

RES: Reshoring variable (measured using narrow definition) of country i in year t.

$LGAUTO$: logarithm of one plus automation imports in thousands of US dollars of country i in year t.

$LGAUTO\_CADCAM$: logarithm of one plus CAD-CAM technology imports in thousands of US dollars of country i in year t.

$LGAUTO\_ICT$: logarithm of one plus ICT technology imports in thousands of US dollars of country i in year t.

$LGAUTO\_REGINSTR$: logarithm of one plus reg instrument technology imports in thousands of US dollars of country i in year t.

$LGAUTO\_ROBOTS$: logarithm of one plus robot technology imports in thousands of US dollars of country i in year t.

$LGAUTO\_WELDING$: logarithm of one plus welding machines imports in thousands of US dollars of country i in year t.

$LGAUTO\_3D$: logarithm of one plus 3D printing technology imports in thousands of US dollars of country i in year t.

$LGPAT$: logarithm of one plus number of patents of country i in year t.

$LGLBPROD$: logarithm of one plus labour productivity of country i in year t.

$LGDIST$: logarithm of one plus distance of country i in year t.

$LANDLOCKED$: dummy variable if country is landlocked or not with 1 is yes and 0 is no.

$LGTEMP$: logarithm of one plus average temperature of country i in year t.

A.3 Product codes for automation imports

We define product codes belonging to different types of automation imports: CAD-CAM, Robots, Automated welding, 3D printing, and Regulating instruments following the method by Foster-McGregor et al. (2019) as follows:

CAD-CAM: 845811; 845891; 845291; 845931; 845951; 845961; 846011; 846021;846031; 846221; 846231; 846241

Robots: 847950; 847989

Automated welding: 851521; 851531

3*Dprinting*: 847780; 847710; 847720; 847730; 847740; 847751; 847759; 847740;847751; 847759; 847790

Regulating instruments: 903210; 903220; 903281; 903289; 903290

ICT: 844351; 847050; 847110; 847130; 847141; 847149;

847150; 847160; 847170; 847180; 847190; 847220; 847290; 847330; 847350; 851721; 851722; 900911; 900912; 851711; 851719; 851730; 851750; 851780; 851790; 852510; 852520; 852790; 853110; 851810; 851821; 851822; 851829; 851830; 851840; 851850; 851890; 851910; 851921; 851929; 851931; 851939; 851940; 851992; 851993; 851999; 852010; 852020; 852032; 852033; 852039; 852090; 852110; 852190; 852210; 852290; 852530; 852540; 852712; 852713; 852719; 852721; 852729; 852731; 852732; 852739; 852812; 852813; 852821; 852822; 852830; 950410; 852330; 852460; 853400; 854011; 854012; 854020; 854040; 854050; 854011; 854012; 854020; 854040; 854050; 854060; 854071; 854072; 854079; 854081; 854089; 854091; 854099; 854110; 854121; 854129; 854130; 854140; 854150; 854160; 854190; 854212; 854213; 854214; 854219; 854230; 854240; 854290; 854890; 852390; 852410; 852491; 852499; 852910; 852990; 854381; 901320

