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The impact of robot adoption on global sourcing ☆

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ABSTRACT

This paper studies the impact of robot adoption on firms' global sourcing activities. Using a rich panel dataset of Spanish manufacturing firms, we investigate how outsourcing and vertically integrated firms changed their sourcing strategies in response to robot adoption. We find that robots increased intermediate input purchases from foreign suppliers while did not affect intermediate input purchases from domestic suppliers between 2006 and 2016. We present a theoretical framework in which the assumptions and predictions are in line with our findings in the dataset. In contrast to rising concerns over reshoring, our findings suggest that robots have yet promoted trade in intermediate inputs.

1. Introduction

Advanced technologies have transformed the organization of production in manufacturing industry during the last decades. Developments in communication and information technologies have accelerated the expansion of production fragmentation and formed global value chains (GVCs) (e.g. Hummels et al., 2001; Johnson and Noguera, 2017). Sourcing intermediate inputs within and across national borders emerged as an attractive form of organizing the production for firms and became dominant feature of international trade. Firms in developed countries gained comparative advantage in terms of labor costs by relocating certain production processes to developing countries and created new job opportunities for offshore workers.[1]

In the meantime, robotics technology improved dramatically since 1990s and industrial robots have become more prevalent in production facilities across many industries. Robots are considered as sophisticated labor-saving technologies because their actions can be modified to perform different tasks without requiring human intervention.[2] Recent studies show that robots reduce employment and depress wages of low-skilled labor in manufacturing industry (e.g. Dauth et al., 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Even though sourcing intermediate inputs produced by cheaper workforce in low and middle-income economies has become a major profitable strategy in international trade, robots offered firms an alternative channel for reducing labor costs. Since robots can substitute particularly low-skilled workers, they can make offshore workers in developing economies redundant if they enable firms to produce intermediate inputs instead of sourcing them from elsewhere. Thus, rapid increase in use of robots and their recently explored displacement effects raised the concerns over the potential disruptions in GVCs and the possibility of widespread reshoring activities of firms in developed economies (e.g. De Backer et al., 2016; Rodrik, 2018; Lund et al., 2019).

In this paper, we study how adopting robots has affected sourcing activities of Spanish manufacturing firms from 2006 to 2016. We present a simple model and use a unique firm-level panel dataset that

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[1] A group of studies regarding production fragmentation focuses on labor market outcomes of offshoring tasks to low-income countries, see Crinò (2009) and Hummels et al. (2018) for comprehensive reviews of this literature. Another group focuses more on firms' decisions on sourcing inputs and contractual frictions, with Helpman (2006) and Antràs and Yeaple (2014) providing extensive reviews of this literature. Our paper is closer to the latter group.

[2] In ISO 8373, the International Organization for Standardization defines an industrial robot as "an automatically controlled, reprogrammable, multipurpose, manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications".

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allows us to assess the impact of robots on intermediate input demand for various sourcing strategies: foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration.[3] Using the instrumental variable strategy in our empirical analysis, we find that adopting robots increased the sourcing activities from foreign suppliers but did not affect sourcing from domestic suppliers. Our findings are robust to imports from low-income countries and various shocks. Hence, the results in this paper indicate that adoption of robots did not lead Spanish manufacturing firms to reshore production between 2006 and 2016.

The main contribution of this paper is to provide a firm-level evidence for the impact of labor-saving technologies (robot adoption) on sourcing decisions. Current studies are predominantly conducted at the macro-level, estimating the effects of exposure to robots in developed countries on industry-level trade with and regional labor markets of developing countries. We are able to approach this issue at the micro-level focusing on firms' input demand and identify the changes in different sourcing strategies. Hence, we analyze whether robot adopting firms reshored their previously offshored production by reducing intermediate input purchases from suppliers and how their sourcing activities changed subsequent to adoption decision. The variables in our dataset allow us to eliminate biases arising from the characteristics of individual countries involved in GVCs because participation in GVCs varies depending on the technological sophistication in production, specialization and natural resources across countries.

The rest of the paper is organized as follows. First, Section 2 provides an overview of the state-of-the-art of several strands of literature that are relevant in the context of our study. In Section 3, we present the theoretical framework and discuss various channels that may affect firms' decision on sourcing after adopting robots. Section 4 describes our data and documents stylized facts about the patterns of adoption and sourcing in Spain. In Section 5, we present our empirical analysis and the obtained results. Finally, Section 6 concludes.

2. Literature review

2.1. Sourcing, trade liberalization and technology adoption

Sourcing activities typically occur in the form of vertical integration or outsourcing. Two types of organizational forms vary on the basis of ownership which determines whether the supplier becomes the subsidiary to sourcing firm. The contractual relationship might take place within the same country (domestic vertical integration and domestic outsourcing) or across different countries (foreign vertical integration and foreign outsourcing). Depending on the organizational firm, different incentives and frictions of incomplete contracts occur between the sourcing firm and supplier.

When a vertically integrated firm integrates with a supplier, trade occurs between two affiliated firms in vertical integration. The input supplier becomes related party to the sourcing firm by ownership and previously two independent firms constitute a single entity. Sourcing firm then owns the production of intermediates located elsewhere and chooses to produce the intermediate inputs required for producing the final product within the boundaries of the firm. In this case, a firm that owns the supplier can exercise the power of control over its supplier, which becomes its subsidiary.

On the other hand, a sourcing firm might engage in an outsourcing activity, a type of sourcing also referred as arm's-length relationship. An outsourcing firm finds a suitable partner and subcontracts with an independent supplier to purchase intermediate inputs without any control over input providing supplier. In this case, input supplier is not owned by the sourcing firm and transactions involve two independent firms. Separately owned buyer and seller agree on a contract that includes the details of traded intermediate input such as input characteristics, product quality and delivery time.

Firms' decisions on both technology adoption and sourcing are predominantly motivated by getting lower marginal costs. In theoretical models of sourcing, the technology used by firms determine their productivity levels and the organization of production across different locations (e.g. Antras and Helpman, 2004; Grossman and Rossi-Hansberg, 2008; Costinot et al., 2013). Despite the central role of technology in the literature of sourcing, empirical evidences for these predictions have been limited. Studying Danish firms, Bøler et al. (2015) find that a reduction in R&D costs promotes international sourcing activities and increases imports of intermediate inputs. Fort (2017) shows that advanced technologies facilitate production fragmentation among US firms by reducing communication and coordination costs. In addition to information and communication technologies, there has been an extensive usage and advances in automation technologies in recent times, specifically in robotics. Displacement effects of industrial robots sparked interest in not only how they affect labor markets in domestic economies, but also how they affect firms' organizational decisions and trade in intermediate inputs.[4]

Empirical evidences also suggest that trade liberalization encourages firms to adopt advanced technologies through new export opportunities (e.g. Lileeva et al., 2010; Bustos, 2011) and import competition (e.g. Bloom et al., 2016). Recently, Bernard et al. (2020) find that offshoring firms increase their skill intensity and reorganize their resources toward more quality upgrading and innovative activities. However, given different characteristics of sourcing activities, firms' responses to trade shocks may vary depending on whether they are involved in related-party (vertical integration) or arm's-length relationship (outsourcing) (e.g. Bernard et al., 2009).

A considerable amount of studies previously focused on foreign sourcing activities such as foreign outsourcing and foreign vertical integration, but domestic sourcing strategies have usually been neglected. A notable exception is Fort (2017) who finds that advanced technologies favor domestic sourcing more than offshoring in the U.S. and create bias in sourcing decisions toward high human capital countries. Moreover, Kee and Tang (2016) document that trade liberalization increased the domestic content in exports and improved the activities of Chinese firms in global value chains.

The literature recently focused on how robots affect trade in intermediate inputs and provided mixed evidence on the role of robots in firms' cross-border activities. Several macro-level studies find negative effects of robots on local labor markets in Mexico (e.g. Artuc et al., 2019; Faber, 2020), in Colombia (e.g. Kugler et al., 2020) and across countries (e.g. Krenz et al., 2021). In contrast to these macro-level studies favoring reshoring trends, Antràs (2020) argues that a fall in participation in global activities is not apparent yet at the aggregate level and a body of literature finds positive effects of robots on imports from low-income countries (e.g. Artuc et al., 2018; Stapleton and Webb, 2020) and employment in Brazil (e.g. Stemmler, 2019).

Some studies investigated the impacts of robots on firm characteristics. Acemoglu et al. (2020) and Bonfiglioli et al. (2020) document that robot adopters increase their productivity and size. Domini

[3] Outsourcing is a sourcing strategy defined as purchasing the intermediate inputs from an unrelated party, an independent supplier. On the other hand, vertical integration is a sourcing strategy in which the production of the intermediate inputs occurs within the boundaries of the firm through a related party. If intermediate inputs are imported from a foreign country, vertical integration and outsourcing are also referred as foreign direct investment (FDI) and offshoring (arm's-length relationship), respectively. Since our data allow us to identify both forms of sourcing and the location of suppliers, we prefer to use outsourcing and vertical integration to be more explicit.

[4] Particularly COVID-19 pandemic accelerated the concerns over disruptions in GVCs and potential slowdown in international trade because many firms began considering reducing their dependency on input suppliers across borders.

et al. (2021) find that adoption of automation technologies increase a firm's net employment growth but do not change the skill composition of French manufacturing firms involved in international trade. Similarly, Humlum (2019) finds that robot adoption increased productivity but widened the wage gap between high and low-skilled workers in Denmark.

Previous theoretical and empirical studies demonstrate that technological developments predominantly foster sourcing activities. One group of empirical studies on robots shows that increased robot usage may increase or decrease intermediate input trade while another group of researches shows that robots may have favorable or detrimental outcomes in labor markets of developing countries. Our study examines whether and how firms changed their purchases of inputs from suppliers after adopting robots. We show that offshoring has not become less attractive for robot adopting Spanish firms as reshoring concerns argue. On the contrary, we find that robot adoption augmented intermediate input sourcing between 2006 and 2016 in our sample.

