Technology Spillovers, Diffusion and Rivalry in Firm Networks*

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Abstract

We provide novel identification of the spillovers from technology adoption exploiting exact links within a firm input-output network, matched with custom and employer-employee data from Turkey. The reflection problem is solved by measuring spillovers from an robot adopting supplier to a non-adopter (vertical diffusion) around an adoption event: spillovers on firm TFPQ, employment, wages, imports and probability of adopting in the future are positive, significant and larger than those from capital deepening. The effects are stronger with higher proximity to the robot adopter, last and accumulate for several years. By exploiting horizontal links between firms sharing the same customers we resolve another thorny issue, that is to identify technology externalities away from rivalry, whose spillovers on firm performance measures are negative due to *business stealing* and are positive on adoption probabilities due to *escape from competition* forces. The positive spillovers are stronger when the robot is imported, even more so from countries like Germany or Switzerland, an evidence on the role of quality. We show how our econometric design can be obtained within a simple model with technology adoption in network with learning.

Keywords: *Technology diffusion, technology adoption, Firm networks, Firm productivity, Imported inputs.*

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1. Introduction

Since the pioneering work by Griliches (1957) economists have made attempts to quantify the extent of positive technology spillovers and/or diffusion and to disentangle them from other complementarities, such as rivalry. Three are the main hurdles (see Atkin et al. (2017)). First, it is often difficult to measure a specific technology adoption: in most cases patents are used, but this measure does not provide exact evidence of the practical adoption. The second and most important hurdle lies in overcoming the Manski (1993) reflection problem: observing two adopters of a similar technology makes it hard to disentangle which of the two firms influenced the other or whether common underlying motives and shocks have caused the adoption. Both require firm level data with information on a technology acquisition by some only and exact firm-to-firm links. Even as problems one and two are solved measuring the spillovers of efficiency gains, the relevant dimension to assess gains for growth, requires to disentangle them from other forms of strategic complementarities, such as rivalry. The impact of the latter tends to be ambiguous too: technology acquisition by a competitor may have a negative impact on firm performance due to business stealing, but it may also foster incentives to innovate to escape competition.[1]

Against this background we offer a new identification that advances on all of the above issues. Broadly speaking we exploit information from the Turkish input-output network of firms whose data are gathered through the VAT filings. The dataset provides information on firm-to-firm links and on their technology adoption, which we proxy with robot adoption, a meaningful technology in modern times. We match this data with the firm's balance sheet, customs and employer-employee data, from which we gather and construct measures of firm performance. Turkey with its growing industrial base provides an ideal setting for this analysis as it is in a stage of development for which technology spillovers may have the bugger bite. Our identification strategy relies on measuring the spillovers on a non-adopter from the event that a direct or indirect supplier adopts the technology (see Breza et al. (2015) for arguing in favour of such strategies). To purge from other forms of strategic complementarities in the baseline specification we select only vertically connected adopters, or suppliers, as those

1 See Arrow (1972). Models of patent race embed the assumption of strategic complementarities. See for instance Aghion et al. (2001).

are unlikely to be in a rivalry relation with the non-adopter. We find a positive, large and significant effect of the adoption event from a supplier on firm TFPQ, employment, wages, imports and the probability of adopting in the future, hence on technology diffusion. The spillovers decline with distance from the supplier, increase when the adopting supplier is more central in the network, persist and accumulate over years, and are stronger than those from capital deepening. We then measure spillovers from rivalry with the same event study, but for the case in which adopter and non-adopter share the same customer base: we find negative and significant spillovers on firm performance measures due to business stealing and positive spillovers on the probability of the adopting the technology, due to escape from competition forces (Arrow (1972)). At last, and in parallel with the concept of quality ladder, we delve into the differential spillovers induced by robots of different qualities, something which we proxy with price: we find that imported robots have larger spillovers than locally produced ones, even more so if imported from Germany and Switzerland.

Our main data comes from an official reporting of firm transactions in Turkey for the period 2007-2019. The data are collected by the Ministry of Finance and cover 1,342,990 manufacturing firms that obliged to report on the buyer, suppliers and the amount transacted. The network provides the full map of direct and indirect firm links. The data is matched with several others. By matching the fiscal codes with those observed in ENOSAD (Industrial Automation Manufacturers Association) we are able to retrieve the acquisition of a locally produced robot, our measure of technology adoption. Through a similar matching with custom data, available at the Ministry of Trade, we are able to uncover the adoption of an imported robot, which by price proxy we classify as of higher quality. Finally, the information from the VAT statements is matched with the firm's balance sheet and an employer-employee dataset that provides several firm measures. Some of these measures are used in structural estimation process, following the procedure outlined in Levinsohn and Petrin (2003) to estimate firm TFPQ, which is one of our outcome variables for assessing efficiency gains. Other outcome variables include employment, wages, imports and exports. We also examine the female to male employment ratio, which we intend as a proxy of development.

Our econometric identification relies first and foremost in distilling the spillover from an

adopter, a firm buying a robot, to a non-adopter. Specifically we run an event study analysis around the year of a robot adoption.[2] To purge from rivalry considerations we examine the spillover from a supplier to a customer firm, examining both direct and indirect links. We find a significant and economically meaningful positive impact on the non-adopter TFPQ, estimated through Levinsohn and Petrin (2003).[3] The effect is persistent and even intensifies over the years, but it diminishes with the distance from the supplier, measured in terms of indirect relationships in the network. To clear doubts about possible pre-trend we adjust the control group using the procedure by Callaway and Sant'Anna (2021). We observe no significant pre-trends. Moreover, when we weight the link with the adopting supplier by its network centrality we find that the spillovers grow with it.

To provide a more comprehensive assessment of the efficiency spillovers that may materialize by being connected to an adopter, we re-estimate the same event study with alternative outcome variables. We find that the adoption event by a supplier significantly increases firm employment, wages and import, with no significant pre-trends. Here too we find that the spillovers persist, build over time and decrease with the distance from the supplier. Other variables, such as exports and sales, also increase after the event, but pre-trends are significant: for exports selection bias is more likely to arise as large evidence has already indicated that exporting firms tend to be more productive (see for instance Bernard and Jensen (1999), Bernard and Jensen (2004)); as such they are also more likely to be connected to other innovative firms ex ante.

To measure other forms of strategic complementarities we re-estimate the same specification between horizontal peers, and again between an adopter and a non-adopter. We identify horizontal peers or competitors as firms that share a customer base. In this case spillovers on firm performance measures are negative, due to **customer stealing**, and those on the probability of adopting the technology are positive, due to an **escape of competition effect**.

2 Clustering of the errors is done at firm level.

3 This method estimates firm level productivity by identifying the coefficients of the production function using the cost of labour input, and as such is immune from mismeasurement related to the lumpy nature of firm investment. It is particularly well suited in our case as it is less likely to correlate with robot adoption. We are able to estimate this through the match with the employer-employee data in which we retrieve the cost of labour.

Our baseline results raise several other questions. First and foremost, to the extent that robots may share commonalities with physical capital one may question whether our results are capturing capital deepening.[4] Leveraging the comprehensive details in our balance sheet data, we recalibrate our event study, taking tangible capital acquisition as the event. In this case we find a positive effect, but much smaller. Moreover indirect spillovers are insignificant in this case.

At last, we examine the role of quality of the technology adopted for the size of the spillovers. Past literature has underscored the role of product quality for growth (see Grossman and Helpman (1991a), Grossman and Helpman (1991b)). Our paper is the first, to the best of our knowledge, to uncover a role for the quality of technology for spillovers, and hence growth. We do so by distinguishing whether the robot is locally produced or imported, imported directly or through affiliates, also differentiating across the country of origin. We rely on robot price as proxy for quality. We find that the positive spillovers are larger when the robot is imported and the more so if it is imported from Switzerland or Germany rather than from China.

In sum, by exploiting rich information from several datasets our study can shed light on the exact quantification of the trade-offs among various forms of complementarities in firm networks and delves into various relevant nuances of the technology transmission, both spillovers and diffusion.

Related Literature: This study primarily contributes to the literature by providing insights into the measurement of technology spillovers and diffusion. Starting from technology spillovers, several theoretical studies examined the impact of R&D, usually measured with patents adoption, on firms strategic interaction and on growth: those include Spence (1984), Grossman and Helpman (1991a), Grossman and Helpman (1991b), Aghion and Howitt (1996), Keller (2004), Jones (2005). Empirically, it has been always difficult to measure the technological spillovers across firms for several reasons (see Atkin et al. (2017)). First, it is hard to find a direct measure of adoption. Second and most important it is hard to control for the Manski (1993) reflection problem by which, with two firms adopting a technology, there is an ambiguity on which is having an impact on the other and on whether latent

4 See for instance Kumar and Russell (2002).

factors have contemporaneously impacted the incentives of both. Both problems are solved within our data, which provides an exact measure of adoption through robot acquisition, and allows us to assess causality by exploiting the impact of an adoption event between an adopting supplier and a non-adopting customer.

Other empirical strategies had been used in the past to measure the extent of technological spillovers. Most were based on staggered policy actions that fostered or limited the flow of information across firms, a key determinants of the technology spillovers. An example is the staggered passage of the Uniform Trade Secrets Act (UTSA henceforth) (see Png (2017); also Hall et al. (2014)), which promotes peers' use of trade secrecy and leads to opaqueness in patent comparisons; as a result, the UTSA attenuates the effect of technology spillover on stock returns. Similar results are obtained with staggered adoption of the Inevitable Disclosure Doctrine (IDD henceforth) (see Klasa et al. (2018), which prohibits employees from working for other firms if confidential information can be revealed as a result. Our identification strategy relies on the observation by Breza et al. (2015) that measuring direct spillover effects is best done by tracking links from the treated node to the untreated connected peer.

Another contentious issue relates to the identification of technology spillovers and other strategic complementarities, such as rivalry. Previous evidence (see Bloom et al. (2013) has addressed those concerns by exploiting differentiation of firms exposure to an adopter, measured as correlation of similar patents, and of firms exposure to competition, measured by product similarity. We provide novel insights on the quantification of the two by distinguishing spillovers among vertically and horizontally connected firms. We also provide further insights on the identification of two opposing competition channels, namely business stealing and the escape competition channel (see Arrow (1972)): both of them feature significantly in our data, but with different signs.

By assessing the impact of the adoption event on the probability that another firm adopts in the future, we contribute also to the literature on knowledge and idea diffusion (see Jones (2005)). Some studies focus on learning within teams (see Jaravel et al. (2018), Zacchia (2020) among others). A recent study by Arqué-Castells and Spulber (2022) examines the

diffusion through the links in the market for technology and exploits tax incentives on R&D to obtain causal identification. Our study contributes by exploiting links within an input-output network and by measuring the impact of the adoption event on numerous measures of firm performance, something which we achieve with a matching across several datasets. Spillovers within the value chain can occur not only through scientists conversations (see also Stein (2008)), which are a very important part, but also through efficiency gains in logistic, knowledge diffusion, strategic incentives. When a supplier adopts a robot such an event is likely to make the whole value chain more productive and is likely to incentivize other firms to adopt. Ding et al. (2022) study structural change through firm level decisions, using US Census Bureau's Longitudinal Business Database (LBD): they show that manufacturers' growth is concentrated in just three: Computer Systems Design, Research and Development (RD).

