Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Document de Treball 2021/08, 46 pàg.
Working Paper 2021/08, 46 pag.

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

Document de Treball 2021/02, 46 pàg.
Working Paper 2021/02, 46 pag.

"The Impact of Robot Adoption on Global Sourcing"

Akin A. Cilekoglu, Rosina Moreno and Raul Ramos

UBIREA
Research Institute of Applied Economics

AQR
Regional Quantitative Analysis Research Group

Institut de Recerca en Economia Aplicada Regional i Pública
UNIVERSITAT DE BARCELONA
WEBSITE: www.ub-irea.com • CONTACT: irea@ub.edu

AQR
Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group
WEBSITE: www.ub.edu/aqr/ • CONTACT: aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

The Research Institute of Applied Economics (IREA) in Barcelona was founded in 2005, as a research institute in applied economics. Three consolidated research groups make up the institute: AQR, RISK and GiM, and a large number of members are involved in the Institute. IREA focuses on four priority lines of investigation: (i) the quantitative study of regional and urban economic activity and analysis of regional and local economic policies, (ii) study of public economic activity in markets, particularly in the fields of empirical evaluation of privatization, the regulation and competition in the markets of public services using state of industrial economy, (iii) risk analysis in finance and insurance, and (iv) the development of micro and macro econometrics applied for the analysis of economic activity, particularly for quantitative evaluation of public policies.

Abstract

This paper studies the impact of robot adoption on firms' global sourcing activities. Using a rich panel dataset of Spanish manufacturing firms, we show that robot adopting firms increased their intermediate input purchases from foreign and domestic suppliers between 2006 and 2016. The effects of robots differ across sourcing strategies: the highest in foreign outsourcing and the lowest in foreign vertical integration. We find that robot adopters fragment their production further by reducing the concentration of purchases from suppliers and the increase in intermediate input purchases is related to quality upgrading to a certain extent. Marginal treatment effects estimates suggest that responses to adoption are heterogeneous: higher probability of adoption intensifies the effects on outsourcing and weakens the effects on vertical integration. In contrast to rising concerns over reshoring, our findings suggest that robots have yet promoted trade in intermediate inputs.

JEL Classification: F14, F23, L23.

Keywords: Robots, Reshoring, Trade, Production fragmentation.

Akin A. Cilekoglu: AQR-IREA Research Group, University of Barcelona. Email: akin.cilekoglu@gmail.com

Rosina Moreno: AQR-IREA Research Group, University of Barcelona. Email: rmoreno@ub.edu

Raul Ramos: AQR-IREA Research Group, University of Barcelona and IZA. Email: rramos@ub.edu

Acknowledgements

Akin A. Cilekoglu is grateful to Erol Taymaz, Banu Demir and the participants at the Middle East Technical University and the PhD student seminar of the University of Barcelona for helpful comments and suggestions. Rosina Moreno acknowledges financial support provided by the Ministerio de Economía y Competitividad for the project entitled 'Innovation and locational factors: Diversification, knowledge and the environmental revolution', ECO2017-86976-R.

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 & 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]

Additionally, 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 & Michaels, 2018; Acemoglu & Restrepo, 2020). Even though sourcing intermediate inputs produced by cheaper workforce in low and middle-income economies has become major profitable strategy in international trade, robots offered firms an alternative channel for reducing labor costs. Because 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 recently explored displacement effects of them 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 use a unique firm-level panel dataset that 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] To analyze the relationship between firm's use of robots

[1]A group of studies regarding the 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 & 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".

[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

and sourcing decisions, we present a simple model of a firm's choice of production location and organizational form. Our econometric analysis relies on instrumenting the robot adoption trends in other European countries (e.g. Acemoglu & Restrepo, 2020) interacted with firms' reliance on foreign technologies and we further estimate the heterogeneity of the outcomes using marginal treatment effects approach.

Production fragmentation typically occurs in form of vertical integration and outsourcing. A vertically integrated final-good producer owns the production of intermediates located elsewhere and the input supplier becomes related party to this final-good producer by ownership. Only high productive firms tend to select into vertical integration because the expansion of firm's boundaries requires large investment and organizational fixed costs. In this case, an input supplier faces a low risk of losing the final-good producer because vertical integration locks both parties into a bilateral relationship that induces weaker incentives for the supplier.

On the other hand, an outsourcing final-good producer finds a suitable partner and subcontracts with an independent supplier to purchase intermediate inputs. Outsourcing does not incur governance costs as in vertical integration because transactions involve unrelated parties. However, it requires a fixed cost of searching input suppliers and contractual frictions, which are generally assumed to be relatively less costly than the costs incurred in vertical integration. In outsourcing, an input supplier faces a relatively higher risk of losing a final-good producer since the sourcing activity is based on a contractual relationship, i.e. creating better incentives for supplier to retain the final-good producer.

In theoretical models of production fragmentation, technology used by firms determine their productivity levels and organization of production across different locations. In Antras & Helpman (2004), technology used by final-good producer is one of the determinants of firms' global sourcing strategies; organizational form and the location (whether to integrate or outsource in home country or abroad) for the production of intermediate inputs. Similarly, Helpman et al. (2004) show that productivity levels determine firms' organizational forms across borders, particularly in which market to serve and invest. In the task trade approach of Grossman & Rossi-Hansberg (2008), improvements in communication and transportation technologies facilitate offshoring and lead to higher productivity. Grossman & Helpman (2005) show that technological developments may not affect the intensity or the locational composition of outsourcing activities. More recently, Costinot et al. (2013) demonstrate that technological changes can create spillovers across countries in GVCs, affecting each country differently depending on the technological change.

Despite the central role of technology in the literature of production fragmentation,

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 form of sourcing and the location of suppliers, we prefer to use outsourcing and vertical integration to be more explicit.

empirical evidences for these predictions have been limited. Studying Danish firms, Bøler et al. (2015) find that a reduction in R&D costs promotes the international sourcing activities and increases imports of intermediate inputs. Fort (2017) shows that advanced technologies facilitate 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 recently, 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]

Recent studies present mixed evidence on the role of robots in firms' cross-border activities. Artuc et al. (2019) and Faber (2020) find that exposure to US robots had negative effects on local labor markets in Mexico through lower exports to US. Using worker-level data, Kugler et al. (2020) find that exposure to US robots had negative impacts on export-oriented local labor markets in Colombia. In contrast to 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. Cross-country estimates of Artuc et al. (2018) show that increased robot intensity in developed countries had positive effects on imports from developing countries. Stemmler (2019) finds that robots in foreign countries increased employment in Brazil through increased input trade. Stapleton & Webb (2020) find that using robots increased imports and the probability of importing from low-wage countries in Spain between 1990 and 2016.

Primary contribution of this paper is to provide a firm-level evidence for the impact of labor-saving technologies on sourcing decisions. Current studies are predominantly conducted at the macro-level, estimating the effects of exposure to robots in developed countries on the industries and regions of input supplier developing countries. Since identifying the behaviour of individual firms is crucial for understanding the patterns in international trade (Bernard et al., 2007), discovering how robots can affect workers in developing countries requires more rigorous approach on the basis of firm-level data. We are able to approach this issue from demand side at the micro-level and identify the changes in different sourcing strategies. 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.

Second, our study relates to the growing but still scant literature on the effects of robots using firm-level data. Koch et al. (2019) find that robot adopters in Spain increase their output and employment considerably in the following years of adoption while

[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.

never adopting firms shrink in size. Acemoglu et al. (2020) and Bonfiglioli et al. (2020) document that robot adopters increase their productivity and size in France. Similarly, Humlum (2019) finds that robot adoption increased productivity but widened the wage gap between high and low-skilled workers in Denmark. While these papers studied the effects of robots on workers and firm productivity, our analysis focuses on how robots affect trade in intermediate inputs. Our paper is more closely related to Stapleton & Webb (2020) but we investigate the changes in firms' various sourcing strategies, taking into consideration both the location of input supplier and their relationship with the input purchasers, rather than focusing on sequential order of using automation technologies and importing.

This paper also contributes to the literature on firms' organization in international trade. Empirical evidences 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. Focusing on the extensive margin of importing, Antras et al. (2017) show the interdependency across locations in sourcing decisions arising from firms' seek of reducing marginal costs. Our analysis captures the details of the relationship between intermediate input suppliers and final-good producer. Since the content of this relationship involves differential risks for both parties, firms' responses may vary depending whether they are involved in related-party (vertical integration) or arm's-length relationship (outsourcing) (e.g. Bernard et al., 2009). In this paper, we analyze the changes in intermediate input purchases of outsourcing and vertically integrated firms after adopting robots.

Finally, our paper extends the literature on domestic sourcing activities of firms. A considerable amount of studies previously focused on foreign sourcing, i.e. foreign direct investment (FDI) and offshoring, but domestic sourcing strategies have usually been neglected. Fort (2017) finds that advanced technologies favour domestic sourcing more than offshoring in the U.S. and create bias in sourcing decisions toward high human capital countries. Kee & Tang (2016) document that trade liberalization increased the domestic content in exports and improved the activities of Chinese firms in GVCs. Our paper additionally considers the content of the relationship with the suppliers located in domestic and foreign country.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework and we discuss various channels that may affect firms' decision on sourcing after adopting robots. Section 3 describes our data and documents stylised facts about the patterns of adoption and sourcing in Spain. In Section 4, we present our empirical analysis and the results. Section 5 concludes.

2 Theoretical Framework

In this section, we provide a simple framework for an initially sourcing firm's behaviour on organizing production following Melitz (2003). We abstract from contractual frictions inherent in global sourcing transactions. Our aim is to explore the conditions for offshoring firm's decision on manufacturing intermediate inputs itself using robots instead of purchasing it from a supplier located elsewhere. To simplify the analysis, we consider the case that firm chooses one of the sourcing strategies from a single location.

The set of varieties Ω consumed as an aggregate good in the form of CES utility function is

$$Q = \left[\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where $\sigma > 1$ is the elasticity of substitution between any two varieties consumed in the market. In a monopolistically competitive industry, a sourcing firm produces differentiated final good $q(\omega)$. Standard aggregate price index is given by

$$P = \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{2}$$

where $p(\omega)$ is the price of unique variety ω. $r(\omega)$ is differentiated final good producing firm's revenue and the aggregate expenditure on the variety of goods in a market is $E = QP = \int r(\omega) d\omega$. Inverse demand function of consumers with Dixit-Stiglitz preferences for ω then becomes $q(\omega) = Q\left(\frac{p(\omega)}{P}\right)^{-\sigma}$.

A variety is produced in combination of two stages. Two types of firm, a headquarter firm and an intermediate input supplier engage in production as in Antras & Helpman (2004). Headquarter firm located in domestic country purchases intermediate inputs from a domestic or foreign supplier and conducts the final stage of the production. Production is carried out by labor or robots. We assume that cost function of combined inputs takes the Cobb-Dauglas form

$$C(c, \gamma) = q\left(\frac{\bar{c}}{\bar{\gamma}}\right)^{\eta} \left(\frac{c}{\gamma^{\zeta}}\right)^{(1-\eta)}, \tag{3}$$

where $\eta \in (0, 1)$. $\zeta \in \{L, R\}$ and $c \in \{w, r\}$ are indexes of production factors, labor L or robots R, and their associated costs, respectively. $(\bar{c}/\bar{\gamma})^{\eta}$ is the cost share of headquarter firm and $(c/\gamma^{\zeta})^{1-\eta}$ is the cost share of intermediate input supplier. γ denotes the productivity of factor used in each stage of production and robots are assumed to have higher productivity than labor, $\gamma^R > \gamma^L$.