2.2. Evidence for spanish firms

There are several papers which used the same Spanish firm-level data to investigate the effects of robots as we do. First, Koch et al. (2021) developed a Melitz-type model relying on a task approach similar to Acemoglu and Restrepo (2020). Confirming their predictions from the model, their empirical results for the 1990–2016 period using longitudinal data from the ESEE demonstrate that high productivity firms tend to adopt robots. Furthermore, robot adopters gain competitive advantage due to increased output and grow in size over time at the expense of non-adopters. Regarding the firms involved in trade activities, they found that only exporters among robot adopters could raise their TFP.

Second, Alguacil et al. (2022) studied the effects of robots on exports at the intensive and extensive margin from 1990 to 2014. To overcome the endogeneity problem, they combine propensity score matching with difference-in-differences estimation as in Koch et al. (2021). Their findings show that robot adoption increases exports while raising the probability of entry to foreign markets for both exporting and importing.

Finally, our paper is more closely related to Stapleton and Webb (2020) but exhibits many differences. Their objective is to analyze how automation has affected trade and multinational activity with lower-income countries between 1990 and 2016. In contrast to rising concerns over reshoring activities, they find that automation technologies affected imports and number of affiliates of Spanish firms positively. Taking this into account, one main difference of our study is that we investigate the changes in firms' various sourcing strategies distinguishing input suppliers' location and their relationship with sourcing firms for the 2006–2016 period.

Our paper also differs from Stapleton and Webb (2020) in that they use multiple automation variables provided in the ESEE dataset such as robots, computer numerically controlled (CNC) machines and flexible manufacturing systems (FMS) rather than utilizing specifically the data on robot usage as in our analysis. Similar to Alguacil et al. (2022), they find that using automation technologies increased the probability of importing from low-wage countries between 1990 and 2016. In terms of the instrument used for the identification strategy, they use industry-level patent titles related to robotics inventions as a proxy for exposure to technological changes in robotics together with an alternative instrument using the same IFR dataset as in our analysis. However, we measure the firm-level exposure to technological changes by interacting the firm's share of imported technology in the industry with industry-level robot installations in several EU countries.

Some of the results shown by Stapleton and Webb (2020) are aligned with those of Koch et al. (2021). In contrast to our approach in theoretical framework relying on cost advantage and disadvantage of robot adoption for the sourcing firm, they develop a Melitz-type model analogous to Koch et al. (2021) using a task based approach. In their empirical analysis, they discover that most productive firms select into automation (e.g. Koch et al., 2021) and offshoring decisions while automated firms are more intensely involved in trade before automating their production processes.

The ESEE dataset allows us to investigate the effects of robot adoption on different sourcing strategies as it reveals the information on the relationship between the sourcing firm and the supplier. Whether a firm is outsourcing from or vertically integrated with foreign or domestic suppliers may be an important factor in determining a firm's reshoring decision because each of these sourcing strategies would incur various kinds of costs for reshoring. The literature has not yet come to a common conclusion of how robots affect firms' intermediate input trade activities involved in different sourcing activities. In this regard, we fill a notable gap in the literature using a unique Spanish firm-level data.

3. Theoretical framework

This section presents a theoretical framework of robot adoption and the subsequent decision on sourcing activity. Robot adoption and potential reshoring decisions occur in a sequential order. Once the firm finds adopting robots profitable, the sourcing firm considers partially or fully reshoring the production of inputs.

Consider a manufacturing firm sourcing input X^s from a supplier located elsewhere denoted by s and carrying out the production of remaining input $X^{\mathbb{1}_R}$ when adopted robots and $\tilde{X}$ when not yet adopted robots itself in its headquarters. The firm ultimately utilizes these two components to obtain the final output of a sourcing firm, Y.[5] The relationship between supplier and sourcing firm may be in form of outsourcing or vertical integration while the supplier may be located in domestic country or in a foreign country. We assume in the model that there are no frictions in communication and shipping between the supplier and the sourcing firm.

In assembly, composite inputs X^s and $\tilde{X}$ of a non-adopting sourcing firm transform into final output in following Cobb–Douglas form $Y = (\tilde{X}^s)^{\beta}(\tilde{X})^{1-\beta}$. We assume that the proportion of composite inputs used in the production of the final good is the same before and after the robot adoption. Hence, adoption of robots do not alter the production structure, i.e. input shares in output β and $1-\beta$ remain the same when the firm adopts robots. The production function of a robot adopting firm is given as

$$Y^{\mathbb{1}_R} = (X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta}. \tag{1}$$

We assume that labor market of the intermediate input supplier is competitive. The composite intermediate input X^s is produced in CES form,

$$X^s = \left[\gamma\left(\Gamma^L L^s\right)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\left(\Gamma^R \mathbb{1}_R R\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where L^s denotes labor of supplier and R denotes robots of the sourcing firm. σ represents the elasticity of substitution between labor and robots. $\sigma > 1$ implies that robots and supplier's workers are gross substitutes such that robots can substitute supplier's workers because they perform the same tasks. On the other hand, $\sigma < 1$ implies that robots and supplier's workers are gross complements and sourcing firm's robots R cannot substitute supplier's labor L^s. Γ^L and Γ^R are the productivity parameters for labor and robots, respectively.

$\mathbb{1}_R$ is a dummy variable for robot adoption. $\mathbb{1}_R = 1$ indicates that robots take place in the production of X^s. $\mathbb{1}_R$ is equal to 0 if only

[5] This final output may also be an input for another firm in the global supply chain, i.e. the sourcing firm may be a supplier to another firm. Since our focus is on whether a robot adopting firm may change its sourcing decisions, we remain agnostic on the case that the sourcing firm may be a supplier or subsidiary at the same time. We would like to thank a reviewer for reminding us to explicitly highlight this issue.

supplier's workers are performing the tasks required to produce X^s and equal to 1 if robots contribute to the production of inputs previously sourced from the suppliers. In this regard, we consider that the firm might produce all inputs previously produced by the suppliers (foreign or domestic) after adopting robots or produce only some of the inputs previously produced by the suppliers (foreign or domestic).[6]

Distribution parameter $\gamma \in [0,1]$ reflects robot intensity in intermediate input production of X^s. $\gamma = 0$ implies that X^s is only produced by robots of sourcing firm. This is equivalent of reshoring all the production given by $X^s = \Gamma^R \mathbb{1}_R R$. On the other hand, $\gamma = 1$ implies that intermediate input is produced solely with workers of the supplier, $\tilde{X}^s = \Gamma^{L^s} L^s$.

In the context of our analysis, reshoring induces that robots can substitute supplier's workers employed for the intermediate input production of X^s. Thus, although robots enters into the production function of the supplier but investment costs in robots are incurred by the sourcing firm. We characterize the cost function of the supplier by

$$C^{X^s} = \tau^l w^s L^s \tag{3}$$

where w^s and L^s denote the wage and the employment of the supplier, respectively. Purchases from suppliers are subject to iceberg transport costs $\tau^l \geq 1$ where l is the index for the location of the supplier. We assume that sourcing inputs from a supplier located abroad entails trade cost $\tau^F > 1$ whereas sourcing inputs from a domestic supplier entails trade cost $\tau^D = 1$, i.e. there is no extra shipping costs for a domestic producer.

We assume that the price of intermediate input P^{X^s} is competitive. A profit maximizing supplier's labor demand can be expressed as

$$L^s = \frac{P^{X^s}(X^s)^{1/\sigma}\varphi^L}{\tau^l w^s} \tag{4}$$

where $\varphi^L = \gamma\left(\Gamma^{L^s} L^s\right)^{\frac{\sigma-1}{\sigma}}$ denotes the share of labor in production of input X^s. Similarly, we define $\varphi^R = (1-\gamma)\left(\Gamma^R \mathbb{1}_R R\right)^{\frac{\sigma-1}{\sigma}}$ as the share of sourcing firm's robots in production of input X^s. The sourcing firm that has not yet adopted robots produces certain inputs required for the final output with Cobb–Douglas technology: $\tilde{X} = \tilde{A}\tilde{L}^{\alpha_L}\tilde{K}^{\alpha_K}$. On the other hand, a robot adopter produces the remaining inputs in the following form:

$$X^{\mathbb{1}_R} = AL^{\alpha_L}K^{\alpha_K} \tag{5}$$

where A is firm productivity, L is labor, K is capital, α_L is labor share in output and α_K is capital share in output.

For the sake of simplicity, we assume that using robots for the production of $X^{\mathbb{1}_R}$ is embedded in capital K. Since we are interested in how robots can substitute workers of a supplier, we abstract from substitution effect of robots on workers of the sourcing firm. Hence, we assume that adoption of robots does not change the production structure of $X^{\mathbb{1}_R}$, i.e. α_L and α_K remain the same following robot adoption decision. Moreover, following the recent empirical evidences (e.g. Acemoglu et al., 2020; Bonfiglioli et al., 2020; Koch et al., 2021), we assume that robot adoption increases productivity, $A > \tilde{A}$. This is an important element of our framework illustrating the increased productivity in final output. As the sourcing firm produces higher input $X^{\mathbb{1}_R} > \tilde{X}$, it demands more input $X^s > \tilde{X}^s$ to obtain more final output produced $Y^{\mathbb{1}_R} > Y$.[7]

We define the cost function of a non-adopter sourcing firm for the production of $\tilde{X}$ as $\tilde{C} = w\tilde{L} + k\tilde{K} + f^{s,l}$. The cost function of a robot adopter sourcing firm for the production of $X^{\mathbb{1}_R}$ is given by

$$C^{X^{\mathbb{1}_R}} = wL + kK + f^{s,l} + \mathbb{1}_R f^R \tag{6}$$

where w is the wage and k is the rental rate of capital of the sourcing firm. We assume competitive markets in labor and capital of the sourcing firm, i.e. the prices of labor and capital are given to the sourcing firm and do not change with robot adoption decision. f^R denotes the fixed cost of robot adoption as in Yeaple (2005) and Bustos (2011), referring to the investment costs incurred once the robots are deployed in production. Notice that the fixed cost of adoption f^R in $C^{X^{\mathbb{1}_R}}$ represents the robot investments to produce $X^{\mathbb{1}_R}$ and not to produce the inputs provided by the supplier X^s. We will show below that at the stage the sourcing firm decides whether to reshore or not, an additional robot investments will be incurred to produce X^s alongside of f^R in $C^{X^{\mathbb{1}_R}}$.