A.4 List of countries by region

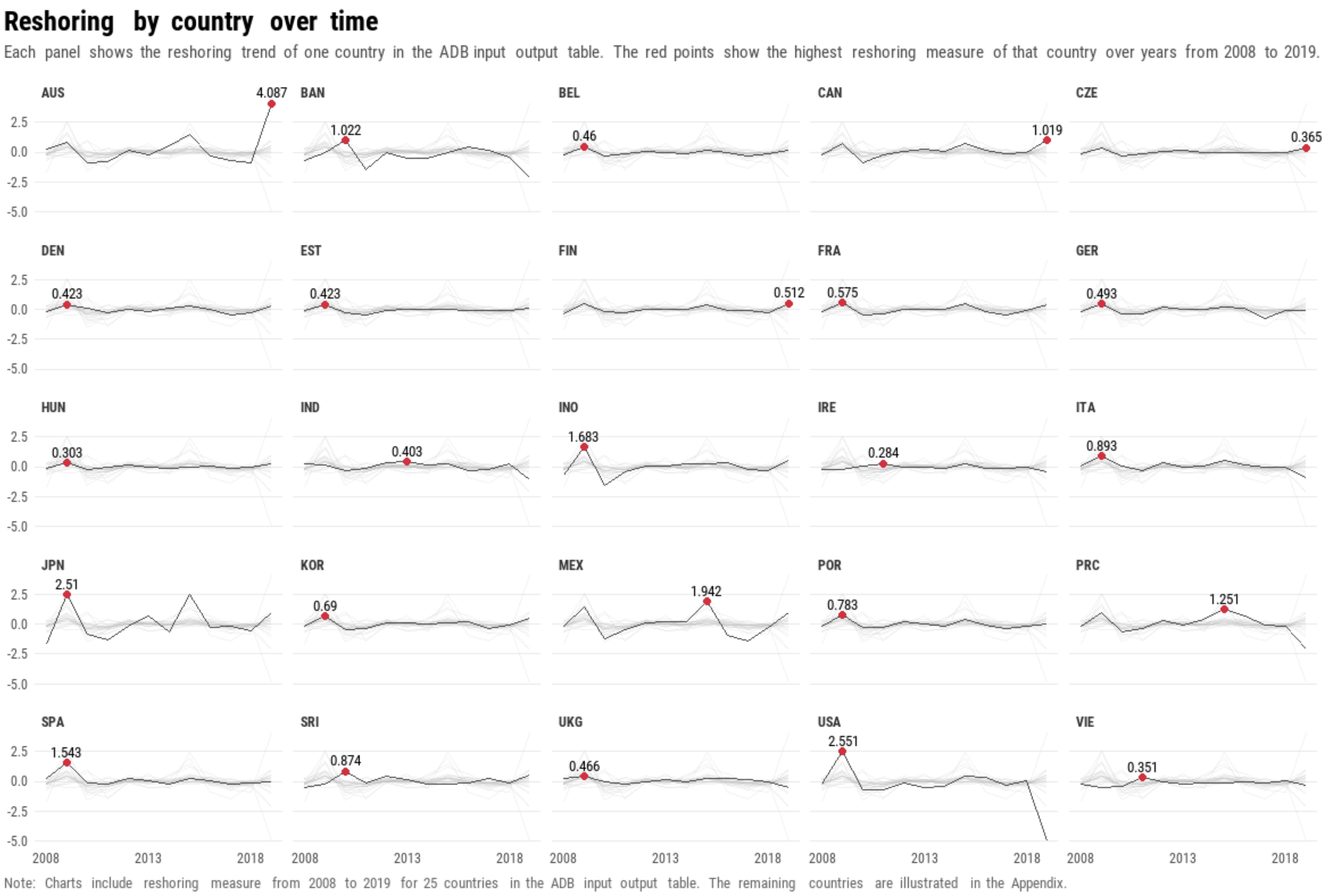

Figure A1: Reshoring (Narrow) by country over time

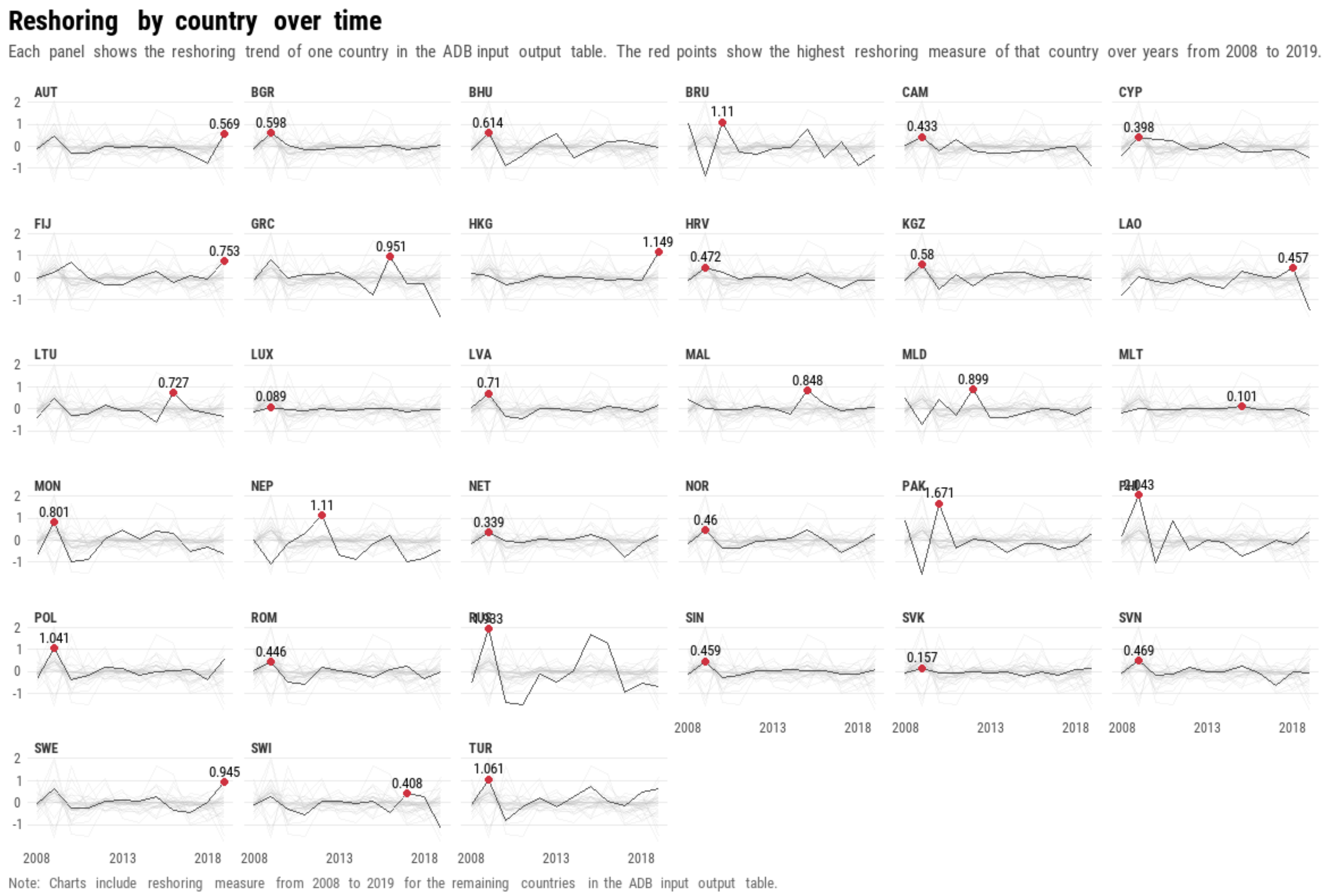

Figure A2: Reshoring (Narrow) by country over time

Table A1: Top 10 Countries by Automation Imports

Rank	Country	Automation	% of count	% of global automation imports
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

Table A2: The impact of automation adoption on reshoring (broad measure)

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$LGAUTO$	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-stage							
$Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003***		0.003***
					(0.001)		(0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A3: The impact of automation adoption on reshoring (long difference - 3 years)

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$LGAUTO$	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-stage							
$Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003***		0.003***
					(0.001)		(0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A4: The impact of automation adoption on reshoring (long difference - 5 years)

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LGAUTO	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
First-stage $Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003*** (0.001)		0.003*** (0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. “Observations” refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A5: The impact of automation adoption on reshoring (long difference - 10 years)

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LGAUTO	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
First-stage $Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003*** (0.001)		0.003*** (0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. “Observations” refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A6: The impact of automation adoption on reshoring - Exclude China

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LGAUTO	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
First-stage $Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003*** (0.001)		0.003*** (0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A7: The impact of automation adoption on reshoring - Exclude 2008 and 2009 financial crisis

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LGAUTO	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
First-stage $Rep \times GDPpc \times GAS$						(0.001)	(0.001)
$LGAUTO \times LGLBPROD$					0.003*** (0.001)		0.003*** (0.001)