The price of the variety ω is equal to constant mark-up over marginal cost:

$$p(\omega) = \frac{(\bar{c}/\bar{\gamma})^{\eta} (c/\gamma^{\zeta})^{(1-\eta)}}{\rho} \tag{4}$$

where $\sigma/(\sigma-1) = 1/\rho > 1$.

There are two locations; domestic country (D) and foreign country (F). Intermediate input purchases of final-good producer from location i are subject to variable costs of transportation, τ, and monitoring, β. Monitoring the input production and communication with intermediate supplier induce variable organizational costs. Similar to Antras & Helpman (2004), we assume that monitoring costs are higher for foreign supplier than for domestic supplier and higher for vertical integration than for outsourcing,

$$\beta^F > \beta^D > 1 \quad \text{and} \quad \beta_{VI} > \beta_O > 1 \tag{5}$$

and the transport cost of shipping goods from foreign country is larger than distributing the goods within domestic country,

$$\tau^F > \tau^D > 1. \tag{6}$$

A sourcing firm pays a sunk cost, f, for previously set up distribution and servicing network. Moreover, a vertically integrated firm must deploy its physical assets in a host country and an outsourcing firm must abandon its relationships with suppliers for reshoring its production (e.g. Antràs, 2020). Perhaps more importantly, producing intermediate inputs requires additional fixed costs for new production facilities, buildings, inventories and other physical assets. This indicates that reshoring decision require large sunk costs, f^R, and $f^R(B) > f$.

Larger the sales of a firm, higher the costs for new facilities because of larger capacity of production. Thus, we assume that investments in robots associated with reshoring is increasing with sales across the markets:

$$f^{R\prime}(B) > 0. \tag{7}$$

From the cost function and pricing rule above, profit functions using labor of sourcing firm and robots in domestic country for manufacturing intermediate inputs can respectively be expressed as

$$\pi = B(\bar{\gamma}/\bar{c}\chi)^{\eta(\sigma-1)}(\gamma^L/w^i\chi^i)^{(1-\eta)(\sigma-1)} - f \tag{8}$$

$$\tilde{\pi} = B(\bar{\gamma}/\bar{c}\chi)^{\eta(\sigma-1)}(\gamma^R/r)^{(1-\eta)(\sigma-1)} - f^R. \tag{9}$$

where $\chi \in \{\beta_s, \tau\}$. $s \in \{VI, O\}$ is the index for sourcing strategy, vertical integration (VI) or outsourcing (O). $i \in \{D, F\}$ specifies the location of intermediate input production. $B = \frac{1}{\sigma}E(P\rho)^{\sigma-1}$ represents the market demand for the final product.

We define the attractiveness of reshoring as relative demand for robots to labor in production of intermediates, $\Psi^i = r/w$. Under the zero profit condition, we can obtain:

$$\Psi^F = \frac{\gamma^R}{\gamma^L}(\tau^F\beta^F)\Big(\frac{f}{f^R(B)}\Big)^{1/(1-\eta)(\sigma-1)} \tag{10}$$

$$\Psi^D = \frac{\gamma^R}{\gamma^L}(\tau^D\beta^D)\Big(\frac{f}{f^R(B)}\Big)^{1/(1-\eta)(\sigma-1)} \tag{11}$$

Equation (10) and (11) represent the cases in which the firm is involved in a foreign and domestic sourcing strategy, respectively. It follows that higher relative productivity of robots to labor employed by the input supplier (γ^R/γ^L) increases the attractiveness of reshoring. On the other hand, larger transportation costs (τ^F, τ^D) between an intermediate supplier and a final-good producer, and higher monitoring cost (β^F, β^D) of intermediate input production also makes reshoring decision more attractive. However, if $f^R(B)$ is sufficiently large, investment costs of reshoring may force the firm to continue offshoring because $f^R(B) > f > 0$.

Suppose the headquarter firm increases its productivity using robots for final-good production and demand more intermediate inputs. Since $\tau^F > \tau^D$ and $\beta^F > \beta^D$, in both vertical integration and outsourcing case, reshoring is more attractive if intermediate input supplier is located abroad. This induces that if firm continues to source because $f^R(B)$ is sufficiently large, the rise in the intensity of intermediate purchases must be larger in domestic than in foreign sourcing case, i.e. $\Psi^D < \Psi^F$. On the other hand, since vertical integration is more costly to monitor, $\beta^F_{VI} > \beta^F_O$ and $\beta^D_{VI} > \beta^D_O$, reshoring must be more attractive in vertical integration case than in outsourcing, i.e. $\Psi_O < \Psi_{VI}$. This induces that the rise in the intensity of intermediate purchases must be larger in outsourcing case than in vertical integration case.

Theoretical framework presented in this section motivates firm's reshoring decision with large investment costs, $f^R(B)$, and eliminates other potential important factors. However, given the complexity of GVCs, there could be several other reasons that we cannot analyze with the current data. First, the characteristics of tasks performed by offshore workers and robots may be different, if this is the case, then replacing robots with offshore workers may be difficult. While robots typically perform routine tasks,, Blinder & Krueger (2013) show that routine tasks are not more likely to be offshorable with respect to other tasks.[5] Consistent with these findings, Stemmler (2019) recently identified that foreign robots increased employment in Brazil for largely non-routine tasks. In our dataset, we are not able to observe the tasks performed in production of intermediate inputs. However, Timmer et al. (2014) find that the share of low-skilled labor in value-added is decreasing in developing countries, reflecting that intermediate inputs may not be necessarily produced with low-skill tasks. 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

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

same, it does not necessarily induce the substitution between them. Recently, Bernard et al. (2020) find 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 impair the possibility of reshoring decisions.

3 Data and Stylised 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.[6]

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).

For our dependent variables, foreign sourcing strategies are specified as the percentage of total imports and domestic sourcing strategies as the percentage of total purchases of the firm. We are able to compute all the sourcing activities in units because the data include the value of imports and purchases. Our dataset contains additional useful variables such as intermediate consumption, concentration of suppliers and intermediate purchases through internet.

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. The data contain further detailed information on imported technologies, skill intensity, various productivity measures and the number of markets the firm is related to.

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

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

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.[7] 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.[8] 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.

Figure 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 main assumptions in the model that robots are more productive than workers and adopting them require large fixed costs of investments. Table A2 in Appendix A provides additional descriptive statistics showing similar patterns.

If firms continued sourcing intermediate inputs from suppliers even after adopting robots, then their intermediate input purchases must have increased because larger amount of producing final goods requires larger amount of intermediate inputs. To see whether this is the case, we regress each sourcing activity (foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration) on sales. Figure 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.[9] All panels depict a 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.

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

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

[9]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.

Table 1 reports summary statistics for the participation in sourcing activities. Robot adopters purchased intermediate inputs more than non-adopters regardless of sourcing strategy and imports destinations. Outsourcing is a more common strategy than vertical integration in both groups. Table 2 presents the intensities of sourcing across the two groups. 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.

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.

4 Impact of Robots on Production Fragmentation

In this section, we investigate how robot adoption affected firms' sourcing strategies. Section 4.1 presents the identification strategy whereas Section 4.2 presents the findings from our instrumental variable (IV) estimates. We elaborate on positive and significant results in Section 4.3 and show that increased sourcing after the adoption is -at least partly- related to quality upgrading. In Section 4.4, we examine the heterogeneity of the outcomes due to the differences in adoption patterns across industries using marginal treatment effects estimation.

4.1 Identification Strategy

Our instrumental variable strategy specifies that firms' adoption decisions are due to technological progresses in robotics. Similar to the approach used by Acemoglu & Restrepo (2020), we instrument adoption decisions using annual industry-level robot installations in four other European Union countries for 2006-2016: Germany, France, Italy and England.[10] We specifically choose countries that have similar macroeconomic structure with Spain; those are in developed country status with same tariff system and experiencing similar demographic patterns. We also construct an alternative instrument using robot installations in Denmark, Finland, Norway and Sweden to examine the robustness of our results. Figure B2 in Appendix B shows the trends in the stock of robots in each country over this period and confirms our expectation that it serves as a technological frontier.[11]

[10]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.

[11]Note that Scandinavian countries in our alternative instrument have substantially smaller population compared to Spain. Therefore, they have actually larger unit stock of robots when measured per worker.

Thus, at the first-stage, we estimate:

$$R_{ijt} = \alpha_1 + \alpha_2 \sum_{c=1}^{4} Robots_{cjt} + \alpha_3 \gamma_{ij2005} + \delta_t + \nu_j + \eta_{ijt} \tag{12}$$

where R_{ijt} equals one if the firm i in industry j adopts robots in period t and zero otherwise. $Robots_{cjt}$ denotes industry-level new installations of robots in country c. δ_t and ν_j represent year and industry fixed-effects, respectively. η_{ijt} is the error term.

Firms already selling more units of products may have more incentives to adopt new technologies that can boost their productivity. Similarly, firms with higher productivity or low marginal cost may adopt new technologies more easily because they are more profitable. For these reasons, we include firm's first reported log sales in the survey from 2005 on, denoted as $\gamma_{ijr2005}$ in the estimation. Note that using annual or lagged productivity levels would likely affect our outcome variable at the second-stage and bias our results. Hence, choosing a time-invariant parameter for each firm allows us to abstract from the violation of exclusion restriction assumption and control for positive selection into adoption decision.

A potential concern with estimating Equation (12) is that robot installations in other European countries are at the industry-level and this specification may not capture the variations in adoption decisions of different firms operating in the same industry. To distinguish firm-level variations, we use each firm's dependency on foreign technology proxied by imported technologies and interact it with industry-level installations.[12] Following a similar functional form as the one used in Rajan & Zingales (1998)[13], we estimate:

$$R_{ijt} = \alpha'_1 + \alpha'_2 TechDependency_{ijt} \times \sum_{c=1}^{4} Robots_{cjt} + \alpha'_3 \gamma_{ij2005} + \delta_t + \nu_j + \eta'_{ijt} \tag{13}$$

where α'_2 is the coefficient that exploits firm and industry-level variations from technological progresses in robots. While there are reasons to expect that α_2 in Equation (12) will be positive, in Equation (13) we expect parameter α'_2 to be negative. In particular, rising installations of robots in an industry where the firm operates (i.e. higher values of $Robots_{cjt}$) can imply a higher probability of adopting the robot at the firm level for two reasons: first, because a higher number of installations can be the result of technological progress in that sector making robots more attractive to the considered firm and second, due to a strategic response by the firm trying not to lag behind competitors in terms of technological adoption. However, in Equation (13) we are considering the interaction between the technological dependency of the firm and sectoral installations of robots. Those firms that are more technologically independent (lower values of $TechDependency_{ijt}$) and

[12] Imports of technology in our data is defined as payments for licences and technical aid from abroad.