$f^{s,l}$ is fixed cost of tangible and intangible assets in sourcing which needs to be incurred once a firm selects into sourcing. s indexes the form of sourcing activity and l indexes the location of the supplier. Fixed costs of sourcing consist of search costs, gathering information on potential suppliers, finding a suitable supplier location, building a buyer–seller relationship and investing in new physical assets, equipments and building new plants.[8] Thus, $f^{s,l}$ may vary if the sourcing firm is outsourcing or vertically integrated with the supplier and if the supplier is located in home or a foreign country. However, we do not assume any ordering on the size of fixed costs for each sourcing strategy for the sake of simplicity.

Robot adoption decision

Sourcing firm carries out investments in robots before considering reshoring the production. We can now describe an equilibrium with robot adoption decision of sourcing firm. Let $\pi^{Y^{\mathbb{1}_R}} = P^{Y^{\mathbb{1}_R}}(X^s)^\beta(X^{\mathbb{1}_R})^{1-\beta} - C^{X^s} - C^{X^{\mathbb{1}_R}}$ be the profit function of a robot adopter and the profit function of a non-adopter can be expressed as $\pi^Y = P^Y(\tilde{X}^s)^\beta(\tilde{X})^{1-\beta} - C^{X^s} - C^{\tilde{X}}$. Notice that the sourcing firm does not yet attempt to substitute workers of the supplier and uses robots only for the production of $X^{\mathbb{1}_R}$. This induces that the cost of sourcing activity, C^{X^s}, or payments to the supplier does not change at this stage.

Suppose that $\pi^{Y^{\mathbb{1}_R}} > \pi^Y$, so that it is profitable for the firm to adopt robots. A firm adopting robots bears fixed technology costs $\mathbb{1}_R f^R$ embedded in $C^{X^{\mathbb{1}_R}}$ but robot adoption may raise its revenue such that $P^{Y^{\mathbb{1}_R}}(X^s)^\beta(X^{\mathbb{1}_R})^{1-\beta} > P^Y(\tilde{X}^s)^\beta(\tilde{X})^{1-\beta}$, making it profitable. Adopting robots may increase (or decrease) the costs of sourcing firm if adoption requires more (or less) workers, $L \geq \tilde{L}$, and capital, $K \geq \tilde{K}$. Notice that if an adopter lowers the demand for labor and capital, $L < \tilde{L}$ and $K < \tilde{K}$, the cost function may still be lower for an adopter, $C^{X^{\mathbb{1}_R}} < \tilde{C}$, if the investments in robots f^R is sufficiently low. In such a case, adopting robots may be profitable even if the revenue does not change: $\pi^{Y^{\mathbb{1}_R}} > \pi^Y$ if $C^{X^{\mathbb{1}_R}} < \tilde{C}$ and $P^{Y^{\mathbb{1}_R}}(X^s)^\beta(X^{\mathbb{1}_R})^{1-\beta} = P^Y(\tilde{X}^s)^\beta(\tilde{X})^{1-\beta}$.

For a sourcing firm, robot adoption decision is determined by the condition that profits in case of adoption and non-adoption balance off. We can use indifference condition for robot adoption to assess the relevant factors that can encourage firm to adopt robots at a point that profits are equal for an adopter and a non-adopter. From $\pi^Y = \pi^{Y^{\mathbb{1}_R}}$, we can obtain the robot adoption decision as

$$\mathbb{1}_R = \frac{\Delta\mathcal{R} - \Delta C}{f^R} \tag{7}$$

where $\Delta\mathcal{R} = P^{Y^{\mathbb{1}_R}}Y^{\mathbb{1}_R} - P^Y Y$ and $\Delta C = (wL + kK) - (w\tilde{L} + k\tilde{K})$. $\Delta\mathcal{R} - \Delta C$ refers to the gains from adoption, which increases the adoption probability. $\Delta\mathcal{R}$ represents how much revenue increases after adopting robots whereas ΔC represents how much the costs of labor and capital increase after adopting robots. Notice that adoption probability is higher with increases in revenue, $\Delta\mathcal{R} > 0$ and reduction in labor and capital costs,

[6] Note that robots can replace the sourcing firm's workers as well. However, this point goes beyond the scope of this paper and we particularly study how robot adoption affects inputs produced by and sourced from suppliers.

[7] In support of this argument, using polynomial figures in the next section, we show that firm sales are linearly increasing with each sourcing activity.

[8] Similarly, Antras and Helpman (2004) defines fixed organizational costs of sourcing wf^s as the sum of supervision, quality control, accounting, marketing practices, search, monitoring and communication activities. See Antràs and Yeaple (2014) for other approaches defining fixed costs of multinational firms in trade.

$\Delta C < 0$. Since the input prices are competitive, increases in costs after robot adoption may arise only if the demands for inputs increase, $L > \tilde{L}$ and $K > \tilde{K}$. Finally, the gains from robot adoption are proportional to the investment costs in robots, f^R, and higher robot investments makes adoption more difficult, i.e. decreases adoption probability.

Reshoring decision

Subsequent to robot adoption decision, sourcing firm considers whether to reshore previously offshored production located elsewhere. In practice, without a change in product or production technique, this can only be possible if the tasks that can be performed by robots of sourcing firm are identical to the tasks performed by the workers of the supplier. If and only if the tasks are the same, sourcing firm's robots can substitute supplier's workforce and make reshoring a feasible option.

Sourcing firm chooses whether to adopt robots $\mathbb{1}_R$ and how much to source intermediate inputs from elsewhere X^s to maximize its profits:

$$\max_{\mathbb{1}_R, X^s} \pi^{Y^{\mathbb{1}_R}} = P^{Y^{\mathbb{1}_R}}(X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta} - C^{X^s} - C^{X^{\mathbb{1}_{\mathbb{R}}}} + \mathbb{1}_S\left(\nu C^{X^s} - \rho C^{X^{\mathbb{1}_R}}\right). \tag{8}$$

The last term $\mathbb{1}_S\left(\nu C^{X^s} - \rho C^{X^{\mathbb{1}_R}}\right)$ represents the gains from reshoring decision. The parameter $\mathbb{1}_S$ denotes the reshoring decision and takes the value 1 for reshoring and 0 otherwise. $1 \geq \nu \geq 0$ governs the cost advantage from reshoring production to home country. Sourcing firm reduces its costs from offshoring if it decides to bring back some of the production to home country, i.e. adding on firm profit by $\mathbb{1}_S \nu C^{X^s}$. The size of νC^{X^s} determines how much sourcing firm benefits from cutting foreign labor costs. $\nu = 1$ indicates that firm reshores all the production to its headquarters and the costs of producing X^s to the supplier C^{X^s} disappears from total profits $\pi^{Y^{\mathbb{1}_R}}$. On the other hand, $\nu = 0$ indicates that firm continues to sourcing input X^s from the supplier, therefore cannot make any cost savings from reshoring decision.

While saving from supplier's labor costs, the sourcing firm needs to carry out further investments to reshore production because of producing additional components and services that are previously sourced from the supplier. We denote additional fixed costs of investments by $\rho > 0$ that indicates how much additional costs firm has to incur if it decides to reshore. Additional fixed costs refer to investments in additional robots for producing X^s, building new factory or additional space for production, inventories, additional workers and technicians. We do not restrict the upper bound of ρ due to the fact that reshoring costs may exceed the initial costs of robot adoption.

The first-order conditions of this problem yield

$$P^{X^s} X^s = \mathbb{1}_R f^R \left(\frac{-1-\rho}{-1+\mathbb{1}_S \nu}\right)\left(\frac{\sigma}{1-\sigma}\right)\left(1+\frac{\varphi^R}{\varphi^L}\right)\left(1+\frac{\varphi^L}{\varphi^R}\right) \tag{9}$$

where the left hand side of Eq. (9) represents the total payments to the supplier for intermediate input purchases of X^s. This is what we observe in our dataset and use as the dependent variable in the empirical analysis. On the right hand side of the equation, $\mathbb{1}_R$ equals 1 if the sourcing firm adopts robots. Notice that conditional on robot adoption decision, investment costs in robots raises the purchases from suppliers $\partial(P^{X^s} X^s)/\partial f^R > 0$ because reshoring becomes more difficult due to the high costs of adopting robots. The term $\frac{\sigma}{1-\sigma}$ refers to substitution effect, indicating that firm continues sourcing inputs when robots and supplier's workers are complements ($\sigma < 0$) and reduces sourcing when robots and supplier's workers are substitutes ($\sigma > 0$). Given $0 \leq \nu \leq 1$, the term $\frac{-1-\rho}{-1+\mathbb{1}_S \nu} > 0$ corresponds to productivity effect because it proportions the cost of production with robots to suppliers. As defined in Eq. (8), ρ augments the costs of production with robots and ν augments the gains from sourcing. Therefore, higher costs of producing with robots compared to sourcing makes production of inputs using robots less profitable and therefore increases sourcing due to productivity increase from using robots. Finally, the last two terms correspond to a constant as $\frac{\varphi^R}{\varphi^L}$ is the relative share of robots to supplier's workers and $\frac{\varphi^L}{\varphi^R}$ is the relative share of supplier's workers to robots in production of input.

Discussion

Theoretical framework presented in this section relies on production and investment costs in motivating the robot adoption and reshoring decisions of a sourcing firm. In the model, we emphasize the advantages and disadvantages of reshoring in terms of costs because after all, bringing the production back to home country must be more profitable for reshoring to be the optimal choice. On the other, while robots and tasks may not be substitutable at all (e.g. Domini et al., 2021), substituting tasks with robots is not a sufficient condition for a firm to reshore the production.