Control variables	N	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	Y	N	Y	Y	Y
Country fixed effects	N	N	Y	N	Y	Y	Y
Random effects	N	N	N	Y	N	N	N
Observations							
R-squared							
F-stat						119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A8: The impact of automation on reshoring - By region

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
LGAUTO_c	0.003***					
	(0.001)					
LGAUTO_ICT	0.003***					
	(0.001)					
LGAUTO_REGINSTR	0.003***					
	(0.001)					
LGAUTO_ROBOTS	0.003***					
	(0.001)					
LGAUTO_WELDING	0.003***					
	(0.001)					
LGAUTO_3D	0.003***					
	(0.001)					
First-stage	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
Rep × GDP_{pc} × GAS						
Control variables	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Country fixed effects	Y	Y	Y	Y	Y	Y
Observations	888,813	888,813	888,813	888,813	888,813	888,813
R-squared	0.6351	0.7742	0.3914	0.6351	0.7742	0.3914
F-stat	119.20	119.20	119.20	119.20	119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(3) report the OLS results, while columns (4)–(6) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.

Table A9: The impact of automation on reshoring - By technology

LGAUTO	OLS						IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LGAUTO_c	0.003***						0.003***					
	(0.001)						(0.001)					
LGAUTO_ICT		0.003***						0.003***				
		(0.001)						(0.001)				
LGAUTO_REGINSTR			0.003***						0.003***			
			(0.001)						(0.001)			
LGAUTO_ROBOTS				0.003***						0.003***		
				(0.001)						(0.001)		
LGAUTO_WELDING					0.003***						0.003***	
					(0.001)						(0.001)	
LGAUTO_3D						0.003***						0.003***
						(0.001)						(0.001)
First-stage Rep × GDP_{pc} × GAS							0.003***					
							(0.001)					
First-stage Rep × GDP_{pc} × GAS								0.003***				
								(0.001)				
First-stage Rep × GDP_{pc} × GAS									0.003***			
									(0.001)			
First-stage Rep × GDP_{pc} × GAS										0.003***		
										(0.001)		
First-stage Rep × GDP_{pc} × GAS											0.003***	
											(0.001)	
First-stage Rep × GDP_{pc} × GAS												0.003***
												(0.001)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations												
R-squared												
F-stat							119.20	119.20	119.20	119.20	119.20	119.20

Notes: Table reports OLS and IV results using the baseline estimation sample. Columns (1)–(6) report the OLS results, while columns (7)–(12) report the IV and corresponding first stage estimates. Robust standard errors are in parentheses. "Observations" refers to the number of non-singleton observations. ***1% level, **5% level, *10% level.