[13] See also Nunn (2007), Fort (2017) and Bernard et al. (2020) for the implementation of the same approach.

operating in robot-intensive sectors will have a higher probability of robot adoption (negative sign of α_2').

At the second-stage, we utilize the following estimation:

$$I_{ijt} = \beta_1 + \beta_2 R_{ijt} + \beta_3 \Delta B_{ijt} + \beta_4 \theta_{ijt} + \beta_5 \mathbb{1}[I_{ijt-1} > 0] + \delta_t + \nu_j + \epsilon_{ijt} \tag{14}$$

where I_{ijt} denotes the IHS transformed values of intermediate input purchases for sourcing. 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 zero valued observations in the sample, which would otherwise be undefined in standard logarithmic form and dropped out of the analysis.[14] $\mathbb{1}[I_{ijt-1} > 0]$ denotes the sourcing status in previous period. θ_{ijt} is a binary variable indicating whether the firm purchased goods or services from its suppliers through internet which may be considered as proxy for a decline in monitoring cost between subcontractors and domestic firms, β, in our theoretical framework presented in Section 2.[15]

A trade shock may increase new sourcing opportunities for firms (e.g. Bernard et al., 2020) and 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). To control for such potential threats to identification, we include ΔB_{ijrt} in the estimation that represents the change in the number of international markets that the firm is related to from period $t-1$ to t. We additionally include regional dummies to mitigate the agglomeration effects in each specification because most productive firms may reside in specific regions that can allow them to enjoy economies of scales or network effects.

4.2 Results

Table 3 presents the baseline IV estimates. Panel B reports the OLS estimates of the first-stage equations (12) and (13), including firm random effects to control for individual unobserved heterogeneity.[16] The first row of the panel shows the results with instru-

[14] 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.

[15] Performing various parts of production processes across different locations intrinsically require communication and coordination between parties involved in production. Internet is one of those technologies that improved communication in production across different locations significantly and reduced the coordination costs (e.g. Grossman & Rossi-Hansberg, 2008; Fort, 2017).

[16] We should take into account that firms in the ESEE dataset are randomly sampled from a large population. This feature makes the choice of treating individual specific terms as randomly distributed across firms appropriate (Greene, 2003). Indeed, if the individuals are a random sample from a higher population, and we are interested in obtaining inference for the whole population, then the unconditional inference that is implicit in the error components approximation, i.e. the random-effects model, seems more accurate. Furthermore, fixed effects estimations would yield imprecise results due to the limited number of time-series observations in our unbalanced sample and perhaps cause incidental parameters problem.

ment using industry-level variations and second row of the panel shows the results with instrument using firm-level variations. The reported standard errors in $Robots_{jt}$ and $TechDependency \times Robots$ are clustered at the industry and firm level, respectively. Except the column (8) that shows domestic vertical integration using the instrument with firm-level variation, all the coefficients on the instruments have statistically significant at the 1% level with expected signs.

Panel A in Table 3 reports the corresponding IV estimates. The impact of robot adoption on sourcing is positive and statistically significant at the 1% level in each sourcing strategy. Interestingly, the coefficients on the robot adoption only slightly vary when we use the interaction term as an instrument ($TechDependency_{ijt} \times \sum_{c=1}^{4} Robots_{cjt}$), suggesting that the effects are not considerably differential across firms. The effects of adopting robots are heterogeneous across sourcing strategies. The highest coefficient estimated is the one for foreign outsourcing (19.183 and 18.492) and the lowest in foreign vertical integration (8.450 and 9.339).

Theoretical framework presented in Section 2 indicated that the differences in the coefficients across sourcing strategies should occur because of organizational costs arising from monitoring the production of intermediate input production (that is higher in vertical integration than in outsourcing due to managerial overload) and the transportation cost between the supplier and the sourcing firm (that is higher for foreign sourcing than for domestic sourcing because of distance).[17] Accordingly, we would expect to see the highest effect on domestic outsourcing than any other sourcing strategy and higher effect on foreign outsourcing and domestic vertical integration than on foreign vertical integration. However, our results suggest that the impact of robot adoption on domestic outsourcing seems to be more moderate. Since domestic outsourcing is very common - almost all firms are involved- and the most intensely pursued sourcing activity (see Table 1 and 2), firms may have switched to other sourcing strategies or some other dynamics may have played a role.

A potential violation of exclusion restriction may arise if firms are not importing intermediate inputs from relatively low-wage countries but one of the European countries we selected in the construction of the instrument. To confirm the robustness of our estimations, we perform the same analysis separately for the imports from Latin America and the rest of the world. Table 4 presents the results for imports from different destinations. The effects of robots are similar to previous results and significant with positive signs as expected.

On the other hand, if intermediate input producers in Germany, France, Italy or

[17] In fact, if we assume that the demand for intermediate inputs increased at the same level for each sourcing strategy, the firms involved in most costly sourcing strategies may have switched to other sourcing strategies or begun producing intermediate inputs themselves (for the tasks that are possible to automate with robots) to some degree.

England begin using robots and become able to compete with those in low-wage countries, Spanish firms may switch their suppliers and start importing from them.[18] If this story was at play, then intermediate input imports of Spain from the EU countries must have increased during this period. Figure B3 in Appendix B displays that in contrast to this possibility, Spain reduced the imports of intermediate inputs from each of these countries selected in the main and alternative instruments over the 2006-2016 period.

Table 5 presents the results from estimating the equations (13) and (14) including the sourcing status in the previous period and log wage defined as labor costs per employee. First stage results at the bottom of the panel are statistically significantly at the 1% level for foreign sourcing, foreign vertical integration and domestic sourcing but at the 5% level for domestic vertical integration. All the coefficients on the instruments have expected signs. At the top panel, the coefficient estimates show that the results are robust to inclusion of lagged sourcing status and wages. Sourcing status in the previous period has a strong, statistically significant positive effect in each case. Except domestic sourcing, the coefficients fall considerably in each sourcing with the inclusion of past sourcing status. In the second columns of each sourcing strategy, log wage is included in the specifications. The coefficient estimates for wage are slightly higher for outsourcing than vertical integration, indicating higher sensitivity of outsourcing firms to changes in wage. Overall, wage appears to have minor effects on intermediate input sourcing.

To assess the robustness of the main estimations, we again perform the same analysis for distinct locations as presented in Table 6. All the columns show statistically significant results. Similar to sourcing strategies, the coefficients on robot adoption are considerably smaller when we include sourcing status in the previous period but they are statistically significant at the 1% level. We also examine the analysis using our alternative instrument constructed from robot installations of Finland, Norway, Denmark and Sweden and the results are presented in Table A3 and A4 in Appendix A. All the coefficient estimates are similar, statistically significant and with expected signs. Thus, the results suggest that robot adoption induced higher demand of intermediate inputs for firms sourcing from both foreign and domestic suppliers.

In the data, we observe the share of purchases coming from the firm's three biggest suppliers, which allows us to assess the degree of fragmentation in production. Put another way, more fragmented production refers to a decline in concentration of suppliers. Estimations for suppliers' concentration are reported in Table 7. The coefficient on robot adoption is negative and statistically significant in all specifications, indicating a decline in purchases from the three biggest suppliers. In Table A5 in Appendix A, we show that

[18] Despite this concern, recent empirical evidences suggest that global supply chains tend to be sticky (Antràs, 2020). A growing body of literature documents that firms respond to macroeconomic shocks temporarily and at the intensive margin rather than extensive margin (e.g. Bernard et al., 2009; Bricongne et al., 2012; Behrens et al., 2013).

the estimates are robust when we use the alternative instrument. In fact, these results are also consistent with the possibility of switching between the sourcing strategies and thus the differences in the increased input purchasing for each sourcing strategy.

We find that using robots increased firms' imports of intermediate inputs from 2006 to 2016. The changes are different for each sourcing strategy, the highest for foreign sourcing and the lowest for foreign vertical integration. Robots appear to have fragmented the production further by widening the range of input suppliers. Despite the growing concerns over reshoring, positive effects of robots are prevalent for all types of sourcing strategies and for specific locations (low and middle-income countries).

4.3 Quality Upgrading Mechanism

One might argue that the positive findings in our estimations may be reflecting increased quality of goods without any change in the amount of products produced. In fact, adopting robots can encourage or unwillingly push firms to demand high-skilled workers to adapt to the new technology easier and improve product quality. Skilled workers are generally needed for producing high quality goods and they can be characterised by higher level of education, employment in R&D activities or higher earnings.

Empirical evidences are also consistent with the idea that offshoring increases product quality (e.g. Bernard et al., 2020) and the wages of domestic skilled labor (e.g. Hummels et al., 2014). Additionally, Verhoogen (2008) finds a strong positive relationship between exporting and demand for skilled labor in Mexico through quality upgrading mechanism. Brambilla et al. (2012) show that exporting to certain destinations can lead to production of higher quality products and thus, higher demand for skilled workers.

To examine the relevance of this quality upgrading mechanism, we utilize skill-intensity, defined as the proportion of engineers and graduates in total personnel in the firm, and the number of employees in R&D employees. The OLS estimates are reported in Table 8. The estimated coefficients for each sourcing strategy are positive and significant at the 1% level, except the coefficient on R&D employment in domestic vertical integration, column (8), which is positive but insignificant.

Table 9 reports the estimates for imports from specific locations. The coefficients on skill intensity in columns (1) and (3) are positive but only significant for the rest of the world at the 5% level. However, the coefficients on R&D employment represented in columns (2) and (4) are positive and significant for both locations.

We find strong support for that the number and the proportion of skilled workers are positively associated with intermediate input imports. The skill composition at the firm-level seems to be related to intermediate input sourcing, both from foreign and domestic suppliers. The OLS results suggest that quality upgrading of sourcing firms may explain the increases in intermediate input purchases after adopting robots at least to a certain degree.

Considering the macro-level studies that documented reshoring patterns of U.S. industries from Mexico (Artuc et al., 2019; Faber, 2020) and Colombia (e.g. Kugler et al., 2020), our results are intriguing. If robots decreased intermediate input demand from some countries but increased from the others with somewhat higher quality, then there may be changing patterns in global trade. More specifically, higher quality demand of robot users in developed countries may lead to concentration of sourcing activities in certain locations. This is consistent with the findings of Fort (2017) that advanced technologies have augmented offshoring of U.S. firms to high human-capital countries more than to low human-capital countries.

4.4 Marginal Treatment Effects

The ESEE dataset only contains a binary measure of robot adoption. Absence of the information regarding the stock of robots at the firm-level does not allow us to estimate the effects of changes in the density of robots on intermediate input purchases. However, we can still evaluate how treatment effects vary with a firm's probability of robot adoption.

Figure 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.

Differential adoption patterns and robot intensities across industries are perhaps because robots are more adaptable to tasks performed in those industries. Heterogeneity in adoption and the installations of robots across industries suggests that the probability of adopting robots may vary across firms depending on the industry they are operating in. Thus, one may expect highly robotized industries to experience larger productivity gains and eventually demand more intermediate inputs.