In our framework, two factors ultimately determine reshoring decision or continuing purchasing more intermediate inputs: elasticity of substitution between robots and supplier's workers, and relative cost of producing intermediate inputs with robots to a supplier. However, given the complexity of global value chains, there could be several other reasons. First, the characteristics of tasks performed by offshore workers and robots may be different and if this is the case, replacing robots with offshore workers may be difficult. While robots typically perform routine tasks, Blinder and Krueger (2013) show that routine tasks are not more likely to be offshorable with respect to other tasks.[9] Consistent with these findings, Stemmler (2019) recently identified that foreign robots increased employment in Brazil for largely non-routine tasks. Robots are typically expected to substitute low-skilled workers in developing countries but such substitution may not occur if fewer low-skilled workers are used in production of intermediates exported from developing countries to developed countries (e.g. Timmer et al., 2014) Similarly, Costinot et al. (2011) find that the shares of vertically integrated firms are higher in less-routine industries in the U.S. Thus, the tasks performed by offshore workers can actually have medium complexity, making substitution between robots and offshore workers difficult.

Second, even if we assume that tasks performed by offshore workers and robots are the same, it does not necessarily induce the substitution between them. Bernard et al. (2020) recently found that Danish firms continue producing and improving the quality of products that they once offshored. This suggests that reshoring may not occur even though robots become capable of producing the same imported intermediate inputs. Finally, international specialization can have a crucial role in the organization of supply chains across firms in different countries and lead to interdependencies across borders (e.g. Antras et al., 2017). Hence, interdependency of suppliers across different locations can also impair the possibility of reshoring decisions.

We present the model in the context of trade between a developing and a developed country because our analysis focuses on the topic of reshoring. However, we acknowledge that Spanish manufacturing firms also imports intermediate inputs from the EU countries substantially. In this regard, elasticity of substitution between robots and suppliers' workers as well as the relative cost of producing with robots to foreign supplier might be different in developed countries than in developing countries.[10] Hence, the model can be evaluated for the case of trade between two developed countries but our study considers Spanish firms' decisions on sourcing from low-income countries after adopting robots.[11]

[9] According to some of their measurements, even larger share of non-routinisable jobs are offshorable compared to routinizable jobs.

[10] More specifically, robots might be complement or substitute to workers in developed countries and the production cost with robots in Spain might be lower or higher than the production cost of suppliers in developed countries.

[11] Additionally, the model could be modified to study the reverse relationship so that reshoring induces robot adoption, or even simultaneous decisions. This is intuitively possible if reshoring facilitates robot adoption by making production more profitable. However, we specifically analyze how robot adoption might affect sourcing activities (potentially reshoring) because robot adoption in developed countries has been regarded as one of the main possible reasons for firms' consideration of reshoring decisions. We thank a referee for pointing out this issue.

Table 1
Participation shares by sourcing strategies.

	Robot adopters			Non-adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Foreign outsourcing	0.577	0.494	5087	0.368	0.482	12 086
Foreign vertical integration	0.175	0.380	5085	0.058	0.234	12 085
Domestic outsourcing	0.942	0.233	5112	0.926	0.262	12 091
Domestic vertical integration	0.251	0.433	5112	0.100	0.301	12 093
Rest of the World	0.286	0.452	9251	0.147	0.354	30 223
Latin America	0.080	0.272	6367	0.040	0.195	15 917

Note: This table presents the percentage of firms participating in sourcing strategies across the two groups between 2006 and 2016. Rest of the world represents the regions except Latin America, the OECD and the EU countries. SD denotes the standard deviations. Sourcing strategies and imports from low-income countries are provided in IHS transformed values.

Table 2
Sourcing intensities.

	Robot adopters			Non-adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Foreign outsourcing	8.767	7.719	5087	5.015	6.752	12 086
Foreign vertical integration	2.814	6.173	5085	0.890	3.624	12 085
Domestic outsourcing	15.511	4.247	5112	13.634	4.280	12 091
Domestic vertical integration	4.012	7.007	5112	1.534	4.649	12 093
Rest of the World	4.172	6.709	9251	2.031	4.969	30 223
Latin America	1.134	3.886	6367	0.537	2.692	15 917

Note: This table reports the IHS transformed means of intermediate input purchases across the two groups from 2006 to 2016. Rest of the world represents the regions except Latin America, the OECD and the EU countries. SD denotes the standard deviations. Sourcing strategies and imports from low-income countries are provided in IHS transformed values.

4. Data and stylized facts

We use firm-level data from the ESEE (Encuesta Sobre Estrategias Empresiales), a panel dataset of Spanish manufacturing firms collected by Fundacion SEPI and the Spanish Ministry of Industry. The survey spans the 1990–2016 period, distinguishes 20 manufacturing industries based on two-digit NACE classification (Classification of Economic Activities in the European Community) and contains a large sum of information on the characteristics of annually surveyed 1,800 Spanish firms with 10 or more employees.[12]

The ESEE is unique in that it conveys information on the sourcing strategies of firms: whether the firm purchases intermediate inputs from an unrelated party (*outsourcing*) or from a related party (*vertical integration*), and whether the supplier is located abroad or in Spain. We are not able to obtain any information about suppliers' characteristics and origin of their countries. However, our data contain the value of imports from specific locations which are used for robustness checks, namely Latin America and the rest of the world (defined as all the regions except Latin America, OECD and EU countries).

The data include the values of firms' total imports and total purchases. Our main dependent variables are foreign sourcing strategies and domestic sourcing strategies. The ESEE dataset provides us sourcing activities as the percentage of intermediate input imports in total imports for foreign sourcing activities and as the percentage of intermediate input purchases in total purchases for domestic sourcing activities. Hence, the values of foreign (domestic) sourcing activities in the data represent the share of foreign (domestic) sourcing activities in total imports (purchases) of firms.[13] Since we can observe the values of total imports and total purchases, as well as what percentages of total imports and total purchases constitute foreign and domestic sourcing respectively, we can compute the values of foreign and domestic intermediate input sourcing.

As our key explanatory variable, the measure of firm-level robot adoption is binary, indicating whether the firm used robots in production process in a given year. Unlike the large majority of current studies that rely on *exposure to robots* at the industry or regional level, we can identify the effects of robots explicitly at the firm-level. Our dataset contains further detailed information on imported technologies, intermediate consumption, materials price index, number of markets the firm is operating in, wage and skill intensity.

For the construction of our instrument, we combine the ESEE dataset with the IFR (International Federation of Robotics) database, which consists of new installations and the stock of industrial robots by industry, country and year. The IFR data cover 50 countries including Spain, and 35 industries within manufacturing from 1993 to 2014.[14] We evaluate the trends in Spain's intermediate input trade with other European Union countries (those selected in construction of our instrument) to test the robustness of the results. To do so, we obtain the data on aggregate intermediate input exports to Spain by country from the The World Integrated Trade Solution (WITS).

In our analysis, we use an unbalanced panel of the data and study the period 2006–2016 for several reasons. First, information regarding the various sourcing strategies in the ESEE dataset are only available for this period. Second, reshoring narrative began to have widespread media coverage after the global financial crisis in 2008.[15] Indeed, Faber (2020) finds no effects of US robots on local labor markets in Mexico for 1990–2000 but for 2000–2015. Third, focusing on the 2006–2016 period allows us to abstract from the trade dispute between US and China that occurred during the Trump administration and COVID-19 pandemic.

Table 1 reports summary statistics for the participation in sourcing activities. The table shows that larger fraction of robot adopters purchased intermediate inputs than non-adopters regardless of sourcing strategy and import destinations. Outsourcing is a more common strategy than vertical integration among both robot adopters and non-adopters. Table 2 presents the intensities of sourcing between adopters and non-adopters across sourcing strategies. Adopters also appear to be sourcing more intensely than non-adopters on average while outsourcing firms purchase intermediate inputs more intensely than vertically integrated firms. These tables document that robot adopters are more actively involved in sourcing activities and outsourcing is more commonly preferred form of intermediate input trade.

Fig. 1 plots the distribution of productivity levels, capital investments and intermediate consumption for robot adopters and non-adopters. We exploit two firm-level productivity measures from our data: the natural log of the firm's sales and labor productivity defined as the natural logarithm of value-added per worker. The distribution of adopters is evidently positioned to the right of non-adopting firms in each plot. The top panel indicates that robot adopting firms are on average more productive whereas the bottom of the panel depicts that adopters invest in capital more (on the left side) and have higher intermediate consumption (on the right side). The differences between the two groups are also consistent with the model that robot adopters have higher productivity $A > \tilde{A}$, $Y^{1_R} > Y$,[16] and higher capital

[12] https://www.fundacionsepi.es/investigacion/presentacion.asp

[13] The definitions are provided by the SEPI Foundation, therefore the distinction in the denominator is not our choice. We presume that the denominators are different for foreign and domestic sourcing strategies (total imports for foreign sourcing strategies and total purchases for domestic sourcing strategies) because firms involved in foreign sourcing *import* intermediate inputs from suppliers in foreign countries to Spain while firms involved in domestic sourcing *purchase* intermediate inputs from suppliers located in Spain. Thus, transactions occur *between* countries in foreign sourcing (therefore imports) and *within* the home country, Spain (therefore purchases).

[14] See Table A1 in Appendix A for the details of matching of our two datasets based on industries.

[15] See Kinkel and Maloca (2009), Pisano et al. (2009), Sirkin et al. (2011) and Home (2013) for early concerns.

[16] Also in Eq. (7), we show that for adopting robots, firm revenues must increase more than the costs to make the adoption more profitable.