In relation to those last observations our paper contributes to the large literature on innovation and technology spillovers among firms participating in international markets. Early papers by Rivera-Batiz and Romer (1991), Eaton and Kortum (1996), Coe et al. (1997), Coe et al. (2009) examine the spillovers across countries. The papers closer to ours are those that leverage microdata and focus on micro spillovers. Part of the literature has exploited links within multinationals, hence between affiliates and parent holdings (see Caves (1974), Griffith et al. (2006), Haskel et al. (2007), Bilir and Morales (2020)). See Keller (2004) for a survey on that.) and others have examined the role of FDI for technology spillovers (see for instance Brambilla et al. (2009)). We also use technology adoption imported through affiliates as a means to identify the role of quality. Theoretically authors have explored various form of spillovers from trade (see Akcigit and Kerr (2018)) or mechanisms rising innovation incentives, such as comparative advantage (see Grossman and Helpman (1991a) or Grossman and Helpman (1995)) or competition (see Dhingra (2013)). In relation to this literature, our paper exploits links within the whole global value chains, measures spillovers on various firm performance and diffusion and distinguishes positive externalities from rivalry.

Econometrically our study also adopts recent methods to control for firms pre-trends in event study analysis (see Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Arkhangelsky

et al. (2021)) and measures efficiency gains directly in terms of firm productivity, by relying on methods that structurally estimate those (see Levinsohn and Petrin (2003)).

Our study also partly relates to a literature that studies the role of network influence on the diffusion of various type of technologies among individuals, firms or households in various areas (see Foster and Rosenzweig (1995), Munshi (2004), Bandiera and Rasul (2006), Kreindler and Young (2014), Carvalho and Voigtländer (2015), Conley and Udry (2010), or Basker and Simcoe (2021)). Many of those papers focus on developing countries. Many others point at the role of central nodes as more powerful in fostering diffusion (see Banerjee et al. (2013), Cai et al. (2015), Phelps et al. (2012)) or to the strength of the ties (see Aral and Walker (2014)) or to the link with sophisticated nodes (see Bursztyn et al. (2014)). We find evidence for many of those hypotheses: we find that weighting the connection by the network centrality, more direct or stronger links and links to producers of higher quality technology all contribute to an increase in the extent of spillovers.

Lastly, our study is also related to the expanding literature studying the role of robot adoption and automation on various firms measures, more prominently employment[5] and on propagation of shocks within network.[6]. Our study focuses on technology diffusion, rather than other shocks. Most importantly, our empirical strategy allows to resolve the pervasive Manski (1993) reflection problem which makes causality within network hard to identify.

The rest of the paper is organized in four sections. Section 2 introduces the dataset. Section 3 presents causal evidence of technology spillovers from robot adopters to their customers and suppliers, highlighting the difference between direct and indirect effects, between robot adoption and capital deepening, between adoption by customers and suppliers, and between adoption of robots of better and worse quality. Section 4 looks at technology diffusion by studying the likelihood that a firm acquires a robot for the first time conditional on earlier robot adoption by a direct supplier. Section 5 concludes.

5 Those include Frey and Osborne (2017), Mann and Püttmann (2018), Dechezleprêtre et al. (2021), Aghion et al. (2020), Acemoglu and Restrepo (2018a), Acemoglu and Restrepo (2018b), Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2020), Bonfiglioli et al. (2020), Bonfiglioli et al. (2021), and Faia et al. (2021).

6 See Acemoglu et al. (2012), Carvalho and Voigtländer (2015), Barrot and Sauvagnat (2016), Bernard et al. (2019), Baqaee and Farhi (2019), Baqaee and Farhi (2020), Carvalho et al. (2021), and Alfaro Urena et al. (2021)

2. Data: Balance Sheet, Custom, Employer-Employee, and Input-Output

The goal of the paper is to assess and quantify technology spillover and diffusion across firms connected by business relations. We achieve this through the matching of four main datasets. First, we leverage on an input-output network of transactions among firms in Turkey during the period 2007-2019. Such network allows us to implement a key feature of our identification design: using the data on transactions we can identify adopter and non-adopter that are connected to each other. We measure spillovers as the impact that an adoption event has on a number of performance measures for the non-adopter around the adoption event. We can construct various measures of performance through the matching of the input-output data with information from the employer-employee dataset. A third matching that enhances our unique identification design is the link with the custom data: the distinction between the acquisition of a locally produced robot relative to one imported from more technologically advanced countries provides a clear assessment of the role of technological quality. The fourth matching on the balance sheet enables us to compare the impact of robot adoption with that of traditional capital and to estimate TFPQ.

In this section we describe each of the datasets and provide some summary statistics to describe the validity of samples for our analysis. To start with, let us note that focusing on Turkey is valuable, not only for the extraordinary combination of firm data that we are able to gather, but also because the country has been on a steep growth path over the last years and its industrial base is growing rapidly. This is precisely the type of environment that makes the study of the benefits from technological adoption meaningful.

The input-output network of transactions across firms is obtained using information from the firm value-added tax statements. These statements, collected by the Ministry of Finance, require all firms in Turkey to report their domestic transactions to the Ministry if the amount exceeds 5000 Turkish Liras, approximately equivalent to 155 U.S. Dollars. In our study we focus on firms in manufacturing, which are the largest robot adopters. The total number of firms times years observations is 1 millions and 300 thousands, which means roughly 103,306

firms per year on average. In sum the data has a very large coverage and the sample of firm is representative of both large and small-medium size firms. These statements contain details on the buyer, seller, and transaction amount, hence the data allows us to track over time, and at an annual basis, suppliers and customers for each firm in the sample.

	Data	Source	Content
1	Value-added tax	Ministry of Finance	Firm-level
2	Customs	Ministry of Trade	Firm-level
3	Employer-Employee	Social Security Institution	Individual level
4	Firm Registry	Ministry of Industry and Technology	Firm-level
5	Balance Sheet	Ministry of Industry and Technology	Firm-level

Table 1: Data Sources

Notes: This table presents the list of data sources employed and matched in this study.

The firm identifier in the input-output network allows us to match with several other datasets. First, the data are merged with the firm registries that provide detailed information about the industrial classification according to the four-digit NACE Rev.2 industry code and the location of the firm, including the city and region at the NUTS2 level. Hence, for our sample we also have information on the sector and geographical composition. We use this information for controls and fixed effects.

To create measures of firm performance, we also match the data with information from the balance sheet and the employer-employee matched dataset, maintained by the social security offices. Specifically, we can structurally estimate the firm total factor productivity, one of our firm performance measures, through the Levinsohn and Petrin (2003) methodology by using balance sheet information such as capital, stocks, sales and intermediate inputs to control for unobservables.[7] Through the employer-employee matched dataset, we gather other firm performance measures, such as wages and employment. Finally, using again the firm identifier, we retrieve information on firms' participation in the international trade network using the customs data obtained from the Ministry of Trade. This data offers insights into export and import transactions for each firm, including the volumes and quantities of each product. These products are classified using a 6-digit Harmonized System (HS) level product

7 Intermediate inputs are calculated through firms VAT transactions and imports.

	Mean	Std dev.	Min	Max
Panel A: Network Statistics of Firm				
# of Suppliers	21.07	54.17	0	5038
% of Automated Suppliers	0.05	0.11	0	1
Panel B: Automation in the Network				
Upstream 1	0.417	0.493	0	1
Upstream 2	0.602	0.489	0	1
Upstream 3	0.636	0.481	0	1
Upstream 4	0.654	0.476	0	1

Table 2: Summary Statistics of the Data

Notes: The summary statistics of the dataset are based on a sample size of 1,342,990. Panel A reports the network statistics of the firm, including the number of suppliers and the percentage of suppliers that adopt robots in the firm's supply chain. Panel B displays the statistics of automation dummies for the firms, where *upstream* refers to the firm's suppliers. The firm assumed to have automation in the upstream by having at least one supplier that has adopted a robot. The subscript indicates the network distance to the firm.

code, along with information about the partner country. Table 1 reports a brief description of all the data used and their source.[8]

Measuring Technology Adoption: To measure technology adoption, we employ a proxy centered on robot adoption at the firm level, drawing on two datasets. The first dataset comprises customs data, allowing us to pinpoint firms that import robots based on the product information specified by the HS codes. In the second dataset, we focus on the acquisition of domestic robots. We observe firms that are members of ENOSAD (Industrial Automation Manufacturers Association) and through their fiscal code we can identify the customers of domestic robot producers. The distinction between domestically produced and imported robots also allows us to discuss the role of quality in technology adoption.

Descriptive Statistics: We now provide some descriptive statistics focusing in particular on automation within the supply chain. Our identification relies on measuring the impact on the performance of a non-adopter connected to a supplier that acquired a robot around

8 For imports, we rely on the six-digit HS codes for industrial robots, specifically 847950.

the event of the first adoption. We also examine the impact of the first time adoption event when the supplier is two, three or four links away. Table C provides some some statistics on the number of suppliers, automated suppliers, and the share of suppliers that adopted a robot one or more links away from each firm. On the terminology, we indicate as upstream a supplier and the number next to it indicates the number of links separating it from the firms whose performance we evaluate.

3. Econometric Design and Causal Identification

One difficulty in measuring technological spillovers across firms is that, among two firms adopting a technology, it is challenging to establish which one influences the other. Firms within a network are also often subject to similar shocks and those may be contemporaneously responsible for the joint adoption of the technology. To overcome these difficulties, we use the information in the value-added transaction to identify first time adopters. We then identify the spillovers as any impact on the performance of a non-adopter linked to an adopter. However, if the same firms are sharing a customer base, it may be the case that the influence they exert on each other stems from other types of complementarities. To rule out this case, we focus on the spillover from a supplier adopting the technology and its customer. The econometric design relies on an event study analysis around the first time of the adoption by the supplier. Specifically, the treated group comprises firms whose suppliers decide to adopt robots during a specific time period, while the control group consists of firms that are never treated. The econometric specification reads as follows:

$$y_{t,i} = \alpha + f_i + f_{s,t} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t} \tag{1}$$

where $y_{t,i}$ is the performance variable of the firm i linked to an adopter j in a year t and it can be TFPQ, employment, wages, import or exports, f_i and $f_{s,t}$ are firm, time and sector-year fixed effects (at one digit NACE), $D_{i,j,t}$ is the dummy capturing the event that a firm i linked to firm j adopts the robot for the first time and $\beta_{i,t}$ is the coefficient of interest capturing the extent of the spillover. Note once again that we consider only firms vertically linked to each

others to purge from other forms of complementarities. The firm fixed effect should control for other unobservable firm characteristics that may explain the change in firm performance and the time fixed effects control for other time trends that affect the performance of several firms in the economy or in specific sectors. At last, to capture the direct spillover, the dummy $D_{i,j,t}$ refers to the adoption of a robot by a direct supplier; we instead capture the indirect effects by setting $D_{i,j,t}$ as the event that a firm vertically but indirectly connected adopts the robot for the first time.