To characterize the heterogeneity in the effects of robots, we implement a generalized version of marginal treatment effects (MTE) using local instrumental variables developed by Heckman & Vytlacil (2005).[19] The MTE allows us to assess the variation in the impact of a treatment that is correlated with the unobserved characteristics. More specifically, the MTE evaluates the heterogeneity in treatment effects (intermediate input imports for firms) at different values of the propensity score (along the distribution of adoption probability). In this way, we can identify how much a firm purchases intermediate inputs if it is more (or less) likely to adopt robots.

[19] See Carneiro et al. (2011) for a detailed application of MTE on estimating returns to education.

Examining MTE requires estimating the propensity score at the first stage. Let us characterize the adoption rule for a firm by $R_i^* = \mu_R(Z_i) – V_i$, where Z_i denotes the observable determinant of the adoption decision, i.e. the instrument, and $\mu_R(Z_i)$ is the mean value of the instrument. V_i is i.i.d. error term indicating unobserved resistance to adoption decision that reduces the propensity score. Define the cumulative distribution function of V_i as $U_R = F_V(V_i)$ and the probability of adoption as $P(Z_i) \equiv \Pr(R_i = 1|Z_i) = F_V(\mu_R(Z_i))$. Hence, $R_i = 1$ if $P(Z_i) \geq U_R$, that is $R_i^* \geq 0$, and $R_i = 0$ otherwise.

Local instrumental variable estimator is expressed as:

$$\Delta^{LVI}(\mathbf{x}, p) = \frac{\partial E(Y_i|\mathbf{X} = \mathbf{x}, P(Z_i) = p)}{\partial p} \tag{15}$$

where $\mathbf{X}$ denotes the vector of covariates. LVI then identifies the MTE in the following equation:

$$\frac{\partial E(Y_i|\mathbf{X} = \mathbf{x}, P(Z_i) = p)}{\partial p} = \Delta^{ATE} + E(U_1 - U_0|U_R = p) = \Delta^{MTE}(p). \tag{16}$$

where Δ^{ATE} represents the Average Treatment Effects (AVE) and Δ^{MTE} represents the Marginal Treatment Effects (MTE).

Figure 4 plots the distribution of the propensity score among adopters (treated) and non-adopters (untreated). Vertically located red dashed lines represent the boundary points of trimming that ensures the full common support.[20] The distribution of the propensity score exhibits a substantial degree of overlap between the adopters and non-adopters, allowing for an appropriate comparability of them to identify the causal effects.

Figure 5 plots the MTE estimates over the range of unobserved resistence to the treatment, i.e. the propensity score. Vertical axis shows the treatment effect while horizontal axis shows the unobserved resistance to receiving the treatment. Units placed to the left of the x-axis represent the low resistence to adoption (high propensity score) and those to the right represent the high resistance to adoption (low propensity score). The panels show a substantial heterogeneity in treatment effects, indicating that the impacts of robots on intermediate input imports are not uniformly distributed. Outsourcing firms with high probability of adoption increase intermediate input imports more than the firms with low probability of adoption (downward sloping curve). In contrast to outsourcing, vertically integrated firms with high probability of adoption increase intermediate input imports less than the firms with low probability of adoption (upward sloping curve). Only the firms involved in foreign vertical integration with the highest probability of adoption, at the tail of the curve, have negative treatment effects (placed in the territory below zero), suggesting that these highly productive firms in fact reduced their input purchases.

[20]We trim the observations for the propensity score below 0.001 or above 0.999. The observations remaining in the common support are preserved while 14 observations from foreign sourcing strategies and 13 observations from domestic sourcing strategies are dropped from the sample.

5 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 sourcing activities from 2006 to 2016 with a considerable variability across sourcing strategies; the highest impact is observed for firms involved in foreign outsourcing and the lowest for firms involved in foreign vertical integration. These findings are robust to alternative instruments and specifications using imports from low and middle-income countries.

We document that robot adopters reduced the intermediate input purchases from their main suppliers while increasing total sourcing activities, suggesting a further fragmentation in production. There is also evidence that increased intensities in sourcing are related to quality upgrading as proxied by skill composition. Our data reveal that robot adopters tend to be more productive, have larger capital investments and involve in international activities more than non-adopters. On the basis of these stylized facts, a firm's choice to continue offshoring in our theoretical framework is motivated by large investment costs of reshoring while differential changes in sourcing arises from monitoring and transportation costs.

Certain industries are more heavily installing robots and they have higher fraction of robot adopters. We estimate the marginal treatment effects to see the implications of such heterogeneity in adoption patterns across industries. We find that responses to adoption vary dramatically across sourcing strategies; higher probability of adoption increases the intensity of sourcing for outsourcing firms but decreases the intensity of sourcing for vertically integrated firms. These results are consistent with the important role of industry characteristics in analyzing the effects of advanced technologies on firms' sourcing decisions (e.g. Fort, 2017).

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 differentially 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.

References

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with robots: Firm-level evidence from france. In *Aea papers and proceedings* (Vol. 110, pp. 383–88).

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Antràs, P. (2020). De-globalisation? global value chains in the post-covid-19 age. *NBER Working Paper*(w28115).

Antras, P., Fort, T. C., & Tintelnot, F. (2017). The margins of global sourcing: Theory and evidence from us firms. *American Economic Review*, *107*(9), 2514–64.

Antras, P., & Helpman, E. (2004). Global sourcing. *Journal of Political Economy*, *112*(3), 552–580.

Antràs, P., & Yeaple, S. R. (2014). Multinational firms and the structure of international trade. *Handbook of International Economics*, 55–130.

Artuc, E., Bastos, P., & Rijkers, B. (2018). Robots, tasks and trade. *World Bank Policy Research Working Paper*(8674).

Artuc, E., Christiaensen, L., & Winkler, H. (2019). *Does automation in rich countries hurt developing ones?: Evidence from the us and mexico* (Tech. Rep.). The World Bank.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *The American Economic Review*, 2121–2168.

Behrens, K., Corcos, G., & Mion, G. (2013). Trade crisis? what trade crisis? *Review of Economics and Statistics*, *95*(2), 702–709.

Bernard, A. B., Fort, T., Smeets, V., & Warzynski, F. (2020). Heterogeneous globalization: Offshoring and reorganization. *NBER Working Paper*(w26854).

Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2007). Firms in international trade. *The Journal of Economic Perspectives*, *21*(3), 105–130.

Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2009). The margins of us trade. *The American Economic Review*, *99*(2), 487–493.

Blinder, A. S., & Krueger, A. B. (2013). Alternative measures of offshorability: a survey approach. *Journal of Labor Economics*, *31*(S1), S97–S128.

Bloom, N., Draca, M., & Van Reenen, J. (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *Review of Economic Studies*, *83*(1), 87–117.

Bøler, E. A., Moxnes, A., & Ulltveit-Moe, K. H. (2015). R&d, international sourcing, and the joint impact on firm performance. *American Economic Review*, *105*(12), 3704–39.

Bonfiglioli, A., Crinò, R., Fadinger, H., Gancia, G., et al. (2020). *Robot imports and firm-level outcomes* (Tech. Rep.). CEPR Discussion Papers.

Brambilla, I., Lederman, D., & Porto, G. (2012). Exports, export destinations, and skills. *American Economic Review*, *102*(7), 3406–38.

Bricongne, J.-C., Fontagné, L., Gaulier, G., Taglioni, D., & Vicard, V. (2012). Firms and the global crisis: French exports in the turmoil. *Journal of International Economics*, *87*(1), 134–146.

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *American Economic Review*, *101*, 304–340.

Carneiro, P., Heckman, J. J., & Vytlacil, E. J. (2011). Estimating marginal returns to education. *American Economic Review*, *101*(6), 2754–81.

Costinot, A., Oldenski, L., & Rauch, J. (2011). Adaptation and the boundary of multinational firms. *The Review of Economics and Statistics*, *93*(1), 298–308.

Costinot, A., Vogel, J., & Wang, S. (2013). An elementary theory of global supply chains. *Review of Economic Studies*, *80*(1), 109–144.

Crinò, R. (2009). Offshoring, multinationals and labour market: A review of the empirical literature. *Journal of Economic Surveys*, *23*(2), 197–249.

Dauth, W., Findeisen, S., Jens, S., Woessner, N., et al. (2017). *German robots-the impact of industrial robots on workers* (Tech. Rep.). CEPR Discussion Papers.

De Backer, K., Menon, C., Desnoyers-James, I., & Moussiegt, L. (2016). *Reshoring: Myth or reality?* (Tech. Rep.). OECD Publishing.

Faber, M. (2020). Robots and reshoring: Evidence from mexican labor markets. *Journal of International Economics*, *127*(103384), 1–34.

Fort, T. C. (2017). Technology and production fragmentation: Domestic versus foreign sourcing. *The Review of Economic Studies*, *84*(2), 650–687.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Grossman, G. M., & Helpman, E. (2005). Outsourcing in a global economy. *The Review of Economic Studies*, *72*(1), 135–159.

Grossman, G. M., & Rossi-Hansberg, E. (2008). Trading tasks: A simple theory of offshoring. *American Economic Review*, *98*(5), 1978–97.

Heckman, J., & Vytlacil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation. *Econometrica*, *73*(3), 669–738.

Helpman, E. (2006). Trade, fdi, and the organization of firms. *Journal of Economic Literature*, 589–630.

Helpman, E., Melitz, M., & Yeaple, S. (2004). Export versus fdi with heterogeneous firms. *American Economic Review*, *94*(1), 300–316.

Home, C. (2013). Reshoring manufacturing. *The Economist*.

Humlum, A. (2019). *Robot adoption and labor market dynamics* (Tech. Rep.). Working Paper.

Hummels, D., Ishii, J., & Yi, K.-M. (2001). The nature and growth of vertical specialization in world trade. *Journal of international Economics*, *54*(1), 75–96.

Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, *104*(6), 1597–1629.

Hummels, D., Munch, J. R., & Xiang, C. (2018). Offshoring and labor markets. *Journal of Economic Literature*, *56*(3), 981–1028.

Johnson, R. C., & Noguera, G. (2017). A portrait of trade in value-added over four decades. *Review of Economics and Statistics*, *99*(5), 896–911.

Kee, H. L., & Tang, H. (2016). Domestic value added in exports: Theory and firm evidence from china. *The American Economic Review*, 1402–1436.

Kinkel, S., & Maloca, S. (2009). Drivers and antecedents of manufacturing offshoring and backshoring—a german perspective. *Journal of Purchasing and Supply Management*, *15*(3), 154–165.

Koch, M., Manuylov, I., & Smolka, M. (2019). *Robots and firms* (Tech. Rep.). CESifo Working Paper.

Kugler, A. D., Kugler, M., Ripani, L., & Rodrigo, R. (2020). Us robots and their impacts in the tropics: Evidence from colombian labor markets. *NBER Working Paper*(w28034).

Lileeva, A., Trefler, D., et al. (2010). Improved access to foreign markets raises plant-level productivity… for some plants. *The Quarterly Journal of Economics*, *125*(3), 1051–1099.

Lund, S., Manyika, J., Woetzel, J., Bughin, J., Krishnan, M., Seong, J., & Muir, M. (2019). Globalization in transition: The future of trade and value chains. *McKinsey Global Institute*.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1695.

Nunn, N. (2007). Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics*, *122*(2), 569–600.