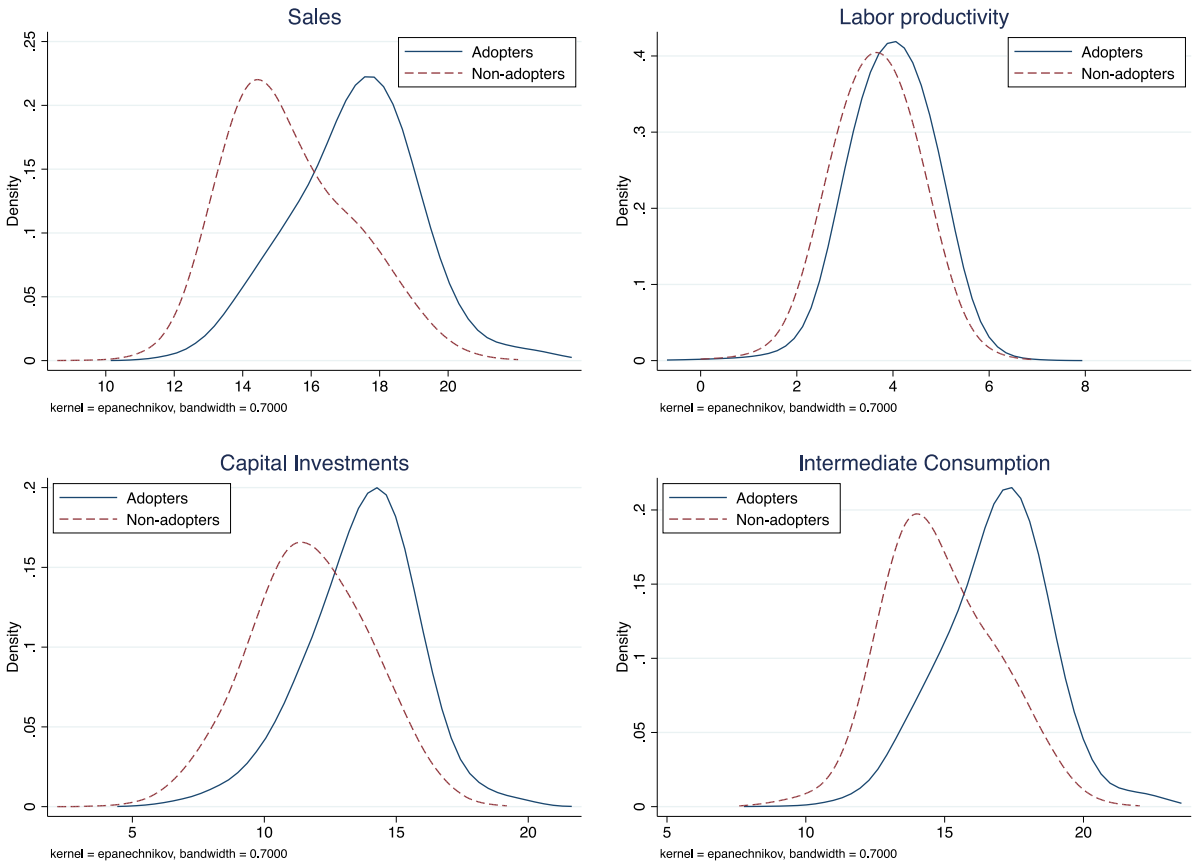

Fig. 1. Patterns of adoption.
Note: This figure presents the distribution of productivity (measured as log sales), labor productivity (measured as log value added per worker), log capital investments and log intermediate consumption. The bold lines show the distributions of robot adopting firms and the dashed lines show the distributions of non-adopting firms.

investments, $f^R > 0$, than non-adopters. Table A2 in Appendix A provides additional descriptive statistics showing similar patterns.

If firms continued sourcing intermediate inputs from suppliers after adopting robots, then their intermediate input purchases must have increased because robots increases productivity and larger amount of producing final goods requires larger amount of intermediate input usage. This mechanism relies on the assumption that the final output is obtained using two composite inputs: $Y^{\mathbb{1}_R} = (X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta}$. To see the empirical validity of it, we regress each sourcing activity (foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration) on sales. Fig. 2 quantifies the differences in various sourcing strategies with 95 percent confidence intervals of local polynomial regressions. Intermediate input purchases for each type of sourcing strategy are larger in higher sales.[17] All panels depict a positive, monotonic and a strongly increasing relationship between sales and sourcing activities. Figure B1 in Appendix B shows similar patterns for the imports from Latin America and the rest of the world. Finally, Figure B2 and Figure B3 present this relationship separately for adopters and non-adopters across sourcing strategies.

Finally, Fig. 3 shows the variability of adopters and robots across industries. The left panel depicts the share of adopters and the right panel shows the average installations of robots in each industry. Vehicles and accessories has the highest share of adopters, almost 80% of the firms, and it is most intensely robotized industry, followed by Fabricated metal products, Plastics and rubber products, Basic metal products and Food and beverages. The remaining industries employ relatively much less robots and have lower share of adopters.

The facts documented in this section point to substantial differences between robot adopters and non-adopters. The empirical analysis conducted in the next section explores the dynamics of the relationship between robot adoption and sourcing activities in greater detail.

5. Empirical analysis

In this section, we empirically investigate how robot adoption affected firms' sourcing strategies and imports from low-income countries. In Section 5.1, we describe the details of our identification strategy and discuss possible threats to identification. In Section 5.2, we present the results of our estimations and test the robustness of our findings.

5.1. Identification strategy

In our empirical specification, we relate time varying sourcing activities of firms to their robot adoption decisions. Potential endogeneity concern is that firm level shocks to demand and productivity may affect both robot adoption decision and firm-level sourcing activity. To address this concern, we need an instrument that is correlated with firm-year robot adoption probability but orthogonal to changes in the firm's productivity and sourcing activity.

Our instrumental variable strategy specifies that firm's robot adoption decision is driven by technological progress in robotics. Adoption

[17] This is consistent with the patterns Antras et al. (2017) discovered that firms with higher sales source their intermediate inputs from a larger number of markets.

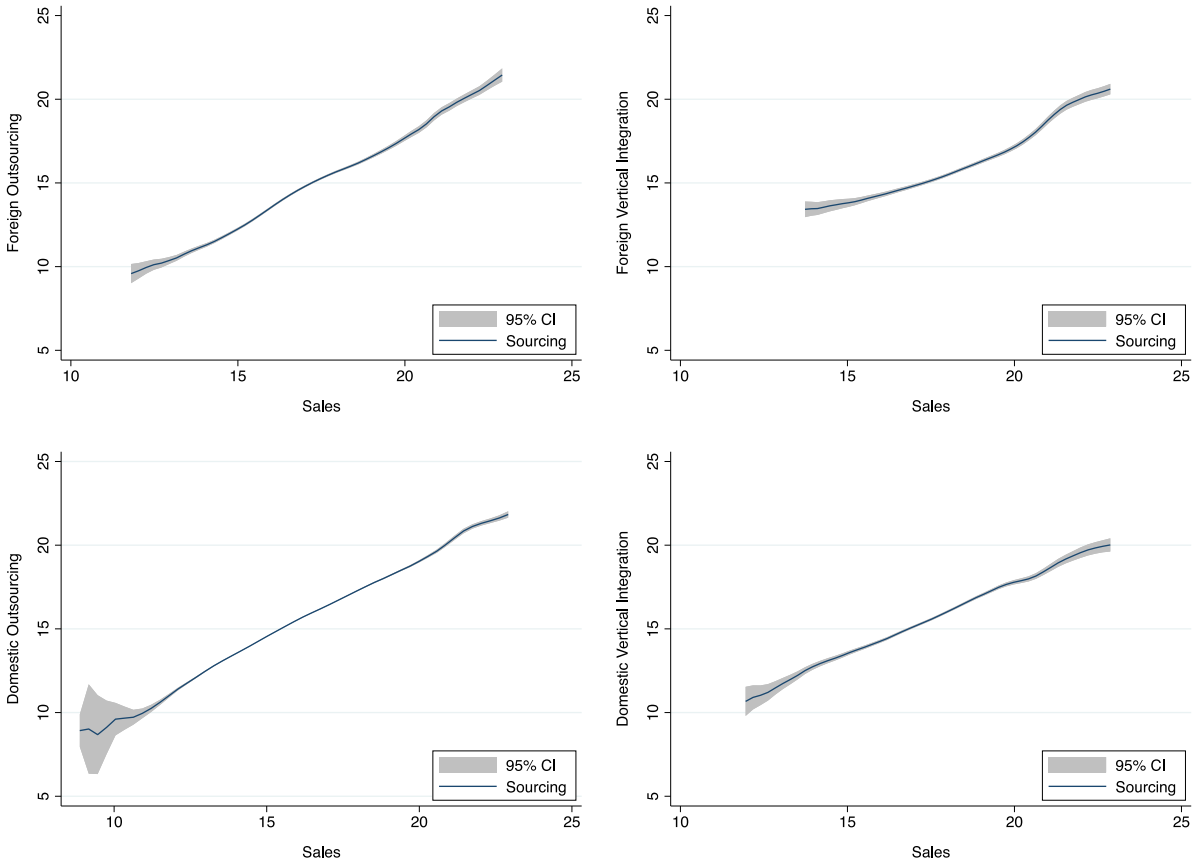

Fig. 2. Sales and intermediate input purchases of sourcing firms.
Note: Figures present the smoothed values with confidence bands from local polynomial regressions of intermediate input sourcing (measured as IHS values of each sourcing activity) on firm productivity (measured as log sales). Firms that were not involved in a sourcing strategy in a given year are excluded from the estimations.

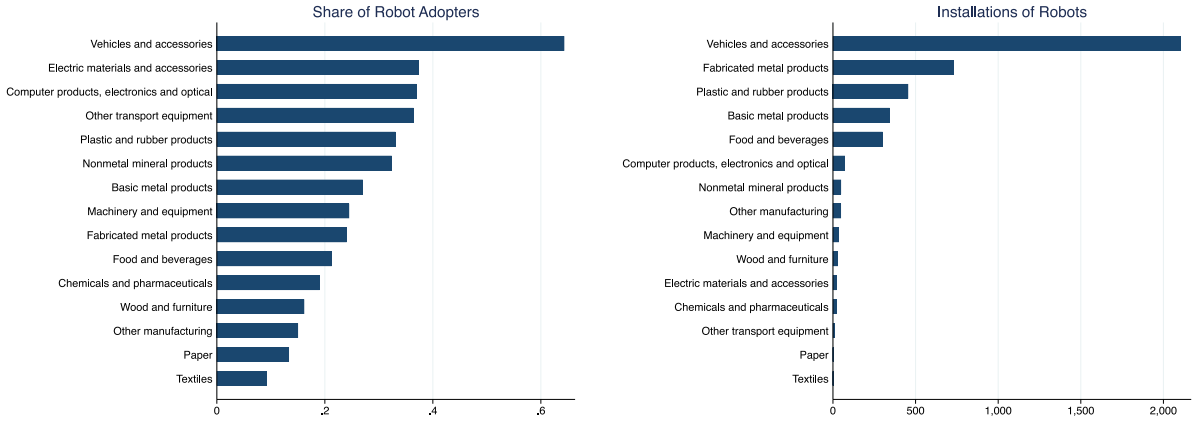

Fig. 3. Robot adopters by industry.
Note: The figure presents the adoption patterns across industries. The left panel displays the share of robot adopting firms by industry and the right panel displays the installations of robots on average in each industry.

probability of firm i in industry j in period t is instrumented by interacting a firm specific pre-sample imported technology share in year 2005 in industry j with robot adoption trends of industry j in other countries. Similar to the approach used by Acemoglu and Restrepo (2020), we use annual industry-level robot installations in four other European Union countries (Germany, France, Italy and the UK) to reflect robot adoption trends.[18] We choose countries displaying similar robot adoption patterns and sectoral structures (e.g. Krenz et al., 2021). Figure B4 in Appendix B shows the trends in the stock of robots in each country over this period and confirms our expectation that it may serve as a technological frontier. We additionally use robot installations in Scandinavian countries for the construction of our alternative instrument to test the robustness of our results.[19] Our instrument is defined

[18] This strategy was primarily used by Autor et al. (2013) and Bloom et al. (2016) in trade literature to account for import competition due to the supply shocks from China.