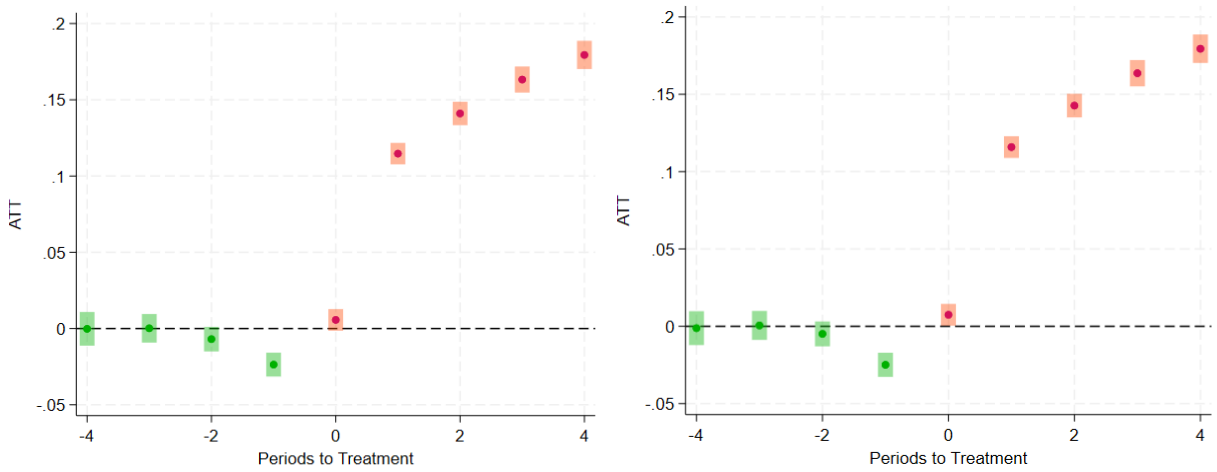
Note that firms may adopt robots for the first time in different years, hence creating a staggering event study. A concern that has been raised in this type of specifications (see Goodman-Bacon (2021) or Callaway and Sant'Anna (2021)) is that groups of firms adopting at different times may also be on different trend growth paths. Therefore the direct comparison of those cohorts of adopter to the non-adopters may conflate those differences in the time trends. To purge from those factors, we adopt the methodology proposed by Callaway and Sant'Anna (2021). Broadly speaking, the method consists in estimating the average treatment effect for the cohort of firms linked to a supplier that adopted for the first time at t against all firms linked to a non-adopter at time t only. This way one can estimate the average treatment effect for the treated sub-population.

In what follows we present the results, starting with the effects of what we dub 'direct' spillovers, namely the spillovers from the first-time adopter supplier of a firm on its TFPQ, employment, wages, import and exports. Estimating the firm TFPQ through the method by Levinsohn and Petrin (2003) has the advantage of using the cost of labour input to identify the production function, rather than the cost of capital, which may happen to follow lumpy patterns and exhibit several zeros, especially in developing countries.

3.1. Results: Direct Spillover on Firm Productivity

We present the results for direct spillovers in two modes. First, in Figure 1 we plot the classical graphical analysis of event studies for firm TFPQ. Second, to assess whether the magnitudes are sizeable, in the first column of Table 3 we report the corresponding estimated coefficients.

Specifically, Figure 1 plots the average treatment effect on the firm TFPQ of the event that a directly linked supplier adopts the robot for the first time and with a four years window around the event. First and foremost, pre-trends before the events are clearly insignificant, hence the decision of the supplier to adopt the new technology was unrelated to the customer productivity. Following the event there is a significant increase in productivity. The magnitudes are economically meaningful: for instance the standardized coefficients in Table 3 show that after four years the event induced an 18% increase in firm TFPQ. The spillovers may be due to various channels, ranging from learning to cost reductions or improvements in production logistics.



(a) Firm TFPQ

(b) Weighted by Network Centrality

Figure 1: Event study of first time robot adoption by a supplier, impact on Firm TFPQ

Notes: The figure plots of the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. Econometric specification is: $y_{t,i} = \alpha + _i + f_t + \beta_{i,t} D_{i,j,t} + \lambda_{ht} + \epsilon_{i,t}$, where $y_{t,i}$ is TFPQ of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time, λ_{ht} is the sector-year fixed effects. The event is defined as the first-time acquisition of a robot by the supplier. Right panel shows the case with the event weighted by the supplier degree centrality.

Another interesting aspect is that the spillovers are very persistent and also increase over time. We can appreciate this by examining the estimates presented in Table 3 for the spillover from the first directly linked suppliers (estimates in column labelled "Upstream 1") over the span of four years. Firm productivity rises 11% one year after the event and 18% four years after the event.

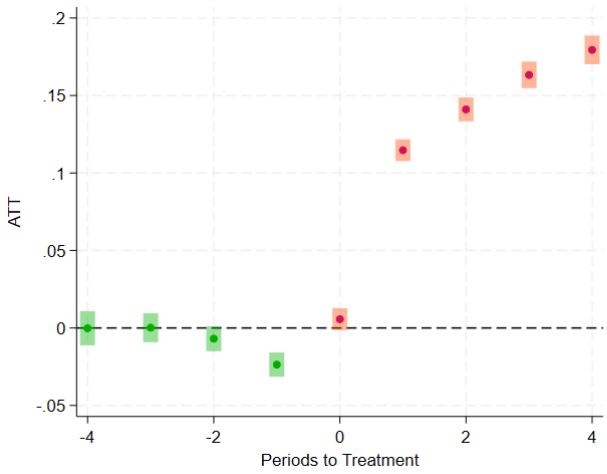
Network Centrality. For robustness the right panel of 1 reproduces the same event study by weighting the adoption dummy by the centrality of the supplier. For each year we compute the outdegree and indegree weighted centrality measure for each supplier.[9] We then interact the centrality measure with the adoption dummy. The treatment group in this case is given by the firms that are linked to a supplier that adopted a robot and exposure to the treatment is given by the supplier centrality in the network. Results show that spillover are slightly stronger when suppliers centrality increases.

3.2. Indirect Spillovers

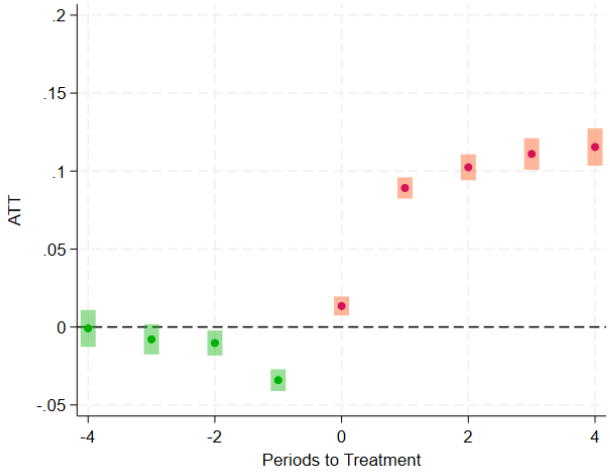
Technological spillovers may be passed through direct or indirect links. Robot acquisition improves firm production efficiency and improvements may be passed on to customers through cost reduction, improved logistic or simply through learning. All these channels can also affect the whole value chain. We therefore test whether this happens by re-estimating the coefficient of the event study for the case in which the first time adopter is a supplier two, three or four links upstream. When we estimate the impact of adoption from a distant supplier, the specification controls for robot adoption by the direct supplier. We present the results graphically in Figure 2 and in the second, third and fourth columns of Table 3, where we can appreciate the magnitude of the estimated coefficients.

Figure 2 shows the impact of robot adoption from firms that are located two, three and four steps upstream on a firm's TFPQ. The impact is again positive, significant and persistent, and there is no evidence of pre-trends. This is also confirmed by the standard errors of the coefficients two, three and four years before the event, all reported in Table 3. The same table shows that the coefficient estimates are positive and significant one year after the event, that last for several years, but they are smaller than the one observed when the adopter is a directly linked firm. Moreover, they decline with the distance from the supplier that acquired the robot. For instance, first-time acquisition of second-order supplier leads to 11.5 % spillovers on TFPQ, that of a third-order supplier leads to 9.9 % spillovers on TFPQ, that of a fourth-order supplier leads to 9.3 % spillovers on TFPQ.

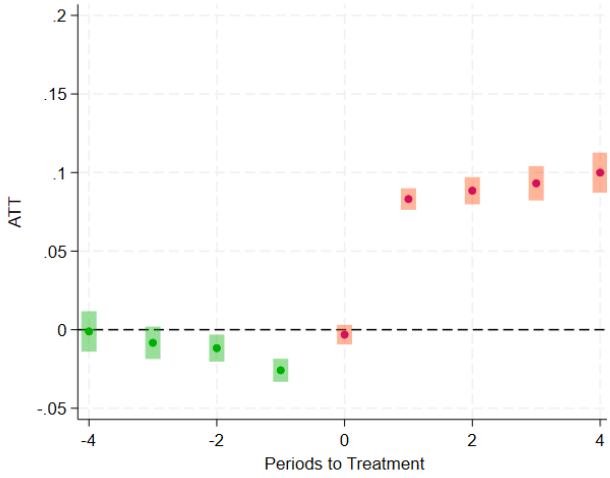
9 Weights are the B2B transactions across firms.



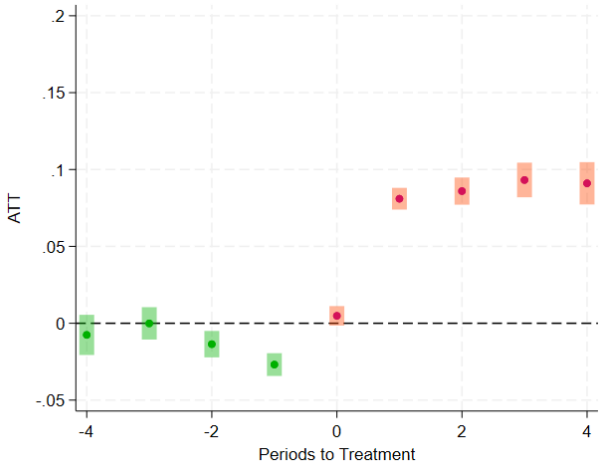
(a) Upstream 1



(b) Upstream 2



(c) Upstream 3



(d) Upstream 4

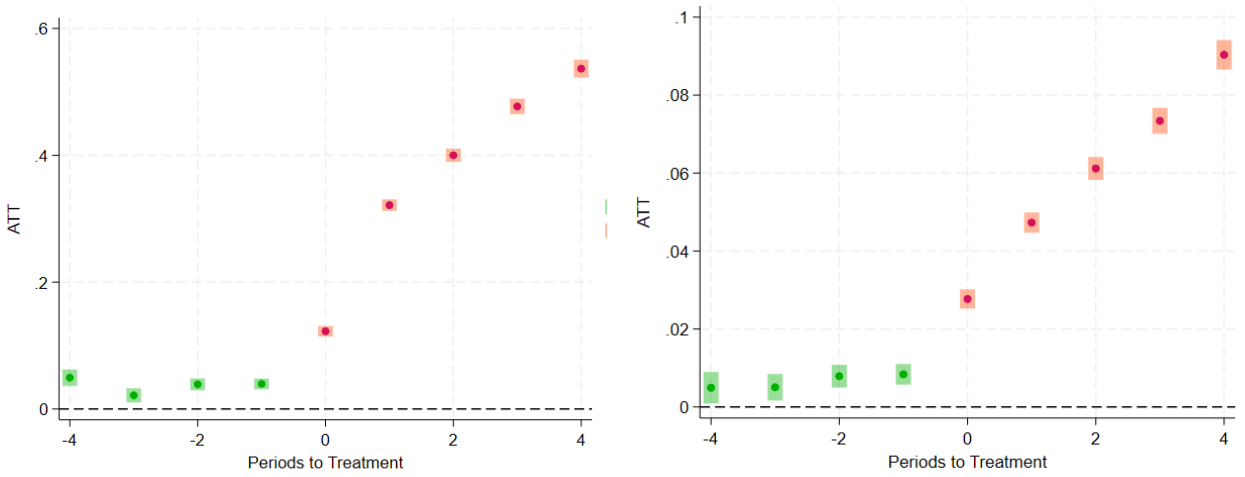
Figure 2: Distance of the Supplier

Notes: The figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time acquisition of a robot by the supplier that is two, three or four steps away. Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + Ups_{i,t} + \epsilon_{i,t}$, where $y_{t,i}$ are employment, wages, import, exports, sales or gender ratio of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time and $Ups_{i,t}$ is the control for the technology adoption in the closer suppliers.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	-0.000	-0.001	-0.001	-0.008
	(-0.03)	(-0.15)	(-0.17)	(-1.14)
Three years before the event	0.000	-0.008	-0.008	-0.000
	(0.03)	(-1.60)	(-1.59)	(-0.01)
Two years before the event	-0.007	-0.010*	-0.012**	-0.014**
	(-1.69)	(-2.51)	(-2.67)	(-3.10)
One year before the event	-0.024***	-0.034***	-0.026***	-0.027***
	(-5.93)	(-9.61)	(-6.89)	(-7.12)
Technological change in supply-chain	0.006	0.014***	-0.003	0.005
	(1.56)	(4.34)	(-1.00)	(1.49)
One year after the event	0.115***	0.089***	0.083***	0.081***
	(31.97)	(25.69)	(23.78)	(22.48)
Two years after the event	0.141***	0.102***	0.089***	0.086***
	(36.01)	(24.14)	(20.02)	(19.06)
Three years after the event	0.163***	0.111***	0.093***	0.093***
	(37.41)	(21.47)	(16.69)	(16.22)
Four years after the event	0.179***	0.115***	0.099***	0.091***
	(38.05)	(18.91)	(15.36)	(12.96)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