Pisano, G. P., Shih, W. C., et al. (2009). Restoring american competitiveness. *Harvard business review*, *87*(7/8), 114–125.

Rajan, R., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, *88*(3), 559–86.

Rodrik, D. (2018). *New technologies, global value chains, and the developing economies. pathways for prosperity commission background paper series; no. 1.* Oxford. United Kingdom.

Sirkin, H. L., Zinser, M., Hohner, D., et al. (2011). *Made in america, again: Why manufacturing will return to the us*. Boston Consulting Group Boston.

Stapleton, K., & Webb, M. (2020). Automation, trade and multinational activity: Micro evidence from spain. *Available at SSRN 3681143*.

Stemmler, H. (2019). *Does automation lead to de-industrialization in emerging economies? evidence from brazil* (Tech. Rep.). University of Goettingen, Department of Economics.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., de Vries, G. J., et al. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, *28*(2), 99–118.

Verhoogen, E. A. (2008). Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. *The Quarterly Journal of Economics*, *123*(2), 489–530.

Tables

Table 1: Participation Shares by Sourcing Strategies

	Robot Adopters		Non-Adopters	
	Mean	SD	Mean	SD
Foreign Outsourcing	0.601	0.490	0.435	0.496
Foreign Vertical Integration	0.168	0.374	0.068	0.251
Domestic Outsourcing	0.948	0.223	0.935	0.247
Domestic Vertical Integration	0.253	0.435	0.109	0.312
Rest of the World	0.358	0.479	0.228	0.420
Latin America	0.087	0.282	0.048	0.213
Observations	4183		8518	

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, OECD and EU countries.

Table 2: Sourcing Intensities

	Robot Adopters		Non-Adopters	
	Mean	SD	Mean	SD
Foreign Outsourcing	9.120	7.652	5.958	6.996
Foreign Vertical Integration	2.721	6.120	1.034	3.878
Domestic Outsourcing	15.668	4.105	14.027	4.105
Domestic Vertical Integration	4.051	7.038	1.681	4.861
Rest of the World	6.808	9.228	4.163	7.744
Latin America	1.631	5.328	0.861	3.882
Observations	4183		8518	

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, OECD and EU countries.

Table 3: Impact of Robot Adoption on Sourcing Strategies

	FO (1)	FO (2)	FVI (3)	FVI (4)	DO (5)	DO (6)	DVI (7)	DVI (8)
Panel A. IV								
Robot adoption	19.183***	18.492***	8.450***	9.339***	9.736***	9.477***	12.147***	12.279***
	(1.372)	(1.197)	(1.779)	(0.893)	(0.759)	(0.652)	(1.188)	(0.942)
Online purchases	0.170	-0.099	-0.051	-0.363*	0.044	-0.092	0.038	0.092
	(0.258)	(0.345)	(0.100)	(0.211)	(0.125)	(0.178)	(0.187)	(0.175)
Δ Markets	0.028	0.168	0.061	0.063	0.020	0.028	-0.016	-0.016
	(0.063)	(0.122)	(0.049)	(0.071)	(0.049)	(0.069)	(0.046)	(0.055)
Panel B. First Stage								
Robots	0.328***		0.309***		0.317***		0.317***	
	(0.104)		(0.102)		(0.103)		(0.103)	
TechDependency$\times$*Robots*		-0.687***		-0.687***		-0.687***		0.045
		(0.162)		(0.162)		(0.162)		(0.039)
Initial productivity	0.103***	0.107***	0.103***	0.107***	0.103***	0.107***	0.103***	0.103***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)
Observations	12701	12701	12701	12701	12701	12701	12701	12701
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effects of robots on sourcing strategies for two different instruments: at the industry level in the odd columns (*Robots*) and at the firm-industry level in the even columns (*TechDependency*$\times$*Robots*). FO, FVI, DO, DVI refer to IHS transformed values of foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration, respectively. First stage in Panel B presents the results for the two instruments with firm's first reported log sales from 2005 on denoted as initial productivity. *Robots* is multiplied by 10^{-5} and *TechDependency*$\times$*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Robust standard errors are clustered at the industry level in the estimation using *Robots* and at the firm level in the one with *TechDependency*$\times$*Robots*. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 4: Impact of Robot Adoption on Imports by Destination

	Rest of the World (1)	Rest of the World (2)	Latin America (3)	Latin America (4)
Panel A. IV				
Robot adoption	17.644***	17.829***	5.049***	5.145***
	(2.775)	(1.418)	(0.620)	(0.798)
Online purchases	0.215	0.223	0.053	0.020
	(0.167)	(0.380)	(0.090)	(0.174)
Δ Markets	0.036	0.195	0.013	0.039
	(0.093)	(0.130)	(0.047)	(0.059)
Panel B. First Stage				
Robots	0.307***		0.395***	
	(0.102)		(0.121)	
TechDependency×*Robots*		-0.687***		-0.687***
		(0.162)		(0.162)
Initial productivity	0.103***	0.107***	0.104***	0.107***
	(0.007)	(0.006)	(0.009)	(0.006)
Observations	12701	12701	12701	12701
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table presents the effects of robots on imports from two locations for two different instruments: at the industry level in the odd columns (*Robots*) and at the firm-industry level in the even columns (*TechDependency*×*Robots*). First stage in Panel B presents the results for two instruments with firm's first reported log sales from 2005 on denoted as initial productivity. *Robots* is multiplied by 10^{-5} and *TechDependency*×*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Robust standard errors are clustered at the industry level for *Robots* and at the firm level for *TechDependency*×*Robots*. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 5: Impact of Robot Adoption on Sourcing Strategies with New Importers

	FO (1)	FO (2)	FVI (3)	FVI (4)	DO (5)	DO (6)	DVI (7)	DVI (8)
Panel A. IV								
Robot adoption	10.654***	10.039***	3.351***	2.878***	9.107***	8.611***	6.494***	5.871***
	(0.765)	(0.790)	(0.362)	(0.374)	(0.577)	(0.596)	(0.585)	(0.582)
Online purchases	-0.189	-0.173	-0.084	-0.072	-0.259	-0.246	-0.094	-0.096
	(0.201)	(0.195)	(0.088)	(0.084)	(0.159)	(0.152)	(0.116)	(0.112)
Δ Markets	0.118	0.116	0.058	0.057	0.096	0.095	0.003	0.005
	(0.115)	(0.114)	(0.070)	(0.070)	(0.074)	(0.072)	(0.069)	(0.069)
Lagged sourcing status	8.167***	8.168***	11.532***	11.490***	8.046***	8.048***	8.669***	8.910***
	(0.230)	(0.223)	(0.277)	(0.271)	(0.469)	(0.461)	(0.266)	(0.261)
Wage		0.644*		0.518***		0.521*		0.457**
		(0.372)		(0.151)		(0.301)		(0.198)
Panel B. First Stage								
TechDependency×*Robots*	-0.696***	-0.733***	-0.698***	-0.736***	-0.723***	-0.761***	-0.308**	-0.347**
	(0.165)	(0.172)	(0.168)	(0.176)	(0.170)	(0.178)	(0.151)	(0.163)
Initial productivity	0.106***	0.112***	0.109***	0.114***	0.108***	0.113***	0.103***	0.107***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)
Observations	11578	11578	11575	11575	11588	11588	11588	11588
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results from estimating the equations (13) and (14). FO, FVI, DO, DVI refer to IHS transformed values of foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration, respectively. Panel B shows first stage results for the instrument and firm's first reported log sales from 2005 on denoted as initial productivity. *TechDependency*×*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. The second columns in the specification of each sourcing strategy includes log wage. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 6: Impact of Robot Adoption on Imports by Destination with New Importers

	Rest of the World (1)	Rest of the World (2)	Latin America (3)	Latin America (4)
Panel A. IV				
Robot adoption	5.201***	5.197***	1.492***	1.483***
	(0.519)	(0.568)	(0.258)	(0.281)
Online purchases	-0.023	-0.023	-0.007	-0.007
	(0.125)	(0.125)	(0.063)	(0.063)
Δ Markets	0.163*	0.163*	0.025	0.025
	(0.093)	(0.093)	(0.054)	(0.054)
Lagged sourcing status	15.369***	15.369***	15.111***	15.111***
	(0.185)	(0.185)	(0.312)	(0.312)
Wage		0.004		0.009
		(0.236)		(0.108)
Panel B. First Stage				
TechDependency$\times$*Robots*	-0.693***	-0.731***	-0.716***	-0.755***
	(0.169)	(0.176)	(0.171)	(0.179)
Initial productivity	0.106***	0.111***	0.107***	0.113***
	(0.006)	(0.007)	(0.006)	(0.006)
Observations	11557	11557	11557	11557
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table presents the results from estimating the equations (13) and (14) by using imports from two locations as the outcome variables. Panel B shows first stage results for the instrument and firm's first reported log sales from 2005 on denoted as initial productivity. *TechDependency*$\times$*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. The second columns in the specification of each sourcing strategy includes log wage. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 7: Production Fragmentation

	(1)	(2)	(3)	(4)
Panel A. IV				
Robot adoption	-27.361***	-26.595***	-27.554***	-26.825***
	(5.042)	(2.952)	(5.892)	(3.174)
Online purchases	-1.458***	-1.579***	-1.456***	-1.583***
	(0.460)	(0.537)	(0.464)	(0.546)
Δ Markets	0.002	-0.057	0.002	-0.063
	(0.234)	(0.218)	(0.234)	(0.219)
Wage			0.190	0.311
			(1.241)	(1.220)
Panel B. First Stage				
Robots	0.301**		0.302**	
	(0.118)		(0.119)	
TechDependency×*Robots*		-0.229*		-0.252*
		(0.128)		(0.137)
Initial productivity	0.104***	0.104***	0.105***	0.107***
	(0.008)	(0.005)	(0.007)	(0.005)
Observations	12097	12097	12097	12097
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table presents the effects of robots on concentration of firm's purchases from three main suppliers for two different instruments: at the industry level in the odd columns (*Robots*) and at the firm-industry level in the even columns (*TechDependency*×*Robots*). First stage in Panel B presents the results for two instruments with firm's first reported log sales from 2005 on denoted as initial productivity. *Robots* is multiplied by 10^{-5} and *TechDependency*×*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Robust standard errors are clustered at the industry level for *Robots* and at the firm level for *TechDependency*×*Robots*. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 8: Quality Upgrading of Sourcing Firms

	FO (1)	FO (2)	FVI (3)	FVI (4)	DO (5)	DO (6)	DVI (7)	DVI (8)
Skill intensity	0.032***		0.024***		0.022***		0.029***	
	(0.008)		(0.006)		(0.006)		(0.007)	
R&D Employment		0.006***		0.005***		0.004***		0.003
		(0.001)		(0.001)		(0.001)		(0.003)
Online purchases	0.410***	0.430***	0.077	0.088	0.177**	0.185**	0.134	0.152
	(0.131)	(0.131)	(0.078)	(0.077)	(0.086)	(0.085)	(0.095)	(0.095)
Δ Markets	0.262***	0.265***	0.094*	0.096*	0.021	0.022	0.028	0.029
	(0.090)	(0.090)	(0.055)	(0.055)	(0.050)	(0.050)	(0.060)	(0.060)
Lagged sourcing status	6.296***	6.321***	8.121***	8.126***	4.310***	4.318***	8.389***	8.401***
	(0.149)	(0.150)	(0.306)	(0.305)	(0.323)	(0.322)	(0.241)	(0.244)
Observations	11973	11973	11970	11970	11982	11982	11982	11982
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: FO, FVI, DO, DVI refer to IHS transformed values of foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration, respectively. Skill intensity is measured as percentage of engineers and graduates at the firm. R&D employment is defined as total personnel engaged in R&D. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