[19] Note that Scandinavian countries in our alternative instrument have substantially smaller population compared to Spain.

as follows:

$$z_{ijt} = \ln\left(\frac{I^{T}_{ij2005}}{I^{T}_{j2005}} \times \sum_{c=1}^{4} Robots_{cjt}\right). \quad (10)$$

$Robots_{cjt}$ denotes industry-level new installations of robots in country c in period t and the data are constructed from the IFR dataset. I^{T}_{ij2005} and I^{T}_{j2005} represent pre-sample technology imports of firm i and industry j in 2005, respectively.

Notice that the shocks arising from our instrument must be exogenous to the firm and they vary across firms over time. $Robots_{jt}$ captures the changes in industry-level robot adoption trends driven by technological advancements in robotics industry. Worldwide technological advances in robotics and robot adoption trends outside of Spain are arguably exogenous shocks to Spanish firms.

A concern for our instrument may arise if an adopting firm exports robots to the EU countries.[20] The exogeneity condition of robot adoption trends of industry j in other countries would then be violated if changes in $Robots$ are driven by robot supply shock from Spanish firm i, though odds are presumably against such a possibility. Spain is not a major robot producer country and therefore Spanish firms very likely import robots from high-income countries such as Japan and Germany. On the other hand, a robot is not an intermediate input that firm i may import, i.e. dependent variable may not affect our instrument and induce reverse causality. Thus, these concerns are unlikely to pose a threat to our identification strategy.

Initial shares $I^{T}_{ij2005}/I^{T}_{j2005}$ measure the firm-level differential exogenous exposure to the industry-level common shocks. Firm i might have imported technology because of a business relationship in the past with some technology exporters abroad set in pre-sample period, which would probably be consistent over time. Or, technology that firm i imports may be particularly crucial for the production of the products firm i produces. Pre-sample data on imported technology allows us to prevent firm-level technological change that may affect input demand across years. In our setting, firm i's exposure to industry-level robot adoption trends increases with imported technology in the pre-sample period.

To present our baseline results, we estimate the following equation:

$$\ln I^{s,l}_{ijt} = \beta R_{ijt} + \varphi_{jt} + \varepsilon_{ijt}, \quad (11)$$

where $I^{s,l}_{ijt}$ denotes the IHS transformed values of intermediate input purchases for sourcing, s indexes the sourcing strategy and l indexes the location of the supplier. We use IHS (inverse hyperbolic sine) transformation of all the outcome variables (sourcing activities and imports from the Rest of the World and Latin America) to preserve the observations with zero values in the sample, which would otherwise be undefined in standard logarithmic form and dropped out of the analysis.[21] R_{ijt} is a dummy variable we instrument for and it takes the value 1 if firm i is robot user in period t and 0 otherwise. φ_{jt} denotes industry-year fixed effects absorbing the time varying shocks to adoption at the industry-level. ε_{ijt} is the error term.

According to our theoretical framework, we expect the parameter β to be positive after adopting robots if the firm continues sourcing. Adoption of robots boosts productivity and the firm needs more inputs to produce larger amount of output. Thus, if $\beta < 0$ would indicate that robot adoption induced a decline in intermediate input purchases from low-income countries, i.e. reshoring the production of some inputs back to home country.[22] In estimation of the true impact of robot adoption conditional on controls, first reason that the firm may increase sourcing inputs after robot adoption is that the firm may substitute foreign inputs with domestic inputs. Since our dataset allows us to distinguish foreign and domestic inputs, we rule out this possibility by controlling for domestic sourcing activities (foreign sourcing activities) when estimating the effects on foreign sourcing activities (domestic sourcing activities). Moreover, the firm may substitute inputs purchased from suppliers for the inputs previously produced within the firm, i.e. starting to source inputs from suppliers. To address this possibility, we control for the lagged sourcing activity that can accurately capture the persistence of sourcing activities.[23] Considering these concerns, we estimate the following equation:

$$\ln I^{s,l}_{ijt} = \beta'_1 R_{ijt} + \beta'_2 \ln I^{s,l}_{ijt-1} + \beta'_3 \ln I^{s,l^-}_{ijt} + \beta'_4 \ln I^{s^-,l^-}_{ijt} + \varphi_{jt} + \varepsilon'_{ijt} \quad (12)$$

where $I^{s,l}_{ijt-1}$ denotes the lagged sourcing activity. s^- and l^- represent the sourcing strategy and the location other than the estimated one: outsourcing if vertical integration is dependent variable and domestic sourcing strategy if foreign sourcing strategy is dependent variable, and vice versa. For instance, I^{s^-,l^-}_{ijt} is domestic vertical integration if dependent variable $I^{s,l}_{ijt}$ is foreign outsourcing.

Second reason of a change in sourcing activities after robot adoption may be due to a productivity shock. For instance, robot installations in developed countries and sourcing activity of firm i may be correlated because an export supply shock from low-income countries (or time-varying demand shocks of inputs from high-income countries) may decrease (increase) input price and foster robot adoption trends in developed countries.[24] Similarly, $Robots_{jt}$ may be correlated with $I^{s,l}_{ijt}$ if increasing robot installations in Germany affects the production of suppliers in low-income countries.[25] To deal with this issues, we incorporate the log of firm-year input price index and industry by time fixed effects to control for time varying shocks to demand. Recall that firms' potential reshoring decisions are also motivated by rising labor costs in emerging markets, beyond other factors. By controlling for the input price index, we also account for the fact that increased imported input costs may incentivize a firm to use robots and reduce its purchases of intermediate inputs.

A trade shock can increase new sourcing opportunities for firms (e.g. Bernard et al., 2020). Import or export tariff changes in Spain are set at the EU level and therefore plausibly exogenous to individual Spanish firms. However, the expansion of sales to new export markets may encourage the firm to invest in productivity enhancing technologies or allow them to bear fixed cost of technology investments more easily (e.g. Lileeva et al., 2010; Bustos, 2011). We include the log of the number of markets as an adequate measure to control for the changes at the extensive margin and export intensity defined as exports to sales ratio to control for demand shocks outside of Spain at the intensive margin.[26]

[20] For instance, a Spanish robot producer may have been producing substantial amount of robots and reducing the price of robots, facilitating the adoption of other countries.

[21] IHS is defined as $\ln(x + \sqrt{x^2+1})$ and it behaves similar to log. However, another common approach to deal with such circumstances is to insert one to each value in the sample before taking logs of them. Conclusions are the same but the results only slightly differ when the variables are treated as such.

[22] In fact, robots may replace *some* tasks performed by suppliers' workers and continue importing other inputs produced by tasks not yet substituted by robots of sourcing firm. If sourcing firm increases its productivity after robot adoption, even if robots replace some tasks, we may find an increase in sourcing activity after robot adoption.

[23] As shown by recent studies using the same dataset, robot adoption may encourage firms to enter into import markets (e.g. Stapleton and Webb, 2020; Alguacil et al., 2022).

[24] $Robots_{jt}$ may increase for two reasons in this scenario. First, firms in developed countries receive lower input prices as a productivity shock which then facilitates their robot adoption decision. Second, robot producers using inputs from low-income countries may increase the supply of robots, therefore reduce robot prices and encourage robot users to employ more robots.

[25] We thank a reviewer for pointing out this possibility.

[26] Our choice of export intensity exploits how the firm performs in foreign markets particularly rather than overall performance in terms of sales.

Table 3
Baseline results with sourcing strategies.

	Foreign outsourcing		Foreign vertical integration		Domestic outsourcing		Domestic vertical integration	
	1st stage (1)	2SLS (2)	1st stage (3)	2SLS (4)	1st stage (5)	2SLS (6)	1st stage (7)	2SLS (8)
Robot adoption		17.87***		25.57***		7.342***		2.021
		(3.639)		(5.920)		(1.595)		(3.111)
Instrument	0.0552***		0.0552***		0.0555***		0.0555***	
	(0.0121)		(0.0121)		(0.0121)		(0.0121)	
Observations	9324	9324	9322	9322	9345	9345	9347	9347
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap F-statistic	20.9		20.7		20.9		20.9	

Notes: This table presents the effects of robots on sourcing strategies. The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Another potential threat to our identification strategy is that a firm specific shock changing the input demand of firm i, $I^{s,l}_{ijt}$, may affect *Robots*. *Robots* may be correlated with the sourcing activity of the firm if the firm is sourcing inputs from Germany, Italy, France or the UK instead of low and middle-income countries.[27] This is unlikely the case since Germany, Italy, France or the UK are not the countries that a Spanish firm may be involved in sourcing inputs to take advantage of lower labor costs.[28] Still, to deal with this issue, we estimate our model using imports from low and middle income countries defined as Latin America and the Rest of the World in our dataset which includes countries except the OECD and the EU.[29]

We also include the log of average wage of the firm in the estimations. Since our wage variable captures all compensations to workers in the firm, we use skill intensity instead of total employment to avoid a potential bias between these variables while controlling for any quality related changes. Finally, our estimation takes the form of the following equation:

$$\ln I^{s,l}_{ijt} = \beta^*_1 R_{ijt} + \beta^*_2 \ln I^{s,l}_{ijt-1} + \beta^*_3 \ln I^{s,l^-}_{ijt} + \beta^*_4 \ln I^{s^-,l^-}_{ijt} + \beta^*_5 \ln P^M_{ijt} + \beta^*_6 \ln M_{ijt} + \beta^*_7 \tilde{X}_{ijt} + \beta^*_8 \ln W_{ijt} + \beta^*_9 \tilde{H}_{ijt} + \varphi_{jt} + \epsilon^*_{ijt}, \quad (13)$$

where P^M_{ijt} is materials price index and M_{ijt} is the number of markets the firm is related to. X_{ijt}, S_{ijt} and $\tilde{X}_{ijt} = \frac{X_{ijt}}{S_{ijt}}$ denote firm i's exports, sales and export intensity, respectively. W_{ijt} denotes the average wage of the firm and $\tilde{H}_{ijt} = \frac{H_{ijt}}{H_{ijt}+L_{ijt}}$ represents the skill-intensity of the firm.