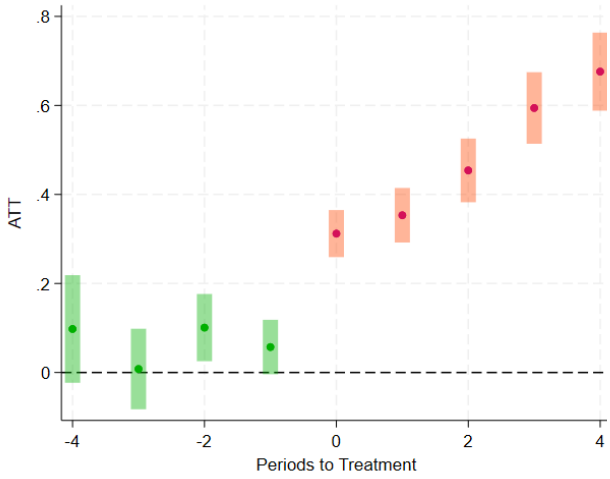
Table 3: Technology Diffusion

Notes: The table reports aggregated treatment effect parameters on the total factor productivity of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$.

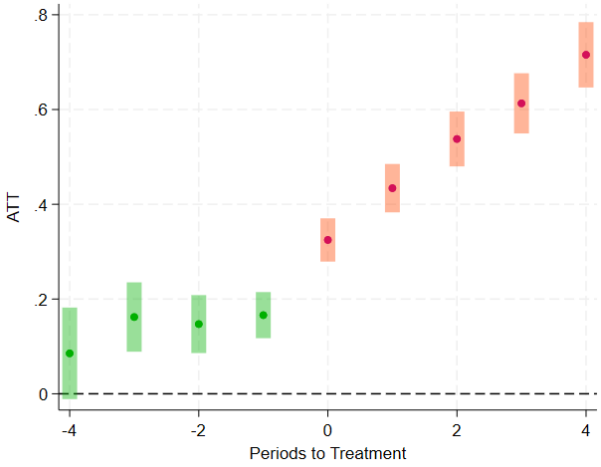


(a) Employment

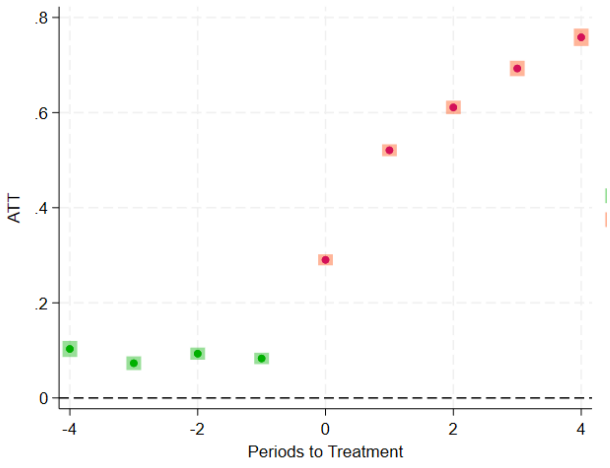
(b) Average Wage



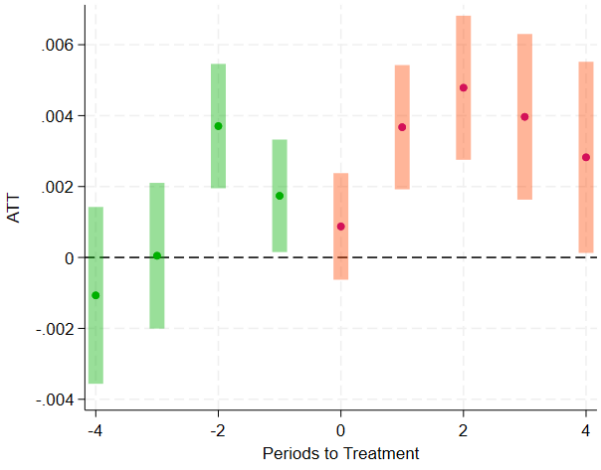
(c) Imports



(d) Exports



(e) Sales



(f) Female-Male Ratio

Figure 3: Event Study of First Time Robot Adoption by a Supplier, Impact on Firm Performance Measures

Notes: This figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time acquisition of a robot by the supplier. Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ are employment, wages, import, exports, sales or gender ratio of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.

3.3. Other Performance Measures

Turning to performance measures other than TFPQ, Figure 3 presents the same type of event study analysis with multiple cohorts of adopters and impacts on employment, wages, import, exports, sales and gender ratio. We use the gender ratio as a measure of development, as the latter may foster female labour force participation. Standardized coefficient estimates are presented in Tables 10 to 15 in Appendix A for the events of adoption from direct and indirect suppliers. First, and as noted above, the possibility of examining the impact of the adoption event on other firm performance measures provides a unique validation of the extent to which spillovers occur and it is made possible by the matching between the production input-output data and the information available in the balance sheets and employer-employee matched dataset.

All firm performance measures increase after the adoption event, but with some qualifications. Wages, imports and employment show no significant pre-trends (see also tables 13 and 15 in Appendix A). In contrast, sales and exports show some pre-trends: in this case selection biases are more plausible as firms that export tend to be more productive (see Bernard and Jensen (1999), Bernard and Jensen (2004) or Das et al. (2007)), and as such they are also more likely linked to innovative suppliers. At last, we find no link with female participation, as proxied by the increase in the female-male ratio.

3.4. Technological Spillovers Versus Capital Deepening

Many aspects of robot acquisition and their role in production resemble those associated with physical capital. Robots can replace labour, or at least some of the tasks performed by workers. Both capital accumulation and robot adoption can potentially foster growth. We are, however, interested in assessing the role of robot acquisition as general purpose technology, that is, a method of improving the production process, with possibly long lasting consequences and spillovers to the rest of the industrial network.

To assess whether robot adoption can indeed qualify as technology adoption and induce spillovers that go beyond those induced by capital deepening, we re-estimate out specification

but substituting robot acquisition with tangible capital acquisition by a connected upstream firm.

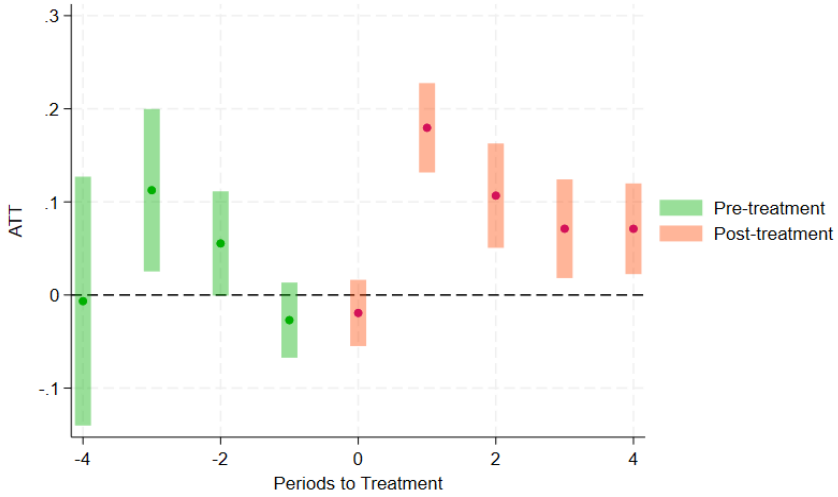


Figure 4: Event study of a first time capital deepening by the supplier

Notes: The figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time capital deepening by the supplier. Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is TFPQ of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i as the physical capital acquisition for the first time, λ_{ht} is the sector-year fixed effects.

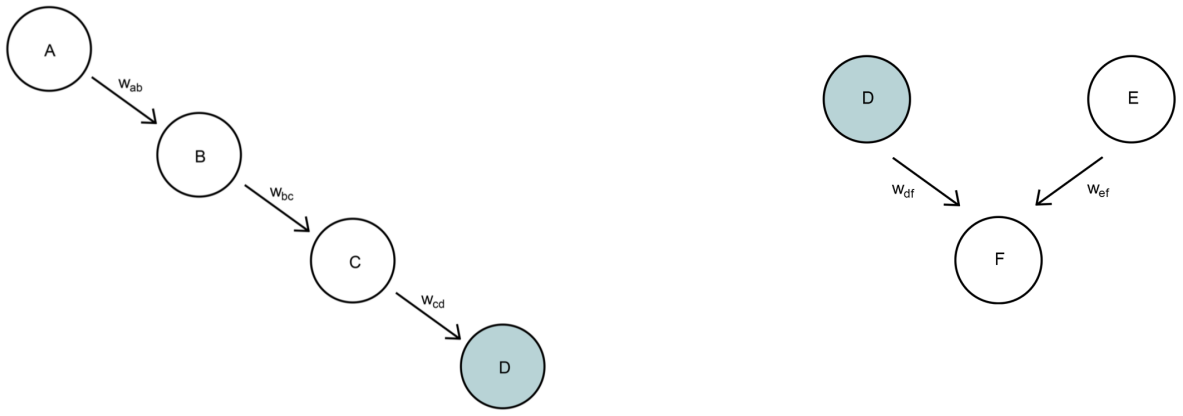
The results of this alternative event study, reported in Figure 4, show that the increase in capital also leads to some technology spillovers, but they are much smaller (at around 7.1% for directly connected supplier) compared with those induced by robot adoption. Additionally, higher-order effects in the chain are insignificant. Note that pre-trends are still insignificant here, a fact that reassuringly confirms the robustness of our econometric design. In sum, robots adoption has distinct and more potent effects than classical capital deepening and as such it qualifies well for studying the role of technology diffusion and spillover within a firm production network.

3.5. Horizontal Spillovers through Rivalry: Customer Stealing versus Escape Competition

A key challenge in identifying the technological spillovers across firms is to disentangle them from other forms of complementarities. One that most likely would interact with the choice of adopting a technology is market competition. Firms who share customers are likely to

adopt a technology also to steal the customer base. If this motive is behind the adoption choice, then the adopting firm may attempt to prevent its peers from benefiting from the spillovers. By stealing customers, the adopter may induce negative spillovers in rival firms. In this scenario, other forms of strategic complementarities may pollute the extent of positive externalities that we observe in the data.