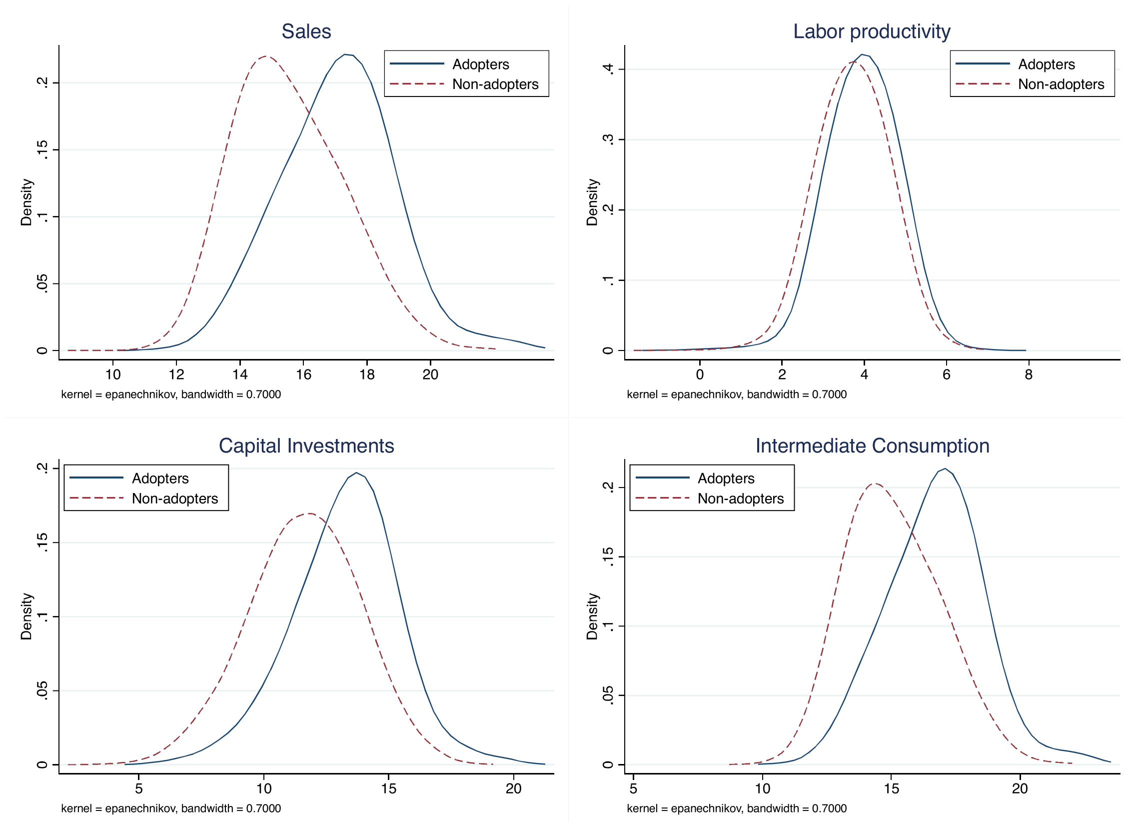
Table 9: Quality Upgrading of Sourcing Firms by Destination

	Rest of the World (1)	Rest of the World (2)	Latin America (3)	Latin America (4)
Skill intensity	0.015**		0.004	
	(0.007)		(0.005)	
R&D Employment		0.004***		0.005***
		(0.001)		(0.001)
Online purchases	0.229**	0.237**	0.116*	0.114*
	(0.110)	(0.110)	(0.064)	(0.063)
Δ Markets	0.436***	0.437***	0.075	0.075
	(0.089)	(0.089)	(0.053)	(0.053)
Lagged sourcing status	12.444***	12.441***	12.467***	12.382***
	(0.177)	(0.178)	(0.331)	(0.332)
Observations	11949	11949	11950	11950
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Note: Skill intensity is measured as percentage of engineers and graduates at the firm. R&D employment is defined as total personnel engaged in R&D. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

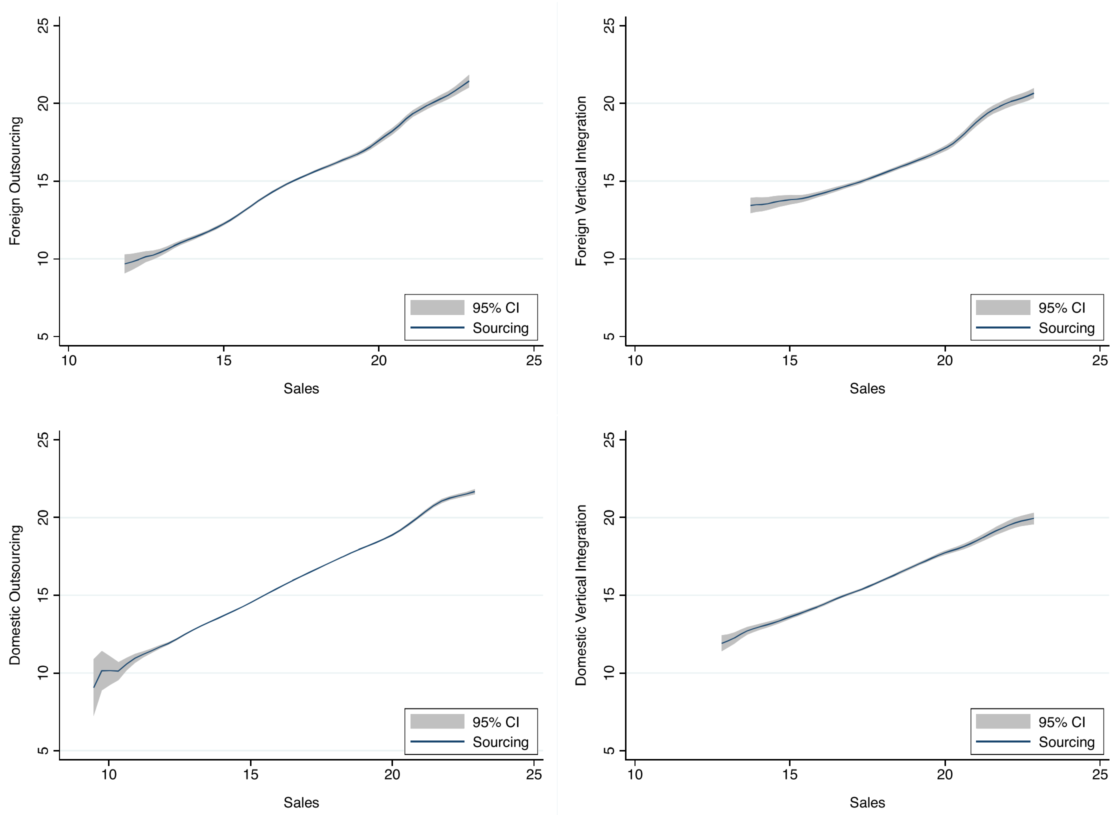
Figures

Figure 1: Patterns of Adoption



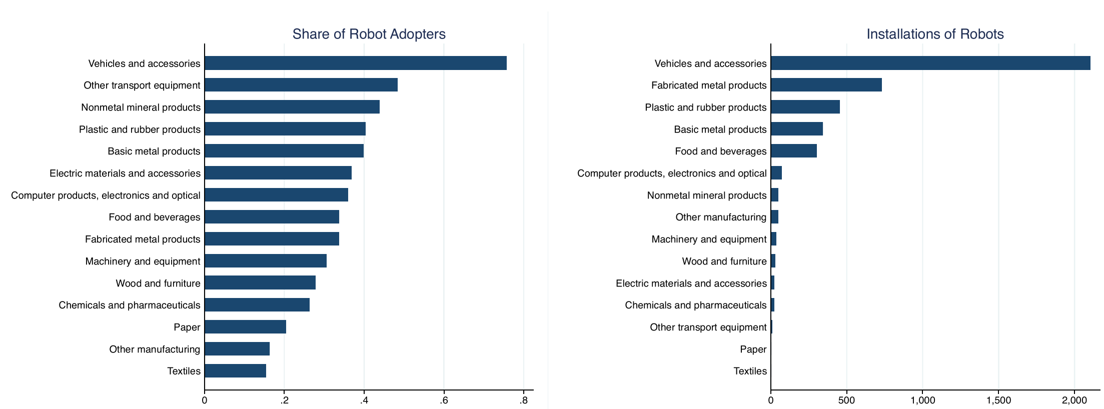
Note: This figure presents the distribution of productivity (measured as log sales), labor productivity (measured as log value added per worker), log capital investments and log intermediate consumption. The bold lines show the distributions of robot adopting firms and the dashed lines show the distributions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

Figure 2: Sales and Intermediate Input Purchases of Sourcing Firms



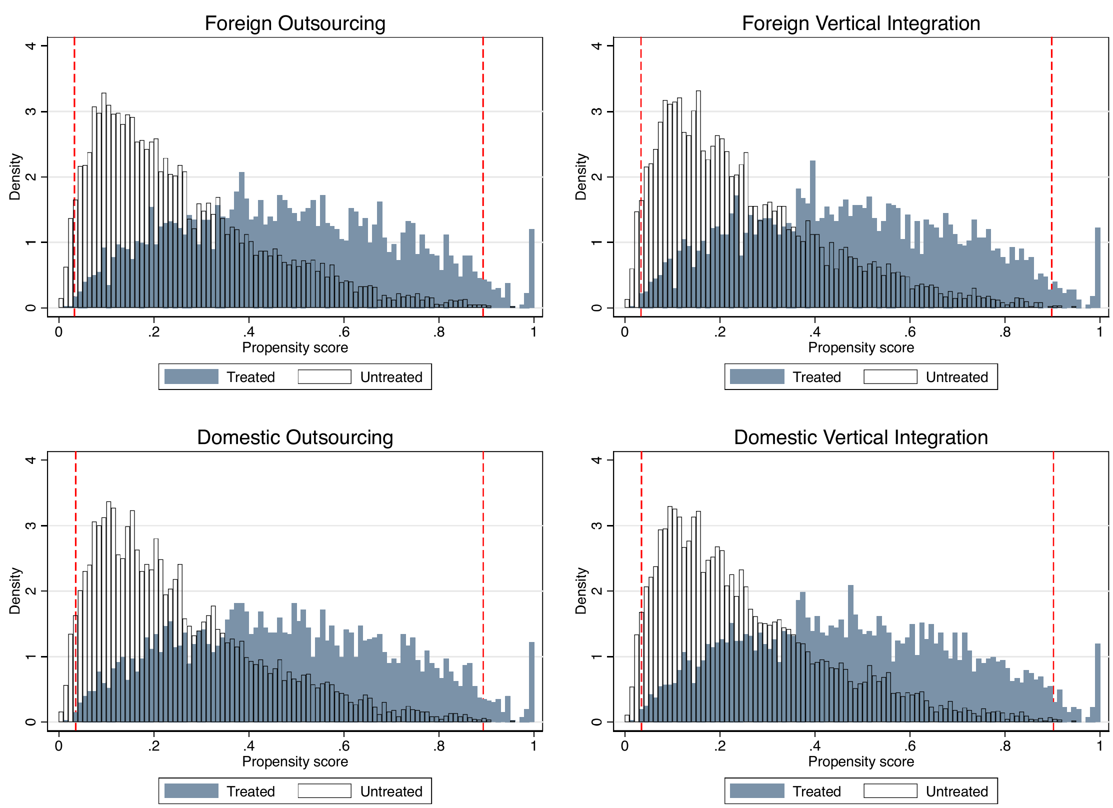
Note: Figures present the smoothed values with confidence bands from local polynomial regressions of intermediate input sourcing (measured as IHS values of each sourcing activity) on firm productivity (measured as log sales). Firms that were not involved in a sourcing strategy in a given year are excluded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