5.2. Results

This section presents the results of our estimations. We test the robustness of our estimations via an alternative instrument in Appendix.

[27] This may be due to the fact that firm i's higher demand for inputs can encourage firms in these countries to use more robots to increase input supply. Another possibility is that increased number of robots in these countries may lead to an input supply shock to firm i in Spain.

[28] We acknowledge that Spanish firms substantially import intermediate inputs from other European (and other developed) countries while these imports have been declining during our sample period (see Figure B5 in the Appendix B). However, we emphasize that such strategies of firms are unlikely driven by cost advantages in intermediate input production. In fact, elasticity of substitution between robots in Spain and suppliers' workers in developed countries might be different than with the suppliers' workers in developing countries.

[29] Even if the firm imports inputs from low-income countries, $I^{s,l}_{ijt}$ may be correlated with *Robots* if the firm is capable of generating a supply shock in low-income countries that can change the demand for robots in high-income countries. However, we disregard this scenario because of its implausibility since a Spanish firm is unlikely to generate a supply shock in input markets of low-income countries.

Table 4
Baseline results with destinations.

	Rest of the World		Latin America	
	1st stage (1)	2SLS (2)	1st stage (3)	2SLS (4)
Robot adoption		11.48***		6.921***
		(2.585)		(2.309)
Instrument	0.0617***		0.0561***	
	(0.00999)		(0.0107)	
Observations	20 016	20 016	13 739	13 739
Year × Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen–Paap F-statistic	38.2		27.5	

Notes: This table presents the effects of robots on imports from two locations. The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 3 reports results from estimating Eq. (11) for sourcing strategies. Our baseline specification only includes industry-year and region fixed effects. The first column in each panel presents the first-stage results and the second column in each panel presents the corresponding 2SLS estimates. The first-stage Kleibergen–Paap F-statistic for the instrument is above 20 in each panel and statistically significant at the 1% level, reported in columns 1, 3, 5 and 7. The coefficients on the instrument are positive as expected because a firm with the higher share of technology imports in an industry would be more exposed to global technological developments. A strong positive correlation between the instrument and robot adoption probability in the first-stage estimates suggests that it is very unlikely that our estimates are biased by weak instruments.

The 2SLS estimates in columns 2, 4, 6 and 8 depict a large and statistically significant relationships between sourcing strategies and robot adoption. The estimated coefficients on foreign outsourcing, foreign vertical integration and domestic outsourcing are respectively 17.87, 25.57 and 7.34 log points and statistically significant at the 1% level. However, we find no impact of robot adoption on domestic vertical integration as the estimated coefficient reported in column 8 is small and statistically insignificant.

In Table 4, we present estimates for specifications in which the dependent variable is imports from low-income countries. Similar to the estimates for sourcing strategies, the first-stage results in columns 1 and 3 demonstrate a strong and significant relationship between the instrument and robot adoption with sufficiently high Kleibergen–Paap F-statistics. Columns 2 and 4 report the corresponding 2SLS estimates of the relationship between robot adoption and imports from low-income countries. The coefficient estimates of these specifications are large and statistically significant at the 1% level.

Notice however that substantially high magnitudes of these estimates point to the possibility of an upward bias due to unobserved

Table 5
Robot adoption and selection into sourcing strategies.

	Foreign outsourcing		Foreign vertical integration		Domestic outsourcing		Domestic vertical integration	
	1st stage (1)	2SLS (2)	1st stage (3)	2SLS (4)	1st stage (5)	2SLS (6)	1st stage (7)	2SLS (8)
Robot adoption		7.177***		6.030***		2.152		−1.268
		(2.277)		(2.328)		(1.476)		(1.241)
Instrument	0.0380***		0.0378***		0.0306***		0.0368***	
	(0.0111)		(0.0123)		(0.0114)		(0.0115)	
Lag foreign outsourcing	0.0107***	0.638***						
	(0.00143)	(0.0312)						
Lag foreign vertical integration			0.00606**	0.767***				
			(0.00238)	(0.0298)				
Lag domestic outsourcing					0.0136***	0.598***		
					(0.00208)	(0.0307)		
Lag domestic vertical integration							0.0121***	0.863***
							(0.00204)	(0.0182)
Foreign Outsourcing					0.0114***	0.0398**	0.0125***	0.0303*
					(0.00151)	(0.0182)	(0.00156)	(0.0173)
Foreign Vertical Integration					0.00507**	0.0103	0.00299	0.0312**
					(0.00242)	(0.0140)	(0.00242)	(0.0126)
Domestic Outsourcing	0.0126***	0.0391	0.0161***	−0.0744*				
	(0.00211)	(0.0369)	(0.00223)	(0.0414)				
Domestic Vertical Integration	0.0118***	−0.0395	0.0125***	−0.0333				
	(0.00202)	(0.0307)	(0.00205)	(0.0318)				
Observations	7948	7948	7946	7946	7956	7956	7957	7957
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap *F*-statistic	11.8		9.5		7.2		10.3	

Notes: This table presents the effects of robots on sourcing strategies. We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 6
Robot adoption and selection into importing from developing countries.

	Rest of the World		Latin America	
	1st stage (1)	2SLS (2)	1st stage (3)	2SLS (4)
Robot adoption		2.425***		0.386
		(0.765)		(0.471)
Instrument	0.0494***		0.0471***	
	(0.0107)		(0.0109)	
Lag imports (Rest of the World)	0.0109***	0.819***		
	(0.00176)	(0.0138)		
Lag imports (Latin America)			−0.00186	0.840***
			(0.00322)	(0.0129)
Imports (Rest of the World)			0.0114***	0.0578***
			(0.00183)	(0.00876)
Imports (Latin America)	−0.00175	0.206***		
	(0.00317)	(0.0156)		
Observations	12 991	12 991	12 210	12 210
Year × Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen–Paap *F*-statistic	21.3		18.7	

Notes: This table presents the effects of robots on imports from two locations. We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

shocks as we discussed in the previous section. In order to evaluate the robustness of our estimates to concern over the substitution between foreign and domestically produced inputs, we include additional covariates and estimate Eq. (12). The results presented in Table 5 show that our findings are robust to changes in sourcing strategies. Specifications for foreign outsourcing and foreign vertical integration deliver statistically significant estimates at the 1% level. As shown in columns 2 and 4, the estimated coefficients are smaller in magnitude than in our baseline results but remain large. The estimated coefficient on domestic outsourcing remains positive, although it is no longer significant while the coefficient on domestic vertical integration turns to negative and remains statistically insignificant. Lagged sourcing activities are statistically significant at the 1% level in each specification, indicating an important role of persistence in sourcing activities.

Conditional on sourcing activity in the previous period and the changes in any switching between foreign and domestic sourcing, our estimation results indicate substantial increase in intermediate input sourcing from foreign suppliers. We find that adopting robots raise the value of intermediate input imports approximately 7 fold for firms involved in foreign outsourcing and 6 fold for firms involved

Table 7
Impact of robot adoption on sourcing strategies.

	Foreign outsourcing		Foreign vertical integration		Domestic outsourcing		Domestic vertical integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		5.962**		6.893**		1.283		−2.200
		(2.706)		(3.359)		(1.727)		(1.857)
Instrument	0.0292**		0.0290**		0.0239**		0.0288**	
	(0.0115)		(0.0126)		(0.0119)		(0.0120)	
Lag foreign outsourcing	0.00823***	0.638***						
	(0.00143)	(0.0288)						
Lag foreign vertical integration			0.00306	0.777***				
			(0.00247)	(0.0288)				
Lag domestic outsourcing					0.0107***	0.603***		
					(0.00204)	(0.0295)		
Lag domestic vertical integration							0.0105***	0.861***
							(0.00201)	(0.0220)
Foreign Outsourcing					0.00871***	0.0405**	0.00934***	0.0290
					(0.00151)	(0.0164)	(0.00155)	(0.0191)
Foreign Vertical Integration					0.00260	0.00288	0.000826	0.0203
					(0.00249)	(0.0108)	(0.00247)	(0.0128)
Domestic Outsourcing	0.00981***	0.0451	0.0119***	−0.0719				
	(0.00207)	(0.0336)	(0.00214)	(0.0444)				
Domestic Vertical Integration	0.0102***	−0.0264	0.0107***	−0.0376				
	(0.00199)	(0.0298)	(0.00203)	(0.0383)				
Materials price index	−0.0246	0.339	−0.0167	−0.0272	−0.0358	−0.339**	−0.0322	−0.247*
	(0.0364)	(0.281)	(0.0366)	(0.274)	(0.0367)	(0.154)	(0.0361)	(0.139)
Markets	−0.000336	0.558***	0.0116	−0.0221	−0.00381	0.124	0.00271	0.0399
	(0.0204)	(0.155)	(0.0209)	(0.164)	(0.0206)	(0.0791)	(0.0204)	(0.0895)
Export intensity	0.140**	0.169	0.159***	−0.935	0.138**	0.0382	0.144**	0.112
	(0.0551)	(0.602)	(0.0560)	(0.755)	(0.0557)	(0.309)	(0.0558)	(0.350)
Wage	0.167***	−0.0194	0.186***	−0.865	0.196***	0.681*	0.190***	1.179***
	(0.0351)	(0.549)	(0.0360)	(0.682)	(0.0352)	(0.396)	(0.0355)	(0.398)
Skill-intensity	−0.117	0.206	−0.117	1.835*	−0.0735	0.566	−0.100	0.800
	(0.124)	(0.979)	(0.126)	(1.086)	(0.126)	(0.546)	(0.125)	(0.617)
Observations	7870	7870	7868	7868	7877	7877	7878	7878
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap *F*-statistic	6.4		5.3		4.1		5.8	

Notes: This table presents the effects of robots on sourcing strategies while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

in foreign vertical integration. Large impacts might be because robot adopting firms are those that do not intensely importing previously, i.e. firms previously importing few amount boost input imports after robot adoption.[30] Although the effects we discover are relatively smaller in magnitude, our estimations are aligned with the results of Stapleton and Webb (2020).

In Table 6, we use imports from low-income countries as dependent variables and present results from estimating Eq. (12). The magnitude of estimated coefficient on imports from the Rest of the World drops to 2.425 log points and remains significant at the 1% level. The coefficient estimate on Latin America is still positive, but close to zero, and becomes statistically insignificant. As in sourcing strategies, lagged sourcing activities seem to play an important role in our estimations as the coefficients we obtain are notably high and significant at the 1% level, implying a location persistence in importing. The results also indicate that imports from two geographies do not substitute each other since the coefficient estimates are positive (0.0578 for the Rest of the World shown in column 4 and 0.206 for Latin America shown in column 2) and statistically significant at the 1% level.[31]

A productivity shock may threaten the validity of our identification strategy if the shock is correlated with robot adoption and sourcing activity and threaten the validity of our identification strategy. We estimate Eq. (13) and assess the robustness of the baseline results to inclusion of the full set of controls that we motivated and described in the previous section. When we condition on productivity shocks, the 2SLS estimates reported in Table 7 are qualitatively similar compared to previous results. Most importantly, the effects on foreign sourcing strategies remain positive and significant. The coefficient estimates on foreign outsourcing and foreign vertical integration are 5.962 and 6.893, both statistically significant at the 5% level. This implies that foreign outsourcing firms increased their intermediate input imports by annually 388 euros on average after adopting robots while firms involved in foreign vertical integration imported around 982 euros more intermediate inputs. The coefficients on domestic outsourcing is positive and the coefficient on domestic vertical integration is negative but both are statistically insignificant. The first-stage estimates become weaker than in baseline specifications. *F*-statistics are within the range of 4.1–6.4 but the instrument remains statistically significant at the 5% level for each sourcing strategy.

The results reported in Table 7 present that firm-level price index has a negative and significant relationship with domestic sourcing strategies, indicating that firms have been responsive to price changes in cases of domestic sourcing while the effects on foreign sourcing strategies are insignificant. The coefficient on the log number of markets is positive and significantly correlated at the 1% level for foreign

[30] Table 2 and the findings of Stapleton and Webb (2020) support this possibility.

[31] If imports from two locations were substitutes, we would have found the coefficients with negative signs, e.g. an increase in imports from Latin America would reduce imports from the Rest of the World.

Table 8
Impact of robot adoption on imports from developing countries.

	Rest of the World		Latin America	
	1st stage (1)	2SLS (2)	1st stage (3)	2SLS (4)
Robot adoption		2.309**		0.559
		(1.155)		(0.737)
Instrument	0.0332***		0.0318***	
	(0.0108)		(0.0110)	
Lag imports (Rest of the World)	0.00640***	0.820***		
	(0.00173)	(0.0131)		
Lag imports (Latin America)			−0.00243	0.840***
			(0.00313)	(0.0133)
Imports (Rest of the World)			0.00707***	0.0584***
			(0.00182)	(0.00861)
Imports (Latin America)	−0.00209	0.201***		
	(0.00308)	(0.0158)		
Materials price index	−0.0688**	0.101	−0.0635*	0.119*
	(0.0344)	(0.150)	(0.0347)	(0.0687)
Markets	0.000475	0.185***	0.00239	0.0601
	(0.0181)	(0.0701)	(0.0185)	(0.0393)
Export intensity	0.192***	−0.0396	0.178***	−0.232
	(0.0510)	(0.301)	(0.0516)	(0.182)
Wage	0.226***	−0.222	0.230***	−0.188
	(0.0298)	(0.290)	(0.0302)	(0.175)
Skill-intensity	0.0456	−0.287	0.0441	0.108
	(0.124)	(0.428)	(0.125)	(0.228)
Observations	12 881	12 881	12 105	12 105
Year × Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen–Paap F-statistic	9.4		8.3	

Notes: This table presents the effects of robots on imports from two locations while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

outsourcing. Moreover, the results suggest no relationship between the export intensity and sourcing activities. Hence, demand shocks outside of Spain do not affect sourcing strategies by no means and only foreign outsourcing is responsive to the changes at the extensive margin. We find that the firm-level wage is decreasing in the intensity of foreign sourcing but increasing in the intensity of domestic sourcing, however, statistically significant only for domestic sourcing strategies and the coefficient on skill-intensity is only significant at the 10% level for foreign vertical integration.

In Table 8, we report our findings from estimating Eq. (13) using the Rest of the World and Latin America as dependent variables. With respect to the previous estimations presented in Table 6, the estimated coefficient on the Rest of the World drops slightly to 2.309 and remains significant at the 5% level. However, we find that the impact of robot adoption on Latin America is insignificant with a low magnitude. Overall, these results confirm that the impact of robot adoption on sourcing is robust to imports from low-income countries.

The estimates indicate that adopting robots increased sourcing with differential impacts across sourcing strategies in this sample. More specifically, we find that firms involved in foreign outsourcing and foreign vertical integration raised their sourcing activities in response to robot adoption. In contrast, our findings suggest that robot adoption did not have an impact on domestic sourcing strategies.

According to our theoretical framework, adoption of robots increases or decreases intermediate input sourcing conditional on the elasticity of substitution between robots and supplier's workers, robot investments and relative production costs of robots to domestic or foreign suppliers. Given that robot investments would not vary depending on foreign or domestic sourcing strategy, positive effects of robot adoption on foreign sourcing strategies might be explained by a productivity effect arising form cost advantage and complementarity between robots in Spain and foreign suppliers' workers.

In our regression results, the impacts of robot adoption on intermediate input imports from foreign suppliers coincide with the large positive effects of robots on sales, value-added and labor productivity. We document that robot adoption induced approximately 6 fold higher intermediate input imports for foreign outsourcing and foreign vertically integrated firms. Table A9 in Appendix A shows that output increased almost by the same amount of input imports. Hence, the findings point out large productivity effects of robots.

Our findings are robust to imports from low-income countries. Spanish firms also import intermediate inputs from developed countries and substitutability of workers in developed and developing countries with robots might be different. However, our estimation results remain significant and positive for the imports from the non-OECD countries. Hence, we find no evidence for a reduction in sourcing activities and the results in this paper imply that Spanish firms continued and increased sourcing rather than reshoring their intermediate input production.

6. Conclusion

In this paper, we use a detailed panel dataset of Spanish manufacturing firms to investigate how adopting robots affect outsourcing and vertically integrated firms' intermediate input purchases from both foreign and domestic suppliers. We find that robot adoption increased foreign sourcing activities and did not affect domestic sourcing activities from 2006 to 2016. These findings are robust to imports from low and middle-income countries.

We theoretically show that the probability of robot adoption is higher when adoption raises the revenue more than it raises costs and when the investment costs in robots are lower. According to our model, the reshoring decision is determined by the elasticity of substitution

between the robots of the sourcing firm and offshore workers as well as the costs associated with bringing the production back to home country. Similar to previous studies, we observe in our data that robot adopting firms differ from non-adopting firms and the stylized facts we present are aligned with the assumptions and predictions in our theoretical framework.

Our dataset is limited to the information provided by Spanish sourcing firms in which we do not observe employment decisions of suppliers in other countries. Hence, this paper shows how the intermediate input trade between sourcing firms and suppliers have changed after sourcing firms adopted robots. However, it does not infer any direct conclusion about the effects on labor markets in offshore countries. Another caveat of the paper is that our sample is limited to the manufacturing sector. Considering the fact that robots are becoming increasingly more prevalent in services sectors, perhaps more research will be needed in the future to assess the effects of robots on offshore services.

Reshoring and widespread use of robots have recently been subject to intense policy debates. Such concerns coincide with the deglobalization arguments and lead to rethinking on international trade policies. However, more empirical evidences on the related literature are needed at the firm-level because the findings yet vary across countries depending on whether the analysis is conducted at the employee level, firm-level or industry-level. The analysis in this paper fills this important gap in the literature based on a dataset that identifies firm-level robot adoption and intermediate input trade between firms.

We show that robot adoption does not yet disrupt trade activities of a developed economy with low-income countries. Robots in Spain seem to be complementary to workers in offshore economies because our estimation results suggest that robot adopting firms imported more intermediate inputs. Increased competitiveness of Spanish firms in trade through technological upgrading did not impair intermediate input imports from countries with cheaper labor force. In this regard, this paper supports the view that shocks to global trade yet tend to be small and temporary (e.g. Antràs, 2020; Goldberg and Reed, 2023).

The findings in this paper emphasize the long-term implications of technological developments on global sourcing. Our firm-level analysis shows that the new technologies may affect trade patterns differently depending on the organizational forms across distinct locations. An important question is to what extent our firm-level findings can be generalized to other countries in today's world economy with complex supply chains and specialization across countries. It remains a mystery yet how firms will organize their production globally in the future as sophisticated labor-saving technologies (e.g. 3D printing and AI) become more widely adapted in the production processes and whether the effects of robots will be parallel with the results presented in this paper.

CRediT authorship contribution statement

Akin A. Cilekoglu: Conceptualization, Data curation, Methodology, Formal analysis, Writing – review & editing, Project administration. **Rosina Moreno:** Conceptualization, Supervision, Funding acquisition, Project administration, Investigation. **Raul Ramos:** Conceptualization, Data curation, Supervision, Project administration, Investigation.

Declaration of competing interest

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We declare that we do not have any competing interest.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2024.104953.

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