Previous literature has attempted to resolve this identification problem by constructing measures of exposure in both the technological and the market space (see Jaffe (1986) or more recently Bloom et al. (2013)). We shed new light on this issue with a novel identification method that allows to distill exactly not only the correct sign of the market and technological spillovers, but also to quantify their extent. We rely once more on information coming from the production network, based on which we are able to classify firms who are linked horizontally by a common customer base. Specifically, we can select two firms sharing the same customer base, one of which is a first time adopter in a specific period t, while the other is not. Contrary to the vertical supplier-customer relation identified in the baseline specification, firms in this type of rivalry relation have clearly no incentives to allow for positive technological spillovers. On the contrary, they have strong incentives to compete for each other's customers. From the point of view of the input-output network, we can



(a) Vertical Diffusion (b) Horizontal Diffusion

Figure 5: Alternative Diffusion Patterns

Notes: The diagrams present the possible diffusion channels. Vertical diffusion refers to the case where each firm produces different levels of products, whereas horizontal diffusion illustrates the case where two firms produce similar types of products.

represent the difference between the vertical connection considered earlier and the horizontal connection considered now through the example depicted in Figure 5.

To understand the difference in the type of spillovers that may materialize in this case we re-estimate our event study specification, but by replacing the adopter with a firm that shares the same customer base. The results of the estimation are shown in Figure 6, where the adoption event produces negative spillovers. In light of the discussion above, the adopter is now stealing customers from its competitors and thus transmitting negative spillovers. Quantitatively, following the adoption event by a direct competitor, firms experience a 52 % decrease in their TFPQ, 30 % decrease after 2 years, 24 % decrease after 3 year. The effects become insignificant in the fourth-year.

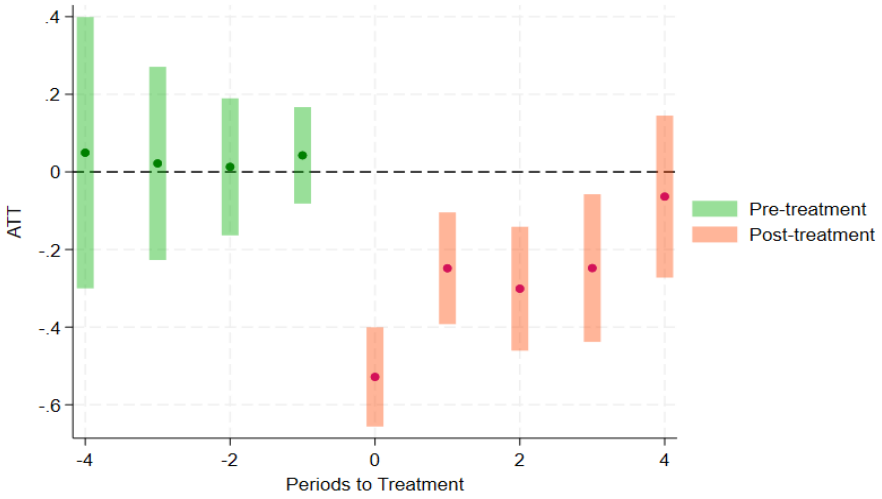


Figure 6: Horizontal Diffusion

Notes: The figure plots the event study of first time robot adoption of the supplier that shares the same customer portfolio. Impact on Firm TFPQ. Specifically it plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time acquisition of a robot by the supplier. Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + \lambda_{ht} + \epsilon_{i,t}$, where $y_{t,i}$ is TFPQ of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time, λ_{ht} is the sector-year fixed effects.

The literature (see for instance Eaton and Kortum (2001) or Akcigit et al. (2018)) has highlighted that rivalry itself may have both negative and positive spillovers. The first are due to customer stealing and are measured by our specification above. The second are due to an escape competition effect and induce the firm, competing with an adopter, to adopt the technology itself. We do find this channel in our data too, something which we illustrate

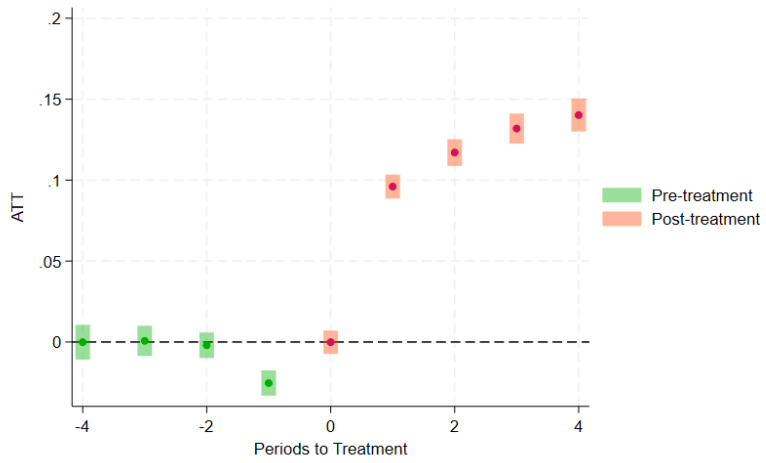
in section 4 where we present a specification linking the probability of acquiring the robot and the adoption event by a supplier.

3.6. Quality of Robots

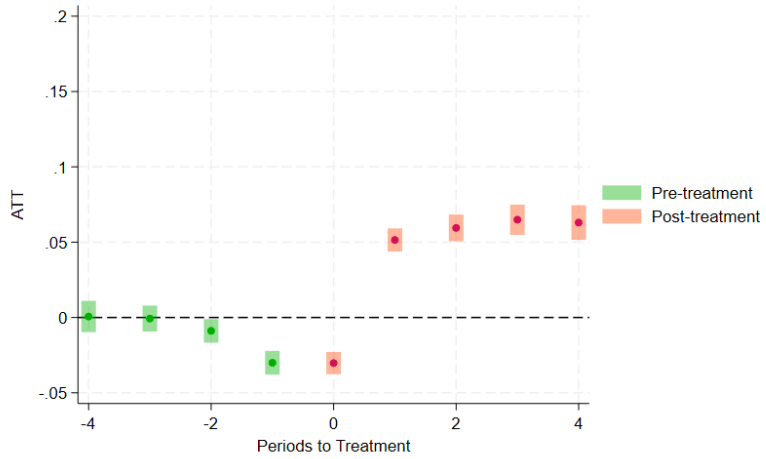
The role of improvement in product quality for growth had been recognized already in past literature (see for instance Grossman and Helpman (1991a) or Grossman and Helpman (1991b)). Much less is known on the role that quality of production technologies have in terms of externalities, and hence growth. The quality of robots is likely to differ depending on the country of acquisition: more technologically advanced countries may export higher quality robots. We therefore exploit the information in our dataset related to the origin of the robot to identify its quality. We proceed in two steps. First, we repeat our event study analysis by distinguishing robots that have been produced locally and imported ones, and among the second we distinguish between those acquired through multinational firms or imported directly. The latter distinction is potentially relevant as the acquisition through multinationals is likely to come also with some assistance service on installation and other logistical operations needed for the efficient functioning of the machine. In a second step, we also distinguish by the country of origin of the robot.[10]

Results for the event study that distinguishes between locally produced and imported robots are shown in Figure 7. The values of the estimates for each case and for each year around the event are reported in Table 11. First, once again the adoption event has significant positive spillovers that last long. However, the spillovers are larger for imported robots, particularly those acquired through multinationals, thereby confirming that quality matters. Quantitatively robots from foreign affiliates lead, four years after the adoption, to a 14 % increase in firm TFPQ, directly imported robots lead to a 9.3 % increase and locally produced ones to a 6.3 % rise.

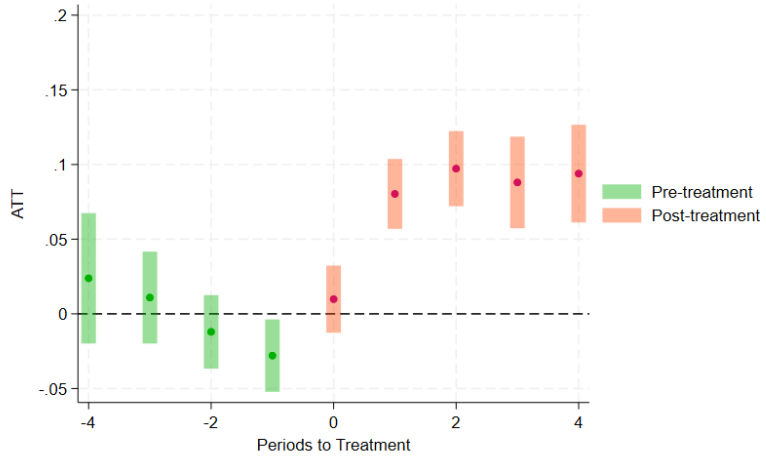
10 When we estimate the impact of each of the options, we control for the remaining cases.



(a) Foreign Affiliate



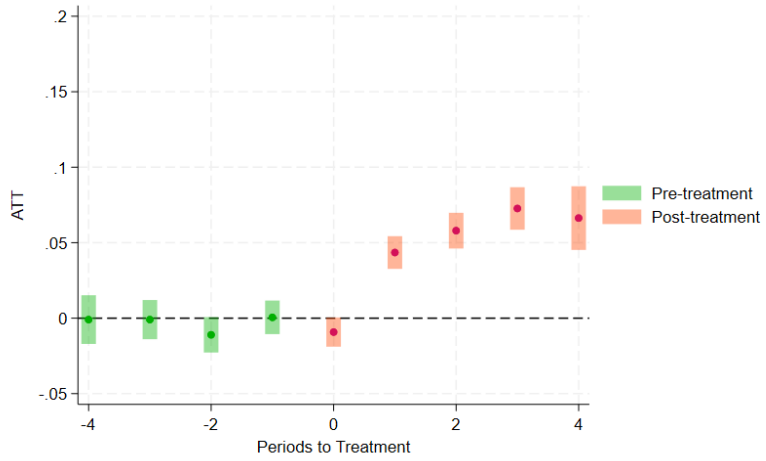
(b) Domestic Producer



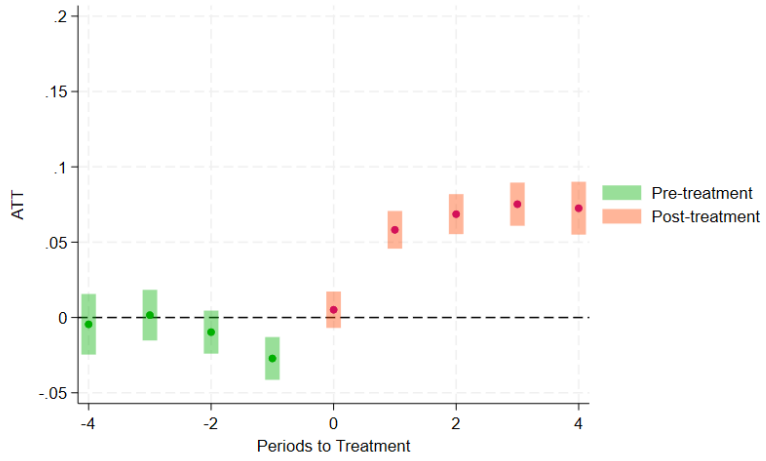
(c) Imported Robot

Figure 7: Origin of the Robot

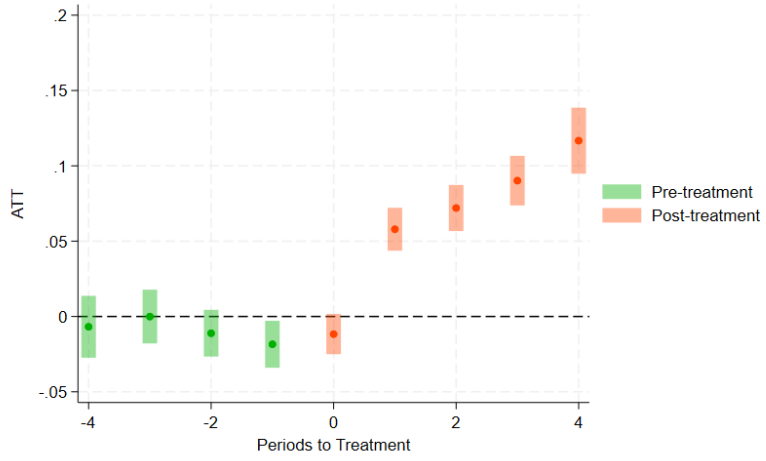
Notes: The figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time acquisition of a robot by the supplier from Foreign MNEs, domestic producers or their imports . Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is the TFPQ of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.



(a) China



(b) Germany



(c) Switzerland

Figure 8: Country of Origin

Notes: The figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time acquisition of a robot by the supplier from China, Germany or Switzerland. Econometric specification is: $y_{t,i} = \alpha + f_i + f_t + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is the TFPQ of firm i linked to an adopter j, f_i and f_t are firm and time fixed effects, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.

	Foreign Affiliates	*Domestic Producers*	*Imports*
Four years before the event	-0.000	0.001	0.024
	(-0.02)	(0.12)	(1.07)
Three years before the event	0.001	-0.001	0.011
	(0.16)	(-0.16)	(0.70)
Two years before the event	-0.002	-0.009*	-0.012
	(-0.50)	(-2.23)	(-0.96)
One year before the event	-0.025***	-0.030***	-0.028*
	(-6.38)	(-7.49)	(-2.26)
Technological change in supply-chain	-0.000	-0.030***	0.009
	(-0.03)	(-8.06)	(0.86)
One year after the event	0.096***	0.051***	0.080***
	(25.52)	(13.14)	(6.73)
Two years after the event	0.117***	0.059***	0.097***
	(27.94)	(13.20)	(7.58)
Three years after the event	0.132***	0.065***	0.088***
	(27.93)	(12.68)	(5.62)
Four years after the event	0.140***	0.063***	0.094***
	(26.91)	(10.74)	(5.63)
Observations	1322011	1322011	1322011
Firm FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Table 4: Locally Produced versus Foreign Technologies

Notes: The table reports aggregated treatment effect parameters on the total factor productivity of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the robot acquisition of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

	China	*Germany*	*Switzerland*
Four years before the event	-0.001	-0.005	-0.001
	(-0.12)	(-0.44)	(-0.65)
Three years before the event	-0.001	0.002	-0.000
	(-0.14)	(0.18)	(-0.01)
Two years before the event	-0.011	-0.009	-0.011
	(-1.84)	(-1.33)	(-1.40)
One year before the event	0.001	-0.027***	-0.018*
	(0.10)	(-3.75)	(-2.32)
Technological change in the supply-chain	-0.009	0.005	-0.012
	(-1.86)	(0.83)	(-1.72)
One year after the event	0.044***	0.058***	0.058***
	(7.88)	(9.12)	(7.97)
Two years after the event	0.058***	0.069***	0.072***
	(9.60)	(10.13)	(9.22)
Three years after the event	0.073***	0.075***	0.090***
	(10.12)	(10.28)	(10.74)
Four years after the event	0.066***	0.073***	0.117***
	(6.16)	(8.11)	(10.43)
Observations	1322011	1322011	1322011
Firm FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Table 5: Country of Origin: China, Germany and Switzerland

Notes: The table reports aggregated treatment effect parameters on the total factor productivity of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the robot acquisition of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

Next, we examine the differential impact on firm TFPQ of robots according to their country of origin, distinguishing among three countries of acquisition, namely China, Germany and Switzerland. To rank their quality, we can use prices as a proxy: Table 10 in Appendix shows that Swiss robots have the highest prices, followed by German and Chinese ones. Results for the event study that distinguishes across the country of origin of the robot are shown in Figure 8. The spillovers originating from Swiss robots are higher than those from other countries and those originating from German robots are slightly higher, but surely more persistent, than those from Chinese robots. The magnitudes of the positive spillovers are 6%, 7% and 11% respectively for Chinese, German and Swiss robots four years after acquisition from the supplier.

4. Technology Diffusion

Growth is fostered by technology spillovers and diffusion, defined as the probability that other firms adopt the technology too. So far we focused on technology spillovers which may encompass several channels. They are externalities that may materialize in many forms, such as knowledge spillovers on new trends and processes in the industry, strategic or opportunistic information, sourcing of skilled workers from the network, but also incentives to adopt the technology. The last channel relates more specifically to technology diffusion and it is an important engine of growth. We now test such a channel through a probit model that links the likelihood that firm i will acquire an industrial robot for the first time to the acquisition by a direct supplier. The econometric specification reads as follows:

$$Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i) \qquad (2)$$

The variable $TechnologicalChange_{i,t}$ takes a value of one if the firm purchases an industrial robot for the first time in the given year t, where β_0 is constant. As for The regressors, $Own_{i,t-1}$ includes the firm's variables and $SupplyChain_{i,t-1}$ includes variables characterizing the supply chain. X_i are firm fixed effects.

We entertain several variants of the above specification: in the baseline one the firm's

variables include capital and employment and the network variables include the number of suppliers and the adoption event by a supplier (results shown in Table 5). This is extended to include indirect suppliers (results shown in Table 7) and the adoption event weighted by the centrality of the supplier, (see Table 9). We also extend it to include the number of customers and the adoption event by a customer (results shown in Table 6): this specification serves the purpose of disentangling various forms of complementarities. Finally, we repeat the estimates by replacing the robot adoption event with capital acquisition (results shown in Table 8). To quantify the contribution of the supplier adoption on the probability of adoption by the customer, we also estimate the regression in terms of marginal change of the dependent variable.

The results largely confirm all the channels we described before. The adoption event significantly increases the probability that a firm acquires the technology and the effect is stronger for direct suppliers and fades away with distance from the supplier. The impact of robot acquisition is much stronger than that of capital acquisition. Finally, robot acquisition by a competitor, namely a firm sharing the same customer base, increases the probability that the firm acquires the robot itself, thereby providing evidence for an 'escape competition effect'. If the robot acquisition allows the competitor to increase its customer base, the only way for the firm to defend its market is to adopt the same technology.

	$TechnologicalChange_t$		
TFP_{t-1}	0.068***	0.055***	0.032**
	(6.06)	(4.64)	(2.67)
$NumberofSuppliers_{t-1}$	0.002***	0.001***	0.000***
	(38.99)	(29.61)	(6.78)
$TechnologicalChangeinSupplier_{t-1}$		0.749***	0.534***
		(37.99)	(26.32)
$Capital_{t-1}$			0.034***
			(7.38)
$NumberofEmployees_{t-1}$			0.144***
			(21.15)
Cons	-3.086***	-3.456***	-4.204***
	(-147.63)	(-133.37)	(-92.71)
Obs.	1047727	1047727	1047727
Firm FE	Yes	Yes	Yes

Table 6: Probit Regression: Baseline

Notes: The table shows the results of the following probit regression: $Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i)$, which includes firm fixed effects and where $Own_{i,t-1}$ includes firm variables such as capital, number of employees and TFP, $SupplyChain_{i,t-1}$ includes the number of suppliers and the event that a supplier acquired a robot.

	$TechnologicalChange_t$			
TFP_{t-1}	0.068***	0.055***	0.070***	0.039**
	(6.06)	(4.64)	(6.28)	(3.17)
$NumberofSuppliers_{t-1}$	0.002***	0.001***	0.002***	0.002***
	(38.99)	(29.61)	(28.87)	(22.48)
$TechnologicalChangeinSupplier_{t-1}$		0.749***		0.581***
		(37.99)		(28.05)
$NumberofCustomers_{t-1}$			-0.000***	-0.001***
			(-3.72)	(-6.66)
$TechnologicalChangeinCustomer_{t-1}$				0.380***
				(21.02)
Cons	-3.086***	-3.456***	-3.077***	-3.526***
	(-147.63)	(-133.37)	(-147.34)	(-132.93)
Obs.	1047727	1047727	1047727	1047727
Firm Fe	Yes	Yes	Yes	Yes

Table 7: Probit Regression: Rivalry

Notes: The table shows the results of the following probit regression: $Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i)$, which includes firm fixed effects and where $Own_{i,t-1}$ includes firm variables such as TFP, $SupplyChain_{,t-1}$ includes the number of suppliers and the event that a supplier acquired a robot, number of customers and the event that a customer acquired a robot.

	$TechnologicalChange_t$				
TFP_{t-1}	0.055***	0.079***	0.079***	0.078***	0.057***
	(4.64)	(6.61)	(6.71)	(6.61)	(4.73)
$NumberofSuppliers_{t-1}$	0.001***	0.002***	0.002***	0.002***	0.001***
	(29.61)	(34.47)	(35.23)	(35.64)	(28.59)
$TechnologicalChangeinDistance1_{t-1}$	0.749***				0.659***
	(37.99)				(29.20)
$TechnologicalChangeinDistance2_{t-1}$		0.522***			0.183***
		(25.66)			(7.37)
$TechnologicalChangeinDistance3_{t-1}$			0.445***		0.045
			(22.44)		(1.82)
$TechnologicalChangeinDistance4_{t-1}$				0.398***	-0.023
				(20.42)	(-0.93)
Cons	-3.456***	-3.415***	-3.372***	-3.345***	-3.543***
	(-133.37)	(-126.71)	(-126.85)	(-127.12)	(-119.57)
Obs.	1047727	1047727	1047727	1047727	1047727
Firm Fe	Yes	Yes	Yes	Yes	Yes

Table 8: Probit Regression: Indirect Suppliers

Notes: The table shows the results of the following probit regression: $Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i)$, which includes firm fixed effects and where $Own_{i,t-1}$ includes firm variables such as TFP, $SupplyChain_{,t-1}$ includes the number of suppliers and the event that a supplier acquired a robot, for direct suppliers and for distant ones.

	$TechnologicalChange_t$				
TFP_{t-1}	0.067***	0.067***	0.066***	0.067***	0.066***
	(5.94)	(5.92)	(5.90)	(5.92)	(5.90)
$NumberofSuppliers_{t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***
	(38.92)	(38.93)	(38.94)	(38.93)	(38.92)
$CapitalDeepeninginDistance1_{t-1}$	-0.035				0.021
	(-1.41)				(0.43)
$CapitalDeepeninginDistance2_{t-1}$		-0.042			-0.009
		(-1.68)			(-0.18)
$CapitalDeepeninginDistance3_{t-1}$			-0.049*		-0.049
			(-1.98)		(-0.98)
$CapitalDeepeninginDistance4_{t-1}$				-0.042	-0.012
				(-1.70)	(-0.24)
Cons	-3.055***	-3.049***	-3.043***	-3.049***	-3.043***
	(-101.33)	(-100.40)	(-100.89)	(-101.22)	(-96.57)
Obs.	1047727	1047727	1047727	1047727	1047727
Firm Fe	Yes	Yes	Yes	Yes	Yes

Table 9: Probit Regression: Capital Deepening

Notes: The table shows the results of the following probit regression: $Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i)$, which includes firm fixed effects and where $Own_{i,t-1}$ includes firm variables such as TFP, $SupplyChain_{,t-1}$ includes the number of suppliers and the event that a supplier acquired physical capital, both for direct suppliers and indirect ones.

	$TechnologicalChange_t$		
TFP_{t-1}	0.055***	0.054***	0.054***
	(4.64)	(4.50)	(4.50)
$NumberofSuppliers_{t-1}$	0.001***	0.001***	0.001***
	(29.61)	(29.15)	(29.15)
$TechnologicalChangeinSupplier_{t-1}$	0.749***		0.037
	(37.99)		(0.31)
$TechnologicalChangeinCentralSupplier_{t-1}$		0.756***	0.720***
		(38.67)	(6.11)
Cons	-3.456***	-3.449***	-3.450***
	(-133.37)	(-134.18)	(-133.44)
Obs.	1047727	1043472	1043472
Firm Fe Yes	Yes	Yes	

Table 10: Probit Regression: Network Centrality

Notes: The table shows the results of the following probit regression: $Prob(TechnologicalChange_{i,t} = 1) = g(\beta_0 + Own_{i,t-1} + SupplyChain_{i,t-1}, X_i)$, which includes firm fixed effects and where $Own_{i,t-1}$ includes firm variables such as TFP, $SupplyChain_{,t-1}$ includes the number of suppliers and the event that a supplier acquired a robot, where the event is weighted by the centrality of the supplier in the network.

5. A Model of Technology Spillovers and Diffusion in Networks

Our setting envisages a set of firms that acquire a technology from a supplier. Our evidence uncovers spillovers on firm productivity from the acquisition within the input-output network, that decline with the distance from the supplier. We also find that the probability of a firm acquiring the robot increases following the supplier's acquisition event. We hereby devise a model of firm network with information spillovers, learning and an acquisition decision. The model is used both to provide a structural benchmark for our econometric design and to discuss the conditions that support our results.

The model builds on Crawford and Shum (2005), in which a set of medical doctors has to acquire a medicine on behalf of patients. Doctors are uncertain about the effects of the treatment and learn about it by receiving signals from their patients' recoveries. We adapt the model in several ways. First, in our model firms have to decide about technology acquisition. Second, they are uncertain about the productivity that the technology will bring to the production process and learn about it over time by receiving signals from the suppliers from whom they acquire the robots.

There is a set $I = \{1, ..., N\}$ of firms indexed by i or j, connected within a network of suppliers and customers for intermediate inputs and technologies (the robots of our econometric analysis). In each period t a firm produces using a concave production function $z_t^i f(k_t^i, \mathbf{x}_t^{i,j})$, where z_t^i is firm productivity, k_t^i is firm capital and $\mathbf{x}_t^{i,j}$ is the array of intermediate inputs that the firm acquires from suppliers j in the production network and that may include robots. The productivity process is not fully known to the firm. The firm holds beliefs about the value of z_t^i at t that are summarized by a normal distribution with mean $\overline{z}_t^i$ and variance $\sigma_{i,t}^2$. The firms holds imprecise information about the process, but can learn about it over time and by acquiring signals from suppliers in the production network. Let τ_0^i denote the precision level of agent i's prior beliefs so that the dispersion of the beliefs $\sigma_{ib,t}^2 = \frac{\sigma_{i,t}^2}{\tau_t^i}$, where the numerator is the the fundamental variance. In each period the firm acquires from a set of suppliers j robots of value $x_t^{i,j}$ and this brings about a signal, s_t^{ij}, which we assume to be

a function of the supplier's proximity, d_t^{ij}, and the supplier's centrality, ξ_t^{ij}. Those signals improve the precision of the firm's information, although the information accumulation decays over time as new ideas enter the production process with decay rate . Therefore the precision process follows the law:

$$\tau_t^i = \tau_{t-1}^i + \sum_{i \neq j} s_t^{ij} \tag{3}$$

The value of the robot provides the extent to which information is passed. Following Crawford and Shum (2005), we assume that this value too follows an independent normal distribution with mean $\overline{z}_t^i$ and variance $\sigma_{i,t}^2$. The mean value of the signals is then given by $\overline{x}_t^{ij} = \sum_1^{s_t^{ij}} \frac{x_t^{ij}}{s_t^{ij}} = \overline{z}_t^i + \epsilon_t^{ij}$, where ϵ_t^{ij} is distributed as $N(0, \frac{\sigma_{i,t}^2}{s_t^{ij}})$. These statistics coupled with the law of motion 3 imply that the firm can update its beliefs about productivity recursively as follows:

$$z_{t+1}^i \tau_{t+1}^i = z_t^i \tau_t^i + \sum_{i \neq j} (\overline{z}_t^i + \epsilon_t^{ij}) s_t^{ij} \tag{4}$$

If we substitute the signals as function of proximity and centrality of the supplier we obtain:

$$z_{t+1}^i \tau_{t+1}^i = z_t^i \tau_t^i + \sum_{i \neq j} (\overline{z}_t^i + \epsilon_t^{ij}) f(d_t^{ij}, \xi_t^{ij}) \tag{5}$$

The above equation quantifies the productivity spillover and allows us to derive the first testable implications that we detail in Lemma 1.

Lemma 1. *The productivity spillover to the firm decays over time and decays with the distance from the supplier and its centrality.* The lemma follows immediately from equation 5.

Technology adoption. We now consider the possibility that, once the firm acquires the robot, it may also decide to develop and adopt the technology itself. The adoption decision is taken through a discrete choice optimization. The firms has to decide among a number $m = \{1, ..., M\}$ of technologies and it does so by comparing the future discounted profits in each of them. Let us define the optimal value function $\tilde{V}^{im}(z_t^{im}, k_t^{im})$ to be the sum of future

discounted profits, as a function of the optimal choice of capital, and for each technology m. This can be written recursively as:

$$\tilde{V}^{im}(z_t^{im}, k_t^{im}, s_t^{ijm}) = z_t^{im} f(k_t^{i,*}, \S_t^{ijm}) + \gamma_t^{im} + \beta E_t[\tilde{V}^{im}(z_{t+1}^{im}, k_{t+1}^{im})] \tag{6}$$

where we have normalized the price of the good to one, γim_t are Gumbel shocks that are technology specific and have a logistic distribution. These shocks capture the relation or intrinsic values of those technologies. Note that the value function depends now upon all the endogenous and exogenous states, including the signals from the network. The optimization problem reads as follows:

$$m = \text{argmax}_{[1,.....,M]}[\tilde{V}^{im}(z_t^{im}, k_t^{im}, s_t^{ijm}) + \gamma_t^{im}] \tag{7}$$

The probability of choosing m in the discrete choice problem in Equation (7) satisfies: $F(\tilde{V}_t^{im} + \gamma_t^{im} \geq \tilde{V}_t^{im'} + \gamma_t^{im'} \; \forall m' \neq m \cup m' \in M)$, where $F(.)$ is the cumulative density of the Gumbel shock. Taking expectations with respect to the current period taste shocks and evaluating at the optimal consumption-saving choice yields:

$$E_{\boldsymbol{\phi}} V_{im}(z_{t+1}^{im}, , k_t^{im}, s_t^{ijm}, \boldsymbol{\gamma_{t+1}}) = E_{\boldsymbol{\gamma}} \max_{m_t} \left[\tilde{V}_t^{im}(z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}) + \gamma_t^{im}\right] \tag{8}$$

where the last equality follows from the properties of the Gumbel distribution. Furthermore, we have:

$$E_{\boldsymbol{\gamma}} \max_{m_t} \left[\tilde{V}_t^{im}(z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}) + \gamma_t^{im}\right] = \ln\Big(\sum_{m_t} \exp(\tilde{V}_j^{im}(z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}))\Big) \tag{9}$$

Combining equations (7) and (9) yields the following closed-form solution for the occupational choice probabilities:

$$\theta_{mi}(m|z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}) = \frac{\exp(\tilde{V}_t^{im}(z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}))}{\sum_m \exp(\tilde{V}_t^{im}(z_t^{im}, k_{t-1}^{im}, s_{t-1}^{ijm}))}. \tag{10}$$

Equation 10 provides the theoretical background for our specification (2).

Lemma 2. *The probabilities of adopting the technology follow a probit specification. They depend upon firms' characteristics, such as their productivity and capital, and on the network structure through the signal spillovers received by the nodes.*

6. Conclusion

Technology spillovers and diffusion are important engines of growth. Quantifying them and distinguishing them from other types of firm complementarities has proven hard. We exploit a unique firm level input-output production network, matched with firm and worker information from the employer-employee dataset and other custom data for Turkey to shed lights on those issues. Turkey is an ideal setting for this research question: it is a developing country with high growth rates, particularly so in its industrial platform. Hence it represents a natural setup that can inform on the role of technological spillover as an engine of growth.

Our identification strategy relies on the link between suppliers adopting the technology, proxied by robot acquisition, and customers that have not yet adopted it in each year of our sample, which starts in 2007. We examine the impact of the continuous adoption event on several firm performance measures: TFPQ, wages, employment, sales, import and exports and also for the probability of adopting the technology. We find significant, large and persistent positive spillovers. These spillovers are much larger than those that we uncover when the supplier is acquiring physical capital, thereby confirming that there is a clear distinction between technology adoption and capital deepening. We are able to distinguish those positive externalities from other forms of strategic complementarities, such as rivalry, by estimating the same type of event study but among firms that share the same customer base: in this case spillovers on firm performance measures are negative whereas the impact on the probability that the customer adopts the technology remains positive.

We also exploit several nuances of our adoption event. We find, for instance, that spillovers

are positive, but smaller, if technology is adopted by a supplier that is not directly connected to the firm.

Finally, we find that the quality of the robot is important in determining the extent and persistence of the spillovers.

Those results have broad validity for the measurement of technology spillovers and diffusion, an important topic that has occupied economists since Griliches (1960). They also provide insights on the role of modern technologies such as robots.

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A. Estimates for Direct and Indirect Effects of Other Performance Measures

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	0.049***	0.053***	0.055***	0.062***
	(7.47)	(7.93)	(7.49)	(8.27)
Three years before the event	0.022***	0.035***	0.049***	0.051***
	(3.79)	(6.44)	(8.38)	(8.55)
Two years before the event	0.039***	0.041***	0.035***	0.032***
	(8.14)	(8.96)	(7.22)	(6.43)
One year before the event	0.039***	0.039***	0.039***	0.030***
	(9.26)	(10.30)	(9.76)	(7.41)
Technological change in supply-chain	0.123***	0.108***	0.079***	0.042***
	(28.93)	(30.89)	(21.49)	(10.43)
One year after the event	0.321***	0.245***	0.189***	0.131***
	(70.18)	(53.27)	(39.83)	(25.30)
Two years after the event	0.400***	0.275***	0.194***	0.117***
	(75.13)	(45.42)	(30.67)	(16.48)
Three years after the event	0.477***	0.292***	0.194***	0.102***
	(76.64)	(38.60)	(24.06)	(11.27)
Four years after the event	0.537***	0.290***	0.174***	0.0720***
	(74.79)	(31.57)	(17.87)	(6.60)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 11: Employment Spillovers

Notes: The table reports aggregated treatment effect parameters on the number of employees of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	0.005*	0.005*	0.006*	0.009***
	(2.40)	(2.18)	(2.43)	(3.42)
Three years before the event	0.005**	0.001	0.001	0.004*
	(2.90)	(0.39)	(0.35)	(2.05)
Two years before the event	0.008***	0.005***	0.002	0.001
	(5.32)	(3.81)	(1.28)	(0.52)
One year before the event	0.008***	0.002*	0.003*	0.001
	(6.21)	(1.97)	(2.14)	(0.77)
Technological change in supply-chain	0.028***	0.014***	0.008***	0.006***
	(22.12)	(12.45)	(7.01)	(4.35)
One year after the event	0.047***	0.026***	0.019***	0.014***
	(35.81)	(19.50)	(12.90)	(8.67)
Two years after the event	0.061***	0.033***	0.025***	0.019***
	(40.91)	(18.93)	(12.50)	(8.25)
Three years after the event	0.073***	0.036***	0.029***	0.023***
	(43.15)	(16.53)	(11.15)	(8.08)
Four years after the event	0.090***	0.043***	0.034***	0.028***
	(46.83)	(16.47)	(10.58)	(8.12)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 12: Spillovers on Wages

Notes: The table reports aggregated treatment effect parameters on the average wage, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	0.098	0.119*	0.055	0.050
	(1.59)	(1.99)	(0.84)	(0.74)
Three years before the event	0.008	0.001	0.017	0.0313
	(0.17)	(0.02)	(0.35)	(0.61)
Two years before the event	0.101**	0.121**	0.052	0.144***
	(2.62)	(3.11)	(1.32)	(3.51)
One year before the event	0.057	0.081**	0.049	0.0767*
	(1.83)	(2.59)	(1.48)	(2.27)
Technological change in supply-chain	0.312***	0.256***	0.247***	0.241***
	(11.57)	(8.81)	(8.00)	(6.95)
One year after the event	0.353***	0.276***	0.211***	0.190***
	(11.31)	(7.13)	(4.73)	(3.76)
Two years after the event	0.454***	0.182***	0.190**	0.174*
	(12.45)	(3.33)	(3.23)	(2.45)
Three years after the event	0.594***	0.092	0.177**	0.107
	(14.49)	(1.45)	(2.59)	(1.29)
Four years after the event	0.676***	0.069	0.0872	0.119
	(15.11)	(0.96)	(1.13)	(1.34)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 13: Spillovers on Imports

Notes: The table reports aggregated treatment effect parameters on the imports of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	0.085	0.0373	0.0926	0.217*
	(1.73)	(0.49)	(1.06)	(2.22)
Three years before the event	0.162***	0.221***	0.138*	0.119
	(4.34)	(3.84)	(2.39)	(1.66)
Two years before the event	0.147***	0.0962*	0.155***	0.0596
	(4.72)	(2.15)	(3.59)	(1.14)
One year before the event	0.166***	0.122***	0.115**	0.144***
	(6.69)	(3.43)	(3.24)	(3.57)
Technological change in supply-chain	0.325***	0.211***	0.251***	0.154**
	(13.95)	(5.61)	(6.87)	(2.99)
One year after the event	0.434***	0.248***	0.337***	0.0676
	(16.66)	(5.20)	(6.55)	(1.02)
Two years after the event	0.538***	0.274***	0.354***	0.0795
	(18.21)	(4.59)	(5.17)	(0.96)
Three years after the event	0.613***	0.321***	0.378***	0.0705
	(18.91)	(4.67)	(4.55)	(0.73)
Four years after the event	0.716***	0.334***	0.434***	-0.0287
	(20.33)	(4.46)	(4.65)	(-0.26)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 14: Spillovers on Exports

Notes: The table reports aggregated treatment effect parameters on the exports of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	0.103***	0.099***	0.102***	0.099***
	(11.99)	(11.71)	(10.99)	(10.82)
Three years before the event	0.073***	0.089***	0.101***	0.106***
	(9.94)	(12.89)	(13.59)	(14.19)
Two years before the event	0.093***	0.096***	0.101***	0.093***
	(14.27)	(16.09)	(15.89)	(14.85)
One year before the event	0.083***	0.106***	0.114***	0.104***
	(13.60)	(19.79)	(20.97)	(19.37)
Technological change in supply-chain	0.290***	0.258***	0.227***	0.200***
	(49.14)	(53.31)	(46.18)	(40.27)
One year after the event	0.521***	0.392***	0.322***	0.254***
	(81.66)	(64.96)	(52.81)	(41.30)
Two years after the event	0.611***	0.410***	0.303***	0.216***
	(84.65)	(53.54)	(37.30)	(26.64)
Three years after the event	0.693***	0.411***	0.291***	0.165***
	(83.81)	(44.03)	(28.28)	(15.68)
Four years after the event	0.758***	0.401***	0.255***	0.115***
	(81.18)	(35.38)	(20.84)	(8.77)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 15: Spillovers on Firm Sales

Notes: The table reports aggregated treatment effect parameters on the sales of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

	Upstream 1	*Upstream 2*	*Upstream 3*	*Upstream 4*
Four years before the event	-0.000	0.001	-0.003	-0.002
	(-0.21)	(0.48)	(-1.72)	(-1.44)
Three years before the event	0.001	0.002	0.003*	0.004**
	(0.67)	(1.51)	(2.10)	(2.69)
Two years before the event	0.005***	0.001	0.002*	0.001
	(5.53)	(1.21)	(2.21)	(0.65)
One year before the event	0.003***	0.003**	0.003***	0.004***
	(3.65)	(3.10)	(3.49)	(5.07)
Technological change in supply-chain	0.005***	0.005***	0.005***	0.009***
	(6.70)	(6.55)	(7.18)	(10.61)
One year after the event	0.007***	0.004***	0.006***	0.009***
	(8.40)	(4.54)	(6.33)	(9.06)
Two years after the event	0.008***	0.003*	0.006***	0.009***
	(7.82)	(2.30)	(4.31)	(6.97)
Three years after the event	0.007***	0.001	0.003	0.009***
	(6.17)	(0.74)	(1.96)	(4.65)
Four years after the event	0.006***	-0.001	0.002	0.007**
	(4.52)	(-0.78)	(0.87)	(2.98)
Observations	1322011	1322011	1322011	1322012
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Table 16: Spillovers on Gender Employment Ratio

Notes: The table reports aggregated treatment effect parameters on the gender-ratio of the firm, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

B. Robot Prices

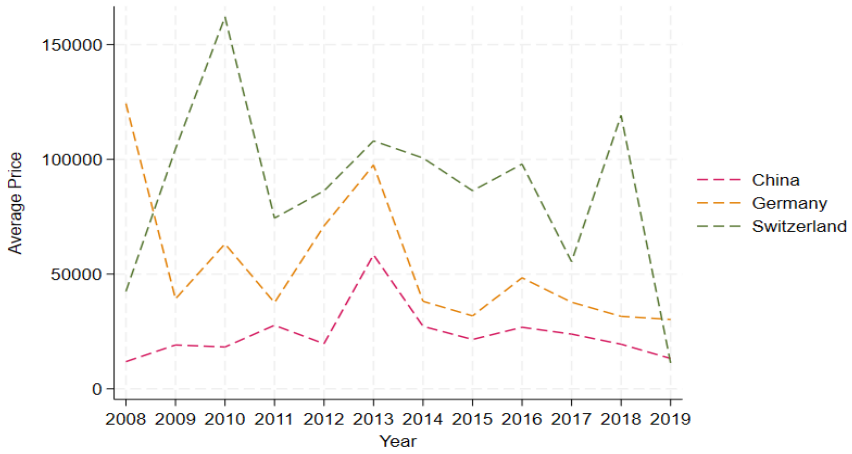


Figure 9: Robot Prices

Notes: The figure illustrates the average prices of imported robot prices over time, measured in U.S. dollars.

C. Descriptive Statistics on Domestically Produced versus Imported Robots

Year	Domestic	Imports
2007	738	79
2008	536	90
2009	368	73
2010	526	72
2011	642	84
2012	558	91
2013	651	82
2014	868	89
2015	717	102
2016	680	83
2017	817	76
2018	645	94
2019	443	76

Table 17: Number of Firms

Notes: The table presents the number of firms adopting robots for the first time, categorized by the origin of the robot

D. Data Construction

This section outlines the dataset utilized in the paper. It draws from a variety of sources, including firm-to-firm transactions, administrative data, employer-employee data, customs data, and a local robot producer list. All data used in this study were obtained from the Ministry of Industry and Technology of Turkey and accessed directly at the Ministry.

D.1. Firm-to-firm Linkages

In Turkey, each firm is obligated to report purchases or sales from other firms if the transaction amount exceeds five thousand Turkish Liras, equivalent to one hundred and seventy U.S. dollars. Compliance with these reporting requirements is mandatory. Failure to report incurs a penalty of around sixty U.S. dollars per missing form for each unreported transaction, in addition to legal consequences. This study focuses on analyzing transactions among firms to construct their production network.

The Ministry of Finance collects firms' statements, associating the tax ID of the firm with that of the partner, thereby identifying suppliers and customers. This process allows us to establish directed and weighted links among firms.

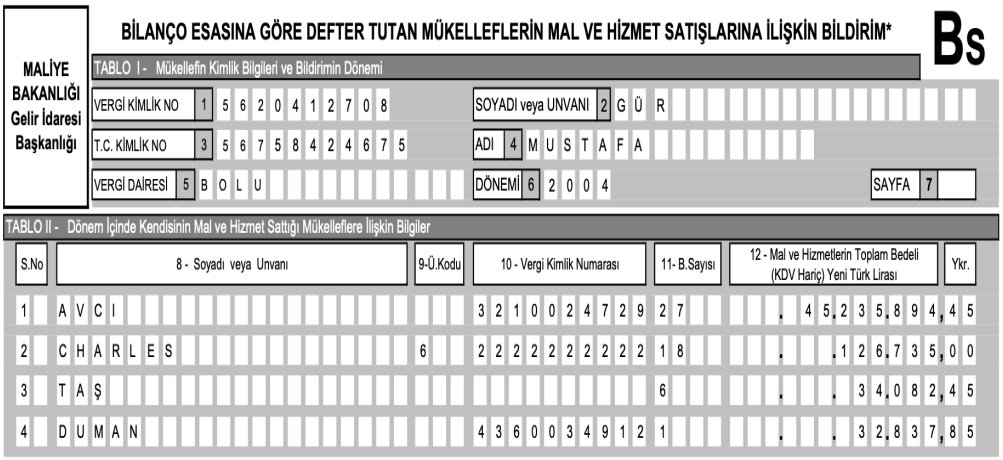


Figure 10: Forms for VAT Statements

Notes: The figure illustrates the VAT statements filled out by firms.

Based on these VAT statements, we construct a firm's production network for each year.

For every bilateral statement, we identify the customer and supplier of each firm. Furthermore, we utilize these statements to trace distant or indirect linkages. For instance, to build an indirect tier-two supplier (upstream 2), we examine these statements and retain only the firms with indirect connections while discarding directly linked ones.

D.2. Administrative Dataset

The administrative data includes firm identifiers linked to their balance sheets. We extract data on the firm's capital and sales from these balance sheets, which are crucial variables for estimating the firm's total factor productivity. Additionally, we monitor the firm's capital deepening over time using the capital variable from the balance sheet data.

Moreover, this administrative data categorizes sectors using the four-digit NACE Rev. 2 code, aligning with European Union sectoral identifiers. Our analysis focuses exclusively on manufacturing firms.

D.3. Employer-Employee Data

We combine these datasets with the employer-employee data by matching the firm identifiers. This datas supplies the number of employees per year, and we also compute the female-to-male ratio of the firms using this information.

D.4. Customs Data

We integrate these datasets with customs data, which specifies whether a transaction is an import or an export. The customs data offers comprehensive information on each transaction with the partner country, encompassing volume and value associated with product codes. Using this data, we extract details on the firm's total imports/exports. Additionally, we identify technological shifts within the firm if it imports an industrial robot with the reported HS code 847950.