Figure 3: Robot Adopters by Industry



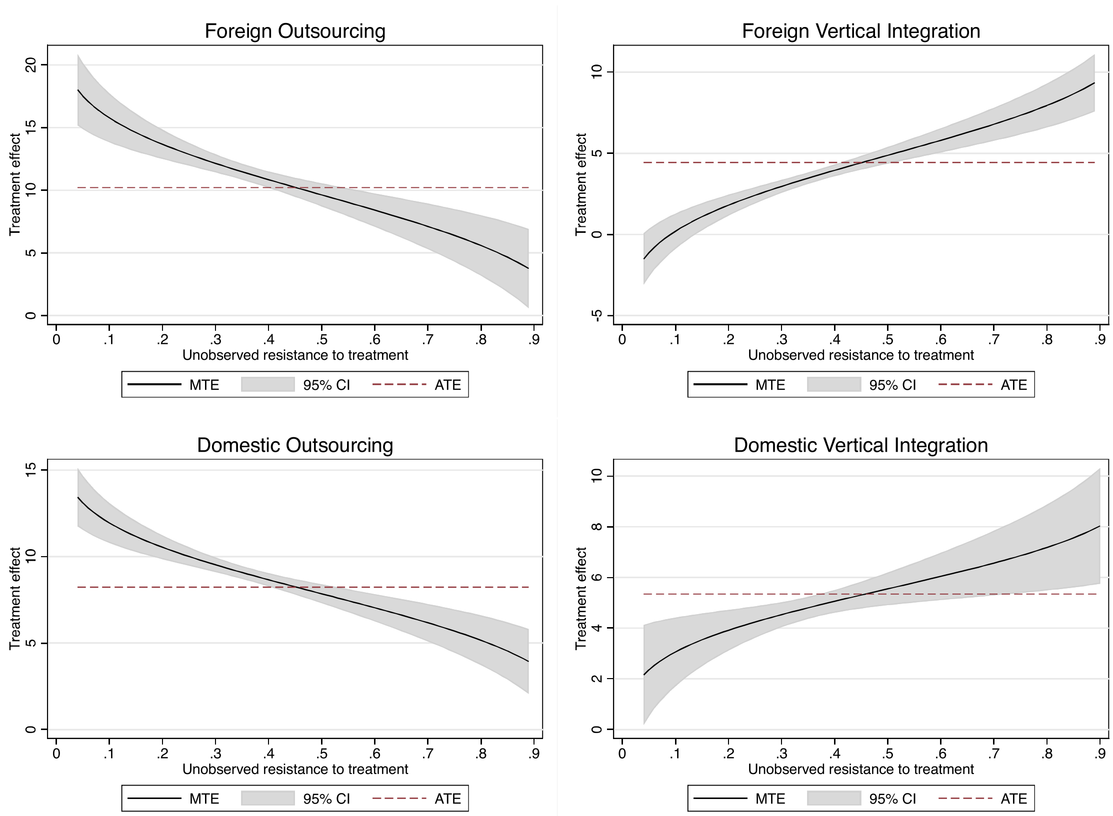
Note: The figure presents the adoption patterns across industries. The left panel displays the share of robot adopting firms by industry and the right panel displays the installations of robots on average in each industry.

Figure 4: Propensity Scores of Adoption



Note: Probabilities of adoption are estimated using equation (13). Gray shaded bars represent the propensity scores of adopters denoted as treated and empty bars represent the propensity scores of non-adopters denoted as untreated. Vertical dashed lines in red represent the trimmed points along the distribution of propensity score.

Figure 5: Marginal Treatment Effects



Note: Each panel depicts the MTE curves for sourcing strategies with 95% confidence intervals of parametric normal MTE. Horizontal dashed lines represent the values of average treatment effects (ATE).

Appendix

A Additional Tables

Table A1: Industry Matching ESEE-IFR

ESEE	IFR
12 - Basic metal products	24 - Basic metals 289 - Metal, unspecified 2931 - Metal (AutoParts)
9 - Chemicals and pharmaceuticals	19 - Pharmaceuticals, cosmetics 20-21 - other chemical products n.e.c. 229 - Chemical products, unspecified
15 - Computer products, electronics and optical	275 - Household/domestic appliances 262 - Computers and peripheral equipment 263 - Info communication equipment, domestic and prof. 265 - Medical, precision, optical instruments 279 - Electrical/electronics unspecified 2933 - Electrical/electronic (AutoParts) 26-27 - Electrical/electronics
16 - Electric materials and accessories	271 - Electrical machinery n.e.c. (non-automotive) 260 - Electronic components/devices 261 - Semiconductors, LCD, LED
13 - Fabricated metal products	25 - Metal products (non-automotive) 24-28 - Metal
14 - Machinery and equipment	28 - Industrial machinery
11 - Nonmetal mineral products	23 - Glass, ceramics, stone, mineral products (non-auto 2934 - Glass (AutoParts)
20 - Other manufacturing	91 - All other manufacturing branches
18 - Other transport equipment	30 - Other vehicles
10 - Plastic and rubber products	22 - Rubber and plastic products (non-automotive) 2932 - Rubber and plastic (AutoParts) 19-22 - Plastic and chemical products
17 - Vehicles and accessories	29 - Automotive 299 - Automotive unspecified 291 - Motor vehicles, engines and bodies 2999 - Unspecified AutoParts 2939 - Other (AutoParts)
7 - Paper 8 - Printing	17-18 - Paper
3 - Beverage 2 - Food and tobacco 1 - Meat products	10-12 - Food and beverages
5 - Leather, fur and footwear 4 - Textiles and clothing	13-15 - Textiles
6 - Timber 19 - Furniture	16 - Wood and furniture

Notes: The table shows the matching of industries between the ESEE dataset (on the left) and the IFR dataset (on the right). The classifications are provided along with the industry definitions.

Table A2: Descriptive Statistics

	Robot Adopters			Non-Adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Output	17.08	1.75	4183	15.55	1.66	8518
Sales	17.06	1.74	4183	15.53	1.67	8518
Value Added	15.78	1.63	4149	14.38	1.51	8453
Labor Productivity	3.97	0.61	4146	3.73	0.64	8452
Wage	10.53	0.32	3997	10.38	0.37	8109
Capital Investments	13.24	2.11	3641	11.61	2.19	6258
Skill Intensity	7.79	8.55	4080	7.21	9.73	8447
R&D Employment	14.50	99.75	4121	4.49	51.63	8479
Intermediate Consumption	16.69	1.85	4183	15.09	1.80	8518
Imports	14.92	2.42	3464	13.30	2.53	5381
Exports	15.70	2.46	3562	14.00	2.60	5715

Notes: This table reports the means, standard deviations and observations of some variables for robot adopting and non-adopting firms. Variables in the table span the period 2006-2016. Output is the log of the sum of sales, the variation of stocks for sale and other current management income. Sales is the log of firms' product sales and value-added is the log of firms' value added on production. Labor productivity represents the log of value added per worker. Wage denotes the log of labor cost per employee. Capital investments is measured as the log of the sum of the purchases in capital goods. Skill intensity is the percentage of engineers and graduates within the total personnel. R&D employment represents the total number of employees engaged in R&D activities. Intermediate consumption is the log of the sum of purchases and external services, minus the variation in the stock of purchases. Imports is the log of value of imports and exports is the log of value of exports.

Table A3: Impact of Robot Adoption on Sourcing Strategies Estimated with Alternative Instrument

	FO	FO	FVI	FVI	DO	DO	DVI	DVI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. IV								
Robot adoption	10.660***	10.047***	3.385***	2.923***	9.113***	8.618***	4.469***	4.091***
	(0.766)	(0.792)	(0.367)	(0.381)	(0.577)	(0.596)	(0.477)	(0.485)
Online purchases	-0.189	-0.173	-0.086	-0.074	-0.259	-0.246	-0.172	-0.162
	(0.202)	(0.195)	(0.088)	(0.084)	(0.159)	(0.152)	(0.107)	(0.104)
Δ Markets	0.118	0.116	0.058	0.057	0.096	0.095	0.040	0.039
	(0.115)	(0.114)	(0.070)	(0.070)	(0.074)	(0.072)	(0.077)	(0.076)
Lagged sourcing status	8.166***	8.167***	11.527***	11.485***	8.046***	8.048***	11.606***	11.613***
	(0.230)	(0.223)	(0.277)	(0.271)	(0.469)	(0.461)	(0.238)	(0.234)
Wage		0.642*		0.507***		0.519*		0.391**
		(0.372)		(0.153)		(0.301)		(0.184)
Panel B. First Stage								
TechDependency×*Robots*	-15.264***	-16.116***	-15.465***	-16.308***	-15.978***	-16.855***	-15.401***	-16.295***
	(3.532)	(3.583)	(3.314)	(3.376)	(3.404)	(3.463)	(3.274)	(3.349)
Initial productivity	0.106***	0.111***	0.109***	0.114***	0.108***	0.113***	0.105***	0.110***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Observations	11578	11578	11575	11575	11588	11588	11588	11588
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results from estimating the equations (13) and (14) using an alternative instrument (constructed from robot installations of Finland, Norway, Denmark and Sweden). FO, FVI, DO, DVI refer to IHS transformed values of foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration, respectively. Panel B shows first stage results for the instrument and firm's first reported log sales from 2005 on denoted as initial productivity. *TechDependency*×*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. The second columns in the specification of each sourcing strategy includes log wage. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table A4: Impact of Robot Adoption on Imports by Destination Estimated with Alternative Instrument

	Rest of the World (1)	Rest of the World (2)	Latin America (3)	Latin America (4)
Panel A. IV				
Robot adoption	5.206***	5.204***	1.491***	1.483***
	(0.520)	(0.570)	(0.258)	(0.281)
Online purchases	-0.023	-0.023	-0.007	-0.007
	(0.125)	(0.125)	(0.063)	(0.063)
Δ Markets	0.163*	0.163*	0.025	0.025
	(0.093)	(0.093)	(0.054)	(0.054)
Lagged sourcing status	15.368***	15.368***	15.111***	15.111***
	(0.185)	(0.185)	(0.312)	(0.312)
Wage		0.002		0.009
		(0.236)		(0.108)
Panel B. First Stage				
TechDependency$\times$*Robots*	-15.391***	-16.266***	-15.827***	-16.705***
	(3.393)	(3.454)	(3.427)	(3.486)
Initial productivity	0.106***	0.111***	0.107***	0.113***
	(0.006)	(0.007)	(0.006)	(0.006)
Observations	11557	11557	11557	11557
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table presents the results from estimating the equations (13) and (14) by using imports from two locations as the outcome variables. In each specification, an alternative instrument is constructed from robot installations of Finland, Norway, Denmark and Sweden. Panel B shows first stage results for the instrument and firm's first reported log sales from 2005 on denoted as initial productivity. *TechDependency*$\times$*Robots* is multiplied by 10^{-10} for the interpretability of the results. Panel A presents the IV estimates. Δ denotes a change in a variable from previous year. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. The second columns in the specification of each sourcing strategy includes log wage. Robust standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

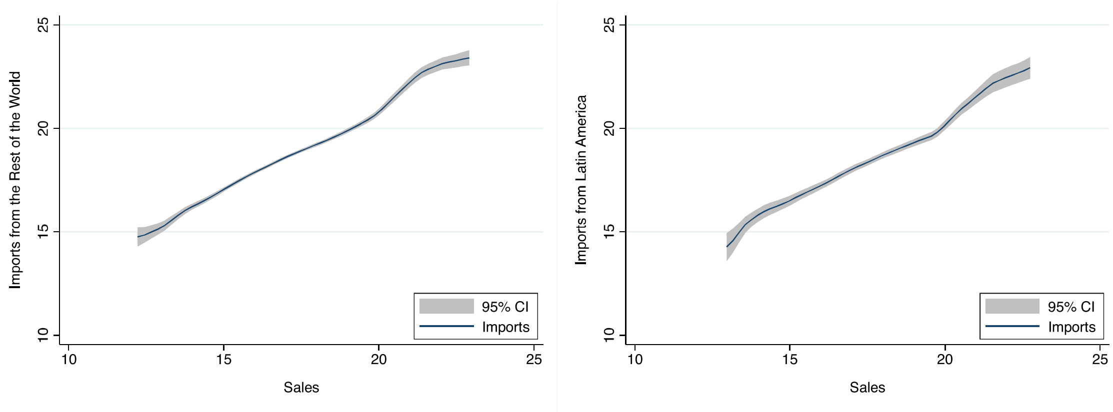
Table A5: Production Fragmentation Estimated with Alternative Instruments

	(1)	(2)	(3)	(4)
Panel A. IV				
Robot adoption	-25.482***	-23.750***	-25.889***	-24.503***
	(4.810)	(3.073)	(6.055)	(3.465)
Online purchases	-1.651**	-1.637*	-1.642**	-1.618*
	(0.644)	(0.845)	(0.673)	(0.854)
Δ Markets	-0.139	-0.273	-0.145	-0.272
	(0.259)	(0.292)	(0.262)	(0.294)
Wage			0.500	0.788
			(1.785)	(1.707)
Panel B. First Stage				
Robots	3.635***		3.703***	
	(0.636)		(0.634)	
TechDependency×*Robots*		-16.404***		-17.252***
		(3.499)		(3.556)
Initial productivity	0.105***	0.108***	0.110***	0.113***
	(0.009)	(0.006)	(0.008)	(0.006)
Observations	12097	12097	12097	12097
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table presents the effects of robots on concentration of firm's purchases from three main suppliers using an alternative instrument (constructed from robot installations of Finland, Norway, Denmark and Sweden). First stage in Panel B presents results for two instruments with firm's first reported log sales from 2005 on denoted as initial productivity. *Robots* is multiplied by 10^{-5} and *TechDependency*×*Robots* is multiplied by 10^{-10} for the interpretability of the results. Lagged sourcing status equals 1 if firm was involved in corresponding sourcing strategy in the previous period, 0 otherwise. The second columns in the specification of each sourcing strategy includes log wage. Robust standard errors are clustered at the industry level for *Robots* and at the firm level for *TechDependency*×*Robots*. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

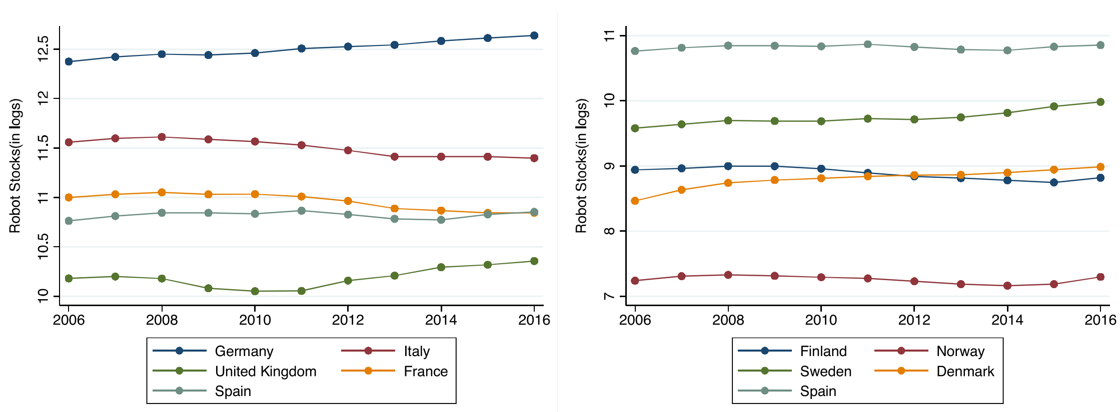
B Additional Figures

Figure B1: Sales and Intermediate Input Purchases of Sourcing Firms by Destinations



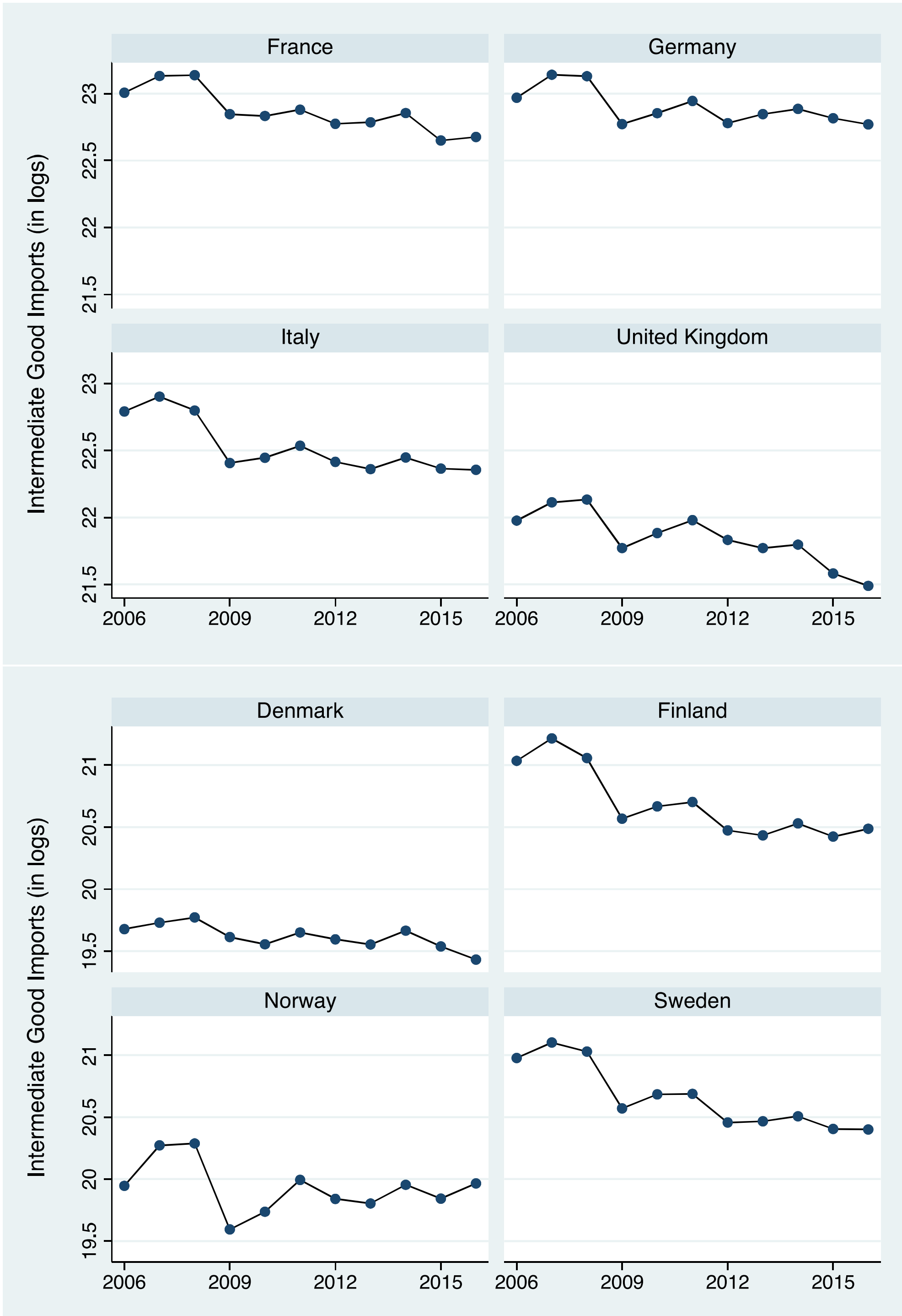
Note: Figures display the smoothed values with confidence bands from local polynomial regressions of IHS transformed imports from the Rest of the World (on the left panel) and from Latin America (on the right panel) on firm productivity (measured as log sales). Firms that did not import in a given year are excluded from the estimations.

Figure B2: Robots in the EU Countries



Note: This figure presents the log stock of robots in the EU countries. The left panel compares the robot stocks in Germany, Italy, France and United Kingdom (the countries selected for our main instrument) with Spain. The right panel compares the robot stocks in Finland, Norway, Sweden and Denmark (the countries selected for our alternative instrument) with Spain.

Figure B3: Spain's Intermediate Good Imports



Note: This figure presents the trends in Spain's log intermediate good imports from the EU countries for 2006-2016.

C Variable Definitions

- Foreign outsourcing: percentage of intermediate imports from other (not related) firms in the same group (over total imports).
- Foreign vertical integration: percentage of intermediate imports from other firms in the same group (over total imports).
- Domestic outsourcing: percentage of intermediate purchases to other (not related) firms in Spain (over total sales).
- Domestic vertical integration: percentage of intermediate inputs purchased from related firms in Spain (over total sales).
- Concentration of suppliers: Percentage of the purchases of the company which come from its three biggest suppliers.
- Imported technology: Payments for licenses and technical aid from abroad, in thousands of Euros.
- Skill intensity: Percentage that engineers and graduates represent on the total personnel of the company on December 31st.

UBIREA

Institut de Recerca en Economia Aplicada Regional i Públic
Research Institute of Applied Economics

WEBSITE: www.ub-irea.com • **CONTACT:** irea@ub.edu

AQR

Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group

WEBSITE: www.ub.edu/aqr/ • **CONTACT:** aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona