Technology Spillovers, Diffusion and Rivalry in Firm Networks*

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Abstract

We show how the benefits of new technology adoption diffuse along a supply chain, improving the performance of firms that do not adopt new technology themselves, and also increasing their likelihood of adopting. We measure new technology adoption in terms of robotization, and firm performance in terms of TFP, wages, employment and adoption probability, with firm level VAT data matched with custom and employer-employee data from Turkey. We find sizable positive causal impacts of upstream robotization on downstream productivity and performance, even beyond direct input-output linkages. We do not find similar impact for upstream capital deepening and spillovers are instead negative if the connected firms share the same customer base, due to rivalry. Spillovers are transmitted primarily through the quality of the technology or the technical support that facilitates knowledge spillover. At last diffusion, the probability of adopting the technology, increases when suppliers and customers adopt a technology, more so if they are technologically advanced, and even when competitors adopt it due to arms races. Our results show the power of the value chain to transmit growth enhancing technological progress. **Keywords**: *Technology diffusion, adoption and propagation; Firm networks; Firm productivity; Imported inputs.*

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1. Introduction

Since the pioneering work by Griliches (1957), economists have advanced in quantifying the extent of technology spillovers and/or diffusion, both crucial for growth. One notion is that both materialize through absorptive capacity, or learning, within a network. Three main hurdles arise in quantifying this process. The first, and most important, hurdle lies in overcoming the Manski (1993) reflection problem, namely causality identification within a network. Second, one must identify learning or knowledge spillover, which contribute positively to growth, from product market rivalry, since firms sharing knowledge often share also the customer base (Bloom et al. (2013)). Rivalry too may have ambiguous effects since acquisition by a competitor may lead to business stealing, but it may also foster innovation races (Arrow (1972), Aghion et al. (2001)). Which of those effects prevail is ultimately an empirical question.

We address both of the above issues by providing a novel within firm-to-firm network identification, which relies on measuring spillovers onto non-adopters (our treatment group) from first-time robot adopters, relative to the rest (Breza et al. (2015)), through a staggered event analysis. We measure technology, acquisition or adoption, based on robots: technology is of course a broader concept, whose measurement, relies on a specific definition. Robots are a good proxy of advanced technologies and, within the firm input-output network, we have precise measures of acquisition and adoption. We identify knowledge spillovers by selecting adopters that are vertically connected to the non-adopter and that do not share customer base with it. We identify rivalry spillovers by selecting firms that are horizontally connected to the non-adopter, and share the same customer base. We use high quality firm level input-output data,[1] which we gather from the Value Added Tax (VAT in short) filings from Turkey, a country that is on a growing trajectory, hence for which the adoption events may have bigger bites, and that is highly reliant on manufacturing, the sector that adopts robots the most. By linking the firm input-output data to the employer-employee and customs data, we can also assess the spillovers on several outcome variables. We find a positive, large and significant effect of the adoption event from a supplier (also referred to as upstream firm)

1 As explained in Appendix B the data is based on official reporting, for which failure to compliance results in significant fines.

on firm productivity, employment, wages, imports and the probability of adopting in the future, hence diffusion.[2] The spillovers accumulate over time, persist with some distance from the adopter, increase with the centrality of the adopter, or when the acquisition occurs through an agent providing technical support. All provides evidence for knowledge spillovers among vertically connected firms. We instead detect minimal spillovers from an event of capital deepening. We also find positive spillovers when the adopter is a customer (or else downstream firm), which is due to a demand pulling that forces competing suppliers into innovation to maintain the customer relation. Spillovers are negative when the adopter is a competitor (Arrow (1972)), due to customer stealing. Lastly, we find that the extent of knowledge spillover depends on the robot's quality (see Grossman and Helpman (1991a) or Grossman and Helpman (1991b)), which we identify either with the country of origin or with price.

Our main data come from official reports of firm transactions in Turkey for the period 2007-2019. The data are collected by the Ministry of Finance and cover firms that are obliged to report on the buyers, 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 fiscal codes with those recorded in ENOSAD (the Industrial Automation Manufacturers Association), we identify robot acquisition, our proxy for technology adoption. By matching further with customs data, available from the Ministry of Trade, we can also identify the origin of the robot, whether it is domestically produced or imported, the country of acquisition and whether it is imported through an agency that provides technical support.[3] As we explain further below the position and role of the adopter in the network allows us to identify the channels. Finally, the matching of the VAT statements with the employer-employee datasets, allows us to measure the spillovers onto several outcome variables, which include employment, wages, imports and firm productivity, which we structurally estimate following Ackerberg et al. (2015). For robustness we also use TFP estimated with Levinsohn and Petrin (2003).

Our baseline econometric specification is a staggered event analysis geared to measure the spillovers, onto one of the firms' outcome variables, from the first time robot acquisition of

2 See Carrillo et al. (2023) for strategies using events to identify misallocation
3 The agencies include intermediaries and foreign affiliates.

other firms, directly or indirectly connected within the input-output network.[4] The control group is made of all firms linked to non-adopters. The events are staggered as they happen across time and firms' cohorts. To purge for possible pre-trends of the firms' cohorts we apply the diff and diff design proposed by Callaway and Sant'Anna (2021).[5] The distance, in time and space, and position in the network of the adopter allows us to quantify the strength of the propagation. While the direction of the link, vertical or horizontal, and the role of the adopter allow us to identify the nature of the spillovers. By selecting as adopter either upstream firms, which do not share customer base with the non-adopter, or agencies, that also offer technical support, we identify knowledge spillover. By selecting, instead, as adopters horizontally connected firms that share the same customer base with the non-adopter, we identify rivalry spillovers. At last, by selecting customer firms, whose demand of higher quality products forces suppliers to adopt, we identify innovations races. The identification of all those potentially conflicting sources of strategic complementarities has often been a thorny issue (Aghion and Jaravel (2015)).

We find a significant and economically meaningful positive impact on the non-adopter productivity, which we estimate through Ackerberg et al. (2015)[6], wages, employment, imports and the probability of adopting.[7] The spillovers accumulate over time, consistently with previous works documenting amplification of shocks through the network (Acemoglu et al. (2012)). Firms productivity increases by 11% on impact and by 18% four years after the event. Wages increase up to 10% four years after the event. The magnitudes are in line with other studies on knowledge spillovers through first time connection to multinational or exporting events (see for instance Alfaro-Urena et al. (2022) or Atkin et al. (2017)). In our case the firm is exposed to more than one event at a time: once the technology spreads

4 Clustering of the errors is done at firm level.

5 With multiple periods and events, the average response may capture firm selection effects or non-parallel trends. Callaway and Sant'Anna (2021) propose to measure the causal impact using the average treatment effect of the estimates for each group at time, where a "group" is defined by the time period when units are first treated.

6 This method estimates firm-level productivity by identifying the coefficients of the production function using the cost of labor input, and as such is immune from measurement issues 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 labor.

7 We do not include exports as for exporting firms there is a well known selection effect, see e.g. Bernard and Jensen (1999), Bernard and Jensen (2004).

within the network, each firm is likely linked to several first time adopters and this magnifies the knowledge spillovers.

Furthermore, both the spillovers and the diffusion persist when the adopter is 2, 3 or 4 links away, they increase with the centrality of the adopter in the network.[8] In sum, we find significant evidence of knowledge spillover through vertically connected firms. The positive impact on wages and employment occurs through rent sharing, and the one on imports through demand spillovers. The benefits of knowledge spillovers to other parts of the economy confirm their role for growth.

Spillovers are positive when the first time adopter is a customer and negative when it is a firm sharing the same customer base. The latter is due to the impact effect of customer stealing. On the other side, when a competitor adopts a robot the probability of adopting the technology increases and this is due to arms races.

A question, also raised in previous studies, is the extent to which technological progress has distinct effects than capital deepening (Kumar and Russell (2002)). This is even more so when the adoption relates to robots, that share many features with tangible capital. By distinguishing between robot and capital first-time adopters, we find that the effects of capital deepening on the same variables are much smaller and do not last long.

Lastly, as a further identification of knowledge spillovers, we refine our estimates, by interacting the adoption with proxies for the quality of the robot, or its technical support. Both of them should transmit larger spillovers. We proxy the robot's quality either with the country of origin, some of them being more technologically advanced than others, or with price. We find that robots imported from technologically advanced countries have stronger spillovers and diffusion. Furthermore, we find that positive spillovers are larger when robots are imported through agencies that provide technical support.

Our study sheds light on several thorny issues of the literature that aims to characterize and quantify technology spillover and diffusion, from the reflection problem to the nature of the spillovers. Our strategy for causal identification is simple and relies entirely on the

8 Using centrality, as opposed to some weighting of firms' trade within the input-output network, provides for a cleaner measure of exposure. Trade weights may indeed depend on firms' size and other confounding factors.

detailed information, reported in our VAT data, about the firm position and role in the value chain network. The unique matching between the VAT data and other datasets also allows us to delve into spillovers that span several dimensions, thereby providing a comprehensive assessment of technological adoption for growth.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 presents the model. Section 4 introduces the matched dataset we use and its sources. Section 5 describes the econometric design. Sections 6 and 7 report our findings with respect to technology spillover and diffusion respectively. Section 8 concludes.

Related Literature. The literature on technology spillover and diffusion is prominent and vast: Aghion and Howitt (1996), Keller (2004) and Jones (2005) are few key contributions. Many of those studies measure technological diffusion with patents. The latter however do not cover the full spectrum of adoption. This implies that it is hard to find a good measure of technology adoption and it is even harder to identify local spillovers in absence of highly disaggregated data (Mairesse and Mulkay (2008)). We solve those measurement issues by exploiting the adoption of robots within firm-to-firm networks. However, when measuring knowledge or technology spillovers within a network one is typically confronted with the Manski (1993) reflection problem, namely the difficulties to obtain causal identification. This issue has so far been addressed with IV strategies (see, e.g., Irwin and Klenow (1994) among others), exploiting local variation (Goolsbee and Klenow (2002)) or by leveraging quasi-natural experimental setting related to policy events affecting the flow of information. Azoulay et al. (2010) use the premature deaths of a number of academic superstars in biomedical sciences, as a source of exogenous variation, and assessed their impact on the structure of their collaborator's networks. Borjas and Doran (2012) rely on the waves of immigration of Russian mathematicians to the US in the 1990s and Waldinger (2012) exploits the expulsion of Jewish scientists from their universities in the 1930s. In contrast, we obtain causal identification by exploiting the exact links between a first-time adopter and a non-adopter, a methodology in line with the one proposed in Breza et al. (2015). Exploiting exogenous events to measure the impact on firm productivity and misallocation is also in line with Carrillo et al. (2023).

The effects we find on TFP, wages and sales are large and generally in line with those found under other event study analysis aimed at detecting the role of knowledge spillovers for emerging markets. Alfaro-Urena et al. (2022) find an increase of up 9% of TFP following the event of exporting to a multinational; Atkin et al. (2017)) find up to 26% increase in profits following first time exporting. In our case the firm is exposed to more than one event at the time: once the technology spreads within the network, each firm maybe linked to several first time adopters at the same time and this magnifies the knowledge spillovers.

Another contentious issue is the identification of countervailing spillovers. If a peer adopts a technology, knowledge spillovers, learning or other forms of strategic complementarities may boost firm performance, creating positive spillovers. However, when a competitor adopts the technology first, the firm may experience both negative and positive spillovers (see Jaffe (1986), and Stein (2008) for a model with countervailing spillovers). The first materialize if the adopter steals the customer base: in this case the firm may experience earning losses. But it may also be the case that competitors' adoption triggers an innovation race, which multiplies the positive knowledge spillovers. Identification of those two forces is typically hard as highlighted by Bloom et al. (2013), who are the first to tackle this issue with an IV strategy relying on variation from federal tax incentives. We offer a novel and alternative identification strategy based on the direction of the link: positive spillovers from knowledge diffusion materialize among vertically linked firms that do not share the customer base, while negative strategic complementarities materialize among horizontally connected competitors.

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 (Jones (2005)). Jaravel et al. (2018) and Zacchia (2020) study diffusion through learning within teams, Arqué-Castells and Spulber (2022) through the links in the market for technology and by exploiting tax incentives on R&D to obtain causal identification, Ding et al. (2022) examine structural change within and between firms. By tracking technology job postings through firm-to-firm linkages, Bastos et al. (2024) show that these positions are highly concentrated within multinational firms and their supply chains. Equally so, our paper relates to the recent literature that studies the impact of robot adoption, or robot imports,

on firms' outcomes, which includes Acemoglu et al. (2020), Aghion et al. (2023) or Bonfiglioli et al. (2024). In our model, we formalize the technology adoption decision through a dynamic discrete choice (see Caliendo et al. (2019) or Allen and Donaldson (2020) for theoretical work on the properties of models with dynamic discrete choices).

Our paper contributes to the large literature on innovation and technology spillovers among firms participating in international markets (see Keller, 2021 for a recent survey). Two other influential papers using the Turkish VAT data (see Demir et al. (2024a) and Demir et al. (2024b)) have studied other aspects, such as human capital or shock diffusion, through the firms' networks. Close to our work are also studies on import-related spillovers with firm-level data (Pavcnik (2002), Amiti and Konings (2007)) or studies that use micro data from multinationals (Caves (1974), Griffith et al. (2006), Haskel et al. (2007), Bilir and Morales (2020)).[9] The mechanisms examined in this literature range from innovation incentives, such as comparative advantage (Grossman and Helpman (1991a), Grossman and Helpman (1995)) or competition (Dhingra (2013)). We provide causal identification of the spillovers within the value chain at firm-level, and exploit the network links to identify the channels.

There is a broader literature studying the technology spillovers and diffusion from interactions among firms or households; many of the papers focus on on developing countries (Foster and Rosenzweig (1995), Munshi (2004), Bandiera and Rasul (2006), Kreindler and Young (2014), Conley and Udry (2010), Basker and Simcoe (2021))). Some of those emphasize the role of central nodes (see Banerjee et al. (2013), Cai et al. (2015), Phelps et al. (2012)), or the strength of the ties (Aral and Walker (2014)) or the links with sophisticated nodes (Bursztyn et al. (2014)). Our results on the relation between the strength of the spillovers and the centrality of the adopter speak to this literature.

9 Spence (1984), Rivera-Batiz and Romer (1991), Eaton and Kortum (1996), Coe et al. (1997), Coe et al. (2009) rely on country data.

2. A Model of Technology Spillovers, Diffusion and Rivalry in Networks

We devise a simple model for a firms' network with information spillovers, through learning, rivalry and an endogenous adoption decision to obtain testable predictions that we bring to the data. Firms in the network are uncertain about their productivity. Any firm, linked to firm i, that adopts a technology can transmit information, through which firm i can learn about its own productivity. By reducing uncertainty, or increasing forecast precision, this increases firms' expected sales, profits and labour demand. The information transmission between any firm i and j, linked by a trading relation, occurs only if one of the two adopts the technology, a robot in our data. The adoption event in the model allow us to mimic the conditions for the experimental setting that we have in the empirical analysis. Furthermore, all firms that also share customers interact also through strategic complementarities, through one of the market competition structure envisaged below: the technology adoption by a competitor in turn reduces firm i profits at time t, through customer stealing.

We model the learning process similarly to the work by Crawford and Shum (2005) and Allen et al. (2019) 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 both their own and other doctors' patients' recoveries. Crawford and Shum (2005) and Allen et al. (2019) devise specific parametric assumption and estimate their model structurally, as they are interested in quantifying the pace of the diffusion process. We are instead interested to gather causal evidence following a technology adoption event. Therefore, we devise the model non-parametrically while accommodating both complementarities in the technology and competition space, to obtain reduced form relations that we bring to the data through event analyses.

Preliminaries. There is a set $\mathcal{I} = \{1, ..., N\}$ of firms indexed by i, connected within a input-output network of suppliers and customers of intermediate inputs. Without loss of generality the network structure is fixed: trading links in value chains are typically long term relations, that are unlikely to change in the short to medium run (see Baker et al. (2002)).[10]

10 The model can be easily extended by assuming a random arrival of suppliers and customers to the firm.

The network has a bipartite lattice structure. The nodes connected to each firm i can be clustered in two main sets. The firms in both sets can be linked to firm i through a trading relation and when one of the two firms adopts a technology, it transmits information to the trading patterns. Those knowledge spillover entails positive complementarities as we explain below. The firms in the second set also happen to share a customer base with firm i. In this case when the trading partner adopts a technology it can steel customer base or engage in dumping practices that reduce firm i profits, thereby inducing negative complementarities.

Firms' Value Function and Choices. There is a set of technologies $Z_t = [z_1, ..., z_h]$ indexed by h, so that the element $z^i_{j,t}$ is technology h adopted by firm i at time t. The firm makes a discrete choice among the ones available, however the logistical process behind each of those is not fully know to the firm, which learns it over time. Given this, the firm chooses the technology to adopt, by solving the dynamic discrete choice problem, that we derive below, based on the conditional forecast of the expected value of the technology, conditional on the information set at time t. In each period t, each firm i produces using a concave production function $z^i_{h,t} f(k^i_t, \mathbf{x}^{ij}_t, n^i_t)$, where $z^i_{h,t}$ is firm productivity, k^i_t is firm capital, n^i_t is labour input and $\mathbf{x}^{ij}_t$ is the array of intermediate inputs the firm acquires from a node j in the production network. Under technology h firm i expected value function is given by:

$$V^i_{h,t}(z^i_{h,t}, k^i_{h,t}, \tau^i_t) = \mathrm{E}_t[z^i_{h,t} \mid \Omega^i_t] f(k^i_{h,t}, n^i_{h,t}, \mathbf{x}^{ij}_{h,t}) - r k^i_{h,t} - w_t n^i_{h,t} + \frac{1}{1+r}[V^i_{h,t+1}(z^i_{h,t+1}, k^i_{h,t+1}, \tau^i))] \tag{1}$$

where τ^i_t is the signal precision, used by the firm to forecast productivity, which we specify below and Ω^i_t is the information set at time t, or else the set of signals that the firm i receives from each trading partner in the value chain. The value function above is recursive as the signal precision is recursive under Bayesian learning. For simplicity, we assume that signal precision is common across technologies. Furthermore, note that we take the expectation of the productivity, as this is uncertain to the firm. However, once the Bayesian updating process is determined the future value function is on a deterministic path. Finally, the firm is price taker on the input markets, hence it takes the labour wage, w_t, and the cost of capital, r, as exogenous. The latter is also assumed to be fixed for simplicity.

Knowledge spillovers. The quality of the production process is not fully known to the

firm, which holds beliefs about the value of $z^i_{h,t}$ at t summarized by a normal distribution with mean $\overline{z}^i_{h,t}$ and variance $\sigma^{i2}_{h,t}$. One can think of productivity as a set of logistical decisions, which may come in different combination, which we index by h. The firm holds imprecise information about productivity, but can learn about it over time, by acquiring signals from its intermediate suppliers in the production network. Let τ^i_0 denote the precision level of firm i's prior beliefs, which is common across technologies. It follows that that the dispersion of the beliefs is $\sigma^{i2}_h = \frac{\sigma^2_{h,t}}{\tau^i_t}$, where the numerator is the fundamental variance of technology h. When precision is high, the variance of the technology is low.

In each period firm i acquires intermediates of value x^{ij}_t, from a set of suppliers j, and if the latter adopt a technology this brings about a signal about the quality of the technology s^{ij}_t on its productivity. To fix ideas, and likewise in our data, firm i may acquire a robot and this would come along with technical support that helps the firm to reduce the uncertainty of its productivity. Note that the signal is a vector with one element for each logistical process h. We assume that the signal is exogenous and is a function of the suppliers' proximity d^{ij}_t and its centrality ξ^j_t, and to the past forecast value of technology h adopted by the supplier j, $z^j_{h,t}$, hence: $s^{ij}_t = f(d^{ij}_t \xi^j_t, \overline{z}^i_{h,t})$. Intuitively the closer and more central is the supplier, the more likely it is to transmit information. The latter is also proportional to the extent of technology adoption of the supplier. The signal increases the precision of the posterior beliefs, but its contribution decays over time due to the arrival of new ideas. We can then write the law of motion for the precision process as follows: $\tau^i_t = \rho\tau^i_{t-1} + \sum_{j\in\mathcal{Z}_t} s^{ij}_t$, where $\delta \in [0,1]$ is the signal decay and $\mathcal{Z}_t$ is the set of trading partners that have adopted a technology. The value of the acquired intermediates captures the extent to which the signal contains useful information. Following Crawford and Shum (2005), we assume that this value of each signal, s^{ij}_t, also follows an independent normal distribution with mean $\overline{z}_h$ and variance σ^2_h. The mean value of the signals is then given by $\overline{v}^{ij}_{h,t} = \sum_{n=1}^{s^{ij}_t} \frac{v^{ij}_{h,t}}{s^{ij}_t} = \overline{z}_h + \epsilon^{ij}_{h,t}$, where $\epsilon^{ij}_{h,t}$ is distributed as $N(0, \frac{\sigma^2_h}{s^{ij}_t})$. Firm i updates its beliefs in each period t based on the signals. Firms i posterior

beliefs in period $t+1$ can then be expressed recursively as a sequence of normal distributions (e.g. De Groot 1970) with mean:

$$\overline{z}^i_{h,t+1}\tau^i_{t+1} = \delta\overline{z}^i_{h,t}\tau^i_t + \sum_{j\in\mathcal{Z}_t}(\overline{z}^i_t + \epsilon^{ij}_{h,t})s^{ij}_t \tag{2}$$

Furthermore, the variance of firm i posterior belief is: $\sigma^{i2}_{h,t+1} = \frac{\sigma^2_h}{\tau^i_{t+1}}$. Substituting the signals with its function of the supplier's proximity and centrality, and re-arranging, we obtain:

$$\overline{z}^i_{h,t+1}(d^{ij}_t, \xi^{ij}_t, z^j_t, \tau^i_t) = \frac{\delta\overline{z}^i_{h,t}\tau^i_t + \sum_{j\in\mathcal{Z}_t}(\overline{z}^i_t + \epsilon^{ij}_t)f(d^{ij}_t, \xi^{ij}_t, \overline{z}^j_{h,t})}{\tau^i_{t+1}} \tag{3}$$

The above equation quantifies the productivity spillover and allows us to derive the first set of testable implications. For the time being we abstract from the nodes in the competition space. Given 3, firms' expected revenues are $r^i(z^i_{h,t}, d^{ij}_t, \xi^{ij}_t, z^j_{h,t}, \tau^i_t) = \overline{z}^i_{h,t+1}(d^{ij}_t, \xi^{ij}_t, \overline{z}^i_{h,t}, \tau^i_t)f(k^i_t, \mathbf{x}^{ij}_t, n^i_t)$. Taking first order conditions of 1 with respect to labour demand, hence employment, leads to:

$$w_t = \frac{\overline{z}^i_{h,t+1}(d^{ij}_t, \xi^{ij}_t, z^j_t, \tau^i_t)f(k^i_t, \mathbf{x}^{ij}_t, n^i_t)}{n^i_t} \Leftrightarrow n^i_t = \frac{\overline{z}^i_{h,t+1}(d^{ij}_t, \xi^{ij}_t, z^j_t, \tau^i_t)f(k^i_t, \mathbf{x}^{ij}_t, n^i_t)}{w_t} \tag{4}$$

Note that under the learning process spelled out above revenues are log-supermodular with respect to the technology space, which implies in a continuum space: $\frac{\delta^2 r^i(.)}{\delta z^i_{h,t}\delta z^j_t} > 0$

Lemma 1. *Expected firm's productivity, sales, employment and wages increase when a supplier adopts a technology and transmits a signal. The spillover to the firm decays with the distance from the supplier and depends on its centrality.*

The lemma follows immediately from equation (3) and from the expressions for expected sales, employment and wages defined above. The lemma leads to our first testable prediction, which links firms' TFP, sales, wages and employment to the technology adoption of a supplier, which in the empirical specification we formalize with a dummy and whose impact we estimate through an event analysis. The impact of the suppliers' adoption decays with distance, but increases with the centrality of the adopter. To test this, the empirical

specification features interaction with proxies for distance from and centrality of the suppliers.

Competition Space. We now focus on the set of nodes with which the firm operates in the competition space, that is the set of nodes that also share a customer base with the firm. This leads to strategic complemetarities so that firms' sales become log-submodular with respect to the actions of other firms. We lay down the conditions for the sub-modularity in a general form, so as to accommodate different forms of market competition structures, such as monopolistic competition, Cournot or Bertrand. Generally speaking interacting in the competition space implies that firms' sale can be written as $\chi_t^i(\overline{a}_t)g(z_{h,t}^i f(k_t^i, \mathbf{x}_t^{ij}, n_t^i))$, where the firm marginal cost, χ_t^i, is the inverse of the mark-up, g is a homothetic transformation of f and $\overline{a}_t$ is the average or aggregate action of the other firms and it may encompass prices or quantities. In Appendix C.1 we provide a specific microfoundation for the case of oligopolistic competition with non-homothetic aggregators. This dependence creates the scope for strategic substitutes. If one or more of the competitors adopt first a technology that reduces their marginal costs, their prices will fall too and their market shares will rise, at the expenses of sales for the firm that did not adopt at time t. This implies that in the interaction with those nodes the revenues are log-submodular or else: $\frac{\delta^2 r^i(.)}{\delta z_{h,t}^i \delta z_t^j} > 0$. This leads to our next testable implications.

Lemma 2. *Firm i revenues, and hence wages and employment, decline at time t when a competitor adopts the technology.*

The lemma above implies that a specification for an event study linking sales, employment and wages to the first time adoption of a competitor may decline on impact. Of course the if the two firms are also linked through a supplier relation positive knowledge spillovers may arise. Hence, the overall impact on firm i revenues will depend on the balance between the two effects, and its sign is ultimately an empirical question.

Technology adoption. Given the above, the firm chooses one of the technology types, $\mathrm{H} = [1, ..., H]$, solving a dynamic discrete choice, in which the firm compares expected value functions under each technology and given a Gumbel shock $\gamma_{h,t}^i$. These shocks capture the relation or intrinsic values of those technologies. Let us define the optimal value function

$\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t}, \tau^i_t)$ to be the sum of future discounted profits, as a function of the optimal choice of capital, and for each technology h. This can be written recursively as:

$$\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t}, \tau^i_t) = \mathrm{E}_t[z^i_{h,t} \mid \Omega^i_t] f(k^{i,*}_{h,t}, n^{i,*}_{h,t}, \mathbf{x}^{ij,*}_{h,t}) + \gamma^i_{h,t} + \frac{1}{1+r}[\tilde{V}^i_{h,t+1}(z^i_{h,t+1}, k^i_{h,t+1}, \tau^i_t)] \quad (5)$$

where we have normalized the price of the good to one, and $\gamma^i_{h,t}$ are Gumbel shocks that are technology specific and have a logistic distribution. The optimization problem reads as follows:

$$h = \mathrm{argmax}_{[1,\ldots,H]}[\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t}, \tau^i_t) + \gamma^i_{h,t}] \quad (6)$$

Solving the optimization problem yields the following closed-form solution for the technology choice probabilities:

$$\theta^i_{h,t}(h|z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}) = \frac{\exp(\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}))}{\sum_h \exp(\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}))}. \quad (7)$$

Lemma 3. *The probabilities of adopting the technology follow a probit specification. They depend on firms' characteristics, such as their productivity and capital, and on the network structure through the signal spillovers received by the nodes.*

The proof of Lemma 3 is in Appendix C.1 and it provides a theoretical foundation to the probit specification, (**??**), that we use below to estimate the impact of a technology adoption event on the adoption probability of other firms.

Model-Data Experimental Setting. Our empirical setting has two reduced forms, one linking firms' performance measures to the event of a connected firm adopting and one based on a probit capturing the adoption probability. The event, upon which a new connected firms adopts, is captured in the model as an expansion in the set of connected adopters, $\mathbf{Z}_t$. Through the lens of the model, the latter in turn expands the set of signals, increasing the precision, as per $\tau^i_t = \rho\tau^i_{t-1} + \sum_{j\in\mathcal{Z}_t} s^{ij}_t$, and increasing the Bayesian forecast of the firm's productivity, as per equation 3. Equally so, it increases employment and wages as per equations 4. At last, it increases the probability of adopting technology h as per equation C.4.

Note that while the adoption of technology h by a trading partner j increases the forecast of $z^i_{h,t}$ for any i linked to j, it improves the signal precision for all equally.

3. Data and Aggregate Statistics

Our paper leverages a unique matched dataset for Turkey for the period 2007-2019, which includes data on firms' input-output linkages, obtained through VAT filings, employer-employee matched data and customs data. The data frequency is yearly. In this section, we describe the data and provide some summary statistics. Table 1 reports a brief description of all the data used and their sources. Appendix B provides further details on the dataset construction.

Value-added tax statements: The firm input-output network data are obtained from the value-added tax (VAT in short) statements, collected by the Ministry of Finance. Firms are required to report their domestic transactions to the Ministry, if the amount exceeds 5000 Turkish Liras, approximately equivalent to 155 U.S. Dollars. We focus on firms in manufacturing, selected using the 4-digit NACE Rev.2. classification, as they are the most intensive 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. The data have an extremely large coverage and the sample covers both large and small-medium size firms. The VAT statements provide information on the buyer, the seller, and the amount transacted, allowing us to track suppliers, customers and their role and position in the network. **Firm Registry:** The firm identifier in the input-output network allows us to

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

Table 1: Data Sources

Notes: This table presents the data sources used in this study. It includes employer-employee data aggregated for each firm, allowing for an analysis of wages and employee counts at the firm level.

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. We then aggregate the firms by region at the NUTS1 level. We use the information on the sectoral and geographical composition for controls and fixed effects.

Employer-Employee: The employer-employee matched dataset, maintained by the social security offices, allows us to track firm employees and their wages, which are then aggregated into firm-level measures. This dataset also enables us to gather additional firm performance metrics, such as wages and employment levels.

Customs: The customs dataset, available at the Ministry of Trade, provides information on firms' exports and imports, including the volumes and quantities of each product and the trading country. The products transacted are classified at the 6-digit Harmonized System (HS) level code.

Balance Sheet: To create measures of firm performance, we also match the data with information from the balance sheet. We estimate firm productivity with the methodology by Ackerberg et al. (2015). For that we use balance sheet information such as capital, stocks, sales and intermediate inputs.[11]

Category	Description
Domestic	Domestic Production: Robots produced locally by domestic manufacturers Intermediaries: Robots sourced from agents, distributors, or foreign affiliates
Imported	Customs Data HS-6 code: 847950 Country of origin

Table 2: Data Sources for Robot Adoption Measurement

Measuring Technology Adoption: We measure technology adoption with first-time robot acquisitions. For this we use the VAT dataset for domestic acquisition and the customs dataset for imported robots. In this case we also observe the country of origin. In the

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

customs data the robots are identified by examining the HS code: the six-digit HS code 847950 corresponds to industrial robots. We retrieve robot first-time adopters in the VAT dataset as follows. First, we select firms that are part of ENOSAD (Industrial Automation Manufacturers Association). Using their fiscal codes, we track those that purchase robots directly from domestic producers, through intermediaries like agents and distributors, or from foreign-affiliated companies operating domestically.[12]

Descriptive Statistics: Table 3 provides summary statistics on the number of suppliers, automated suppliers, and the share of suppliers, or else upstream firms, that adopted a robot one or more links away from each firm (indicated in Table 3 with the number situated next to the label "Upstream"). The network appears highly connected and fairly sparse, thereby excluding that results may be driven by specific large clusters.

	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 3: 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 is 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.

4. Econometric Design and Causal Identification

One challenge in identifying spillovers, or diffusion, within a firm network is given by the reflection problem, namely the difficulty to identify causal relation among a group of connected

12 We identify industrial robot transactions by setting a minimum value threshold of fifty thousand U.S. dollars, which aligns well with the typical industrial robot pricing and effectively filters out smaller, unrelated sales.

firms. We resolve it since we can observe first-time adopters and all firms connected to them through input-output relations. To rule out any possible selection effect, we also initialize our sample on all firms that never adopted robots before the start of our time period. From that time onward we measure the spillovers from a firm that adopts a robot for the first time, at any moment in our time sample, to other firms that are either, directly or indirectly (up to 4 nodes away), connected to the adopter. We focus on first time adoptions as those are more likely to be unrelated to other factors that may affect sample selection of the firms connected within the network. Spillovers are measured as the impact on any of the following outcome variables: firm productivity à la Ackerberg et al. (2015), wages, firm employment, or imports.[13] Diffusion is measured as the impact on the probability of adopting a robot. In sum, the treated group consists of 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:

$$y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t} \tag{8}$$

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 firm productivity, employment, wages, or imports. f_i denotes the firm fixed effects, and f_{st} represents the sector-year fixed effects (at the one-digit NACE Rev.2. level), and f_{rt} captures region fixed effects (at the NUTS-1 level). The variable $D_{i,j,t}$ is the dummy capturing the event that a firm i linked, either directly or indirectly, 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. The firm fixed effect controls 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.

The above specification amounts to a staggered event analysis with multiple events and multiple periods. As noted in Goodman-Bacon (2021) or Callaway and Sant'Anna (2021), firms that are treated at different times are unlikely to share the same pre-trend. This

13 Estimating firm productivity through the method by Ackerberg et al. (2015) has the advantage of using the cost of labor input to identify the production function, rather than the cost of capital, which may follow lumpy patterns and exhibit several zeros, especially in developing countries.

implies that the direct comparison of those cohorts of adopters 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), which 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 amounts to estimating the average treatment effect for the treated sub-population. We then estimate the event study coefficients for each cohort g of firms, and aggregate the results across cohorts, weighting the estimated coefficients by the size of each cohort. If N_g represents the number of firms in each cohort g, the average effect is given by $\beta_{i,t} = \frac{\sum_g N_g \cdot \beta_{i,t,g}}{N}$.

The Speed of Diffusion and the Channels. Given the baseline specification in (8),we then entertain several variants by changing the type of adopter and the type of adoption. These variants allow us to qualify the channels and to quantify the strength of the diffusion. As before, we have two groups of firms, treated and control, but we vary the treated group across specifications, as we explain next. In those cases, we also adjust the control group by selecting only firms that have never experienced the specified treatment.

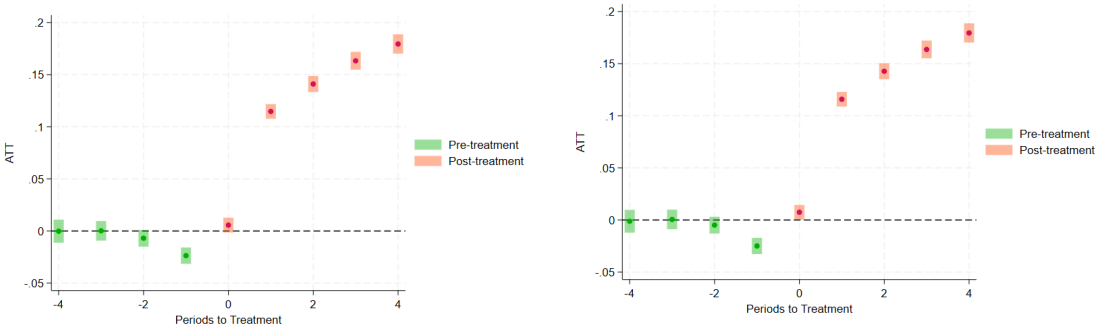
First, we measure the speed of diffusion as the impact, or the estimated coefficients, for some periods after the adoption. We further assess the pace of the diffusion within the network, by estimating the impact of the event on firms that are 2, 3 or 4 links away from the adopter. When we estimate the impact of adoption from a distant supplier, the specification controls for robot adoption by the direct supplier. We also assess the estimates based on the adopters' position and influence in the network. In this case, we triple interact the event dummy with the adopter centrality, or with the intensity of its network relations. Note that centrality is a much better proxy of exposure to knowledge spillovers than weighting factors within the network as the latter are indeed correlated with firms' size and other confounding factors.

Second, through further interaction dummies we identify the channels. Knowledge spillovers materialize when the adopter is a supplier, positive spillovers from innovation race materialize when the adopter is a customer that demands technologically advanced inputs, and negative spillovers from customer stealing materialize when the adopter is an horizontally connected

competitor. We provide further insights on the strength of the learning spillovers through interaction dummies that capture whether the robot was acquired through an agency providing technical support. Third, we distinguish spillovers induced by technological change from those arising from capital deepening, in order to estimate the impact of robots versus capital purchases. Lastly, we delve into the role of quality of the technology, by re-estimating our baseline specification for the set of adopters that buy domestic robots, relatively to those that buy imported robots, and from technologically advanced countries. We classify the latter based on the price of the robots, which we take as a proxy for quality.

5. Results: Technology Spillovers

We present our results progressively starting from the direct, and indirect, effects of an adoption event from a supplier onto customer firms' productivity and the other outcome variables. Next, we examine the results when the adopter is a competitor or a customer. Then, we distinguish the impact of technological change versus capital deepening. We conclude with the results on the quality of the robots.

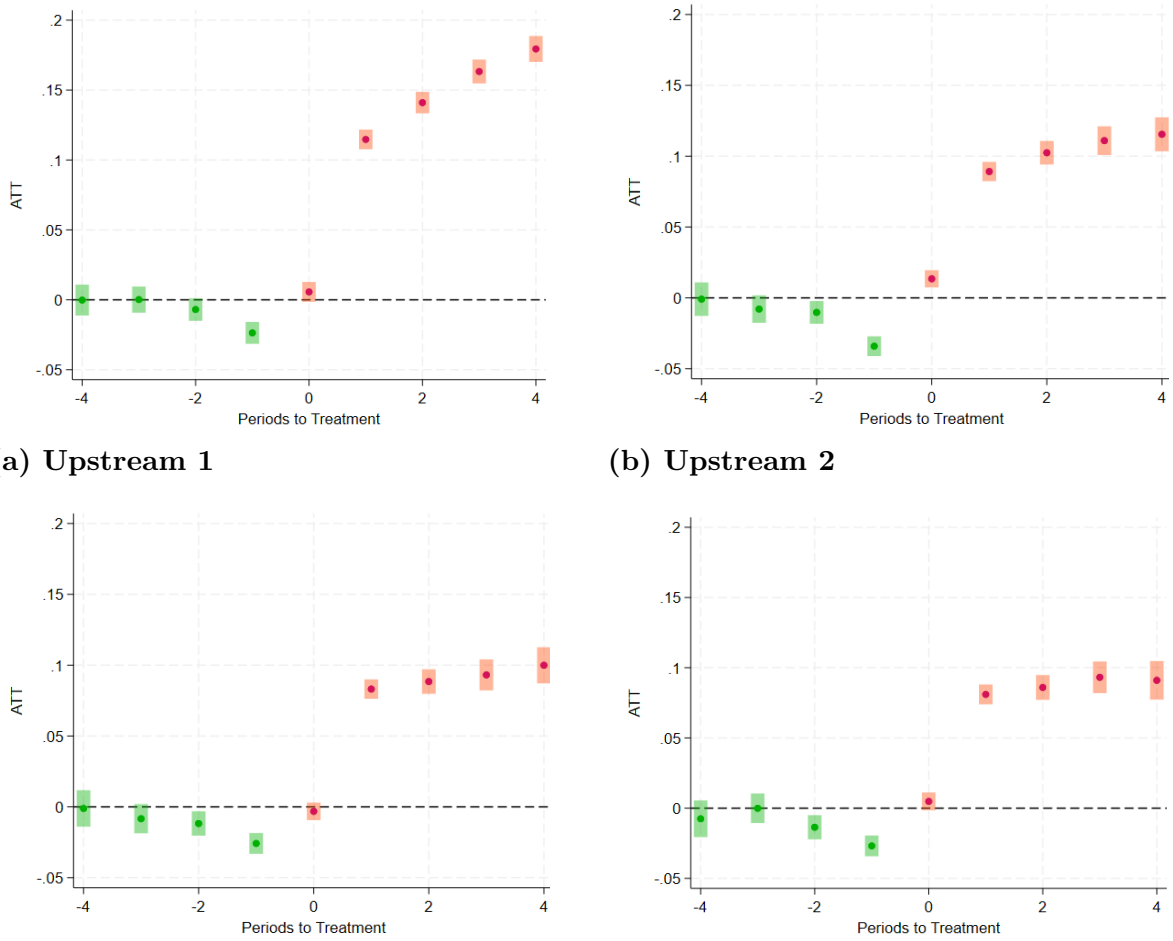


(a) Firm Productivity **(b) Weighted by Network Centrality**

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

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: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is productivity of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time. 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.

5.1. Direct and Indirect Spillovers on Firm Outcomes from Supplier Adoption



(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) and 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. The econometric specification reads as follows: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + Ups_{i,t} + \epsilon_{i,t}$, where $y_{t,i}$ are employment, wages, import or gender ratio of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ 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.

Figure 1 plots the average treatment effect on firm productivity of the event that a directly linked supplier adopts the robot for the first time, and with a four years window around the event. To appreciate the magnitudes of the spillovers, and how they decay over time, Table 4 reports the estimated coefficients and their significance. Table 16 in Appendix A.2 repeats the same estimates but using firm TFP estimates based on Levinsohn and Petrin (2003): results are similar. The rows show the coefficient over time and the columns show

the coefficient for directly linked adopters and for those 2, 3 and 4 links away. Furthermore, Figure 2 presents the event study for the adoption of indirectly connected firms, which are positioned 2, 3 or 4 links away.

	Upstream 1	Upstream 2	Upstream 3	Upstream 4
Four years before event	-0.000	-0.001	-0.001	-0.008
	(-0.03)	(-0.15)	(-0.17	(-1.14)
Three years before event	0.000	-0.008	-0.008	-0.000
	(0.03)	(-1.60)	(-1.59)	(-0.01)
Two years before event	-0.007	-0.010*	-0.012**	-0.014**
	(-1.69)	(-2.51)	(-2.67)	(-3.10)
One year before event	-0.024***	-0.034***	-0.026***	-0.027***
	(-5.93)	(-9.61)	(-6.89)	(-7.12)
Adoption Supplier	0.006	0.014***	-0.003	0.005
	(1.56)	(4.34)	(-1.00)	(1.49)
One year after event	0.115***	0.089***	0.083***	0.081***
	(31.97)	(25.69)	(23.78)	(22.48)
Two years after event	0.141***	0.102***	0.089***	0.086***
	(36.01)	(24.14)	(20.02)	(19.06)
Three years after event	0.163***	0.111***	0.093***	0.093***
	(37.41)	(21.47)	(16.69)	(16.22)
Four years after event	0.179***	0.115***	0.099***	0.091***
	(38.05)	(18.91)	(15.36)	(12.96)
Obs	1,322,011	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 4: 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, and region-year fixed effects at the NUTS1 level. The event is the suppliers robot acquisition depending on the distance of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

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. Recall that the average effects are obtained through the Callaway and Sant'Anna (2021), which is intended to control for pre-trends. Following the event, there is a significant increase in productivity: the magnitudes are economically meaningful, as the standardized coefficients,

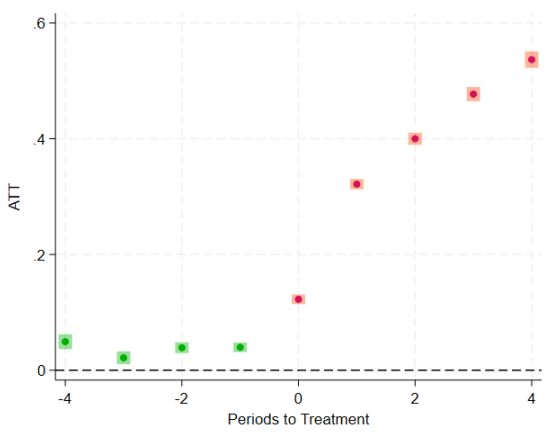
reported in Table 4, imply that, on impact, the spillovers from direct suppliers amount to an increase in firm productivity of 11%. Spillovers are positive and significant also four periods after the event, and for firms that are up to four links away from the adopter. Once again magnitudes are meaningful. For instance, four years after the event there is an 18% increase in productivity. More interestingly, the spillovers accumulate over time and are very persistent even with some distance from the adopter. This is in line with previous studies that uncover amplification of shocks through the network (see Acemoglu et al. (2012)).

Network Centrality. Next, we are interested in assessing whether the position and influence of the adopter in the network affect the strength of the spillovers. For each year, we compute the weighted outdegree centrality measure for each supplier.[14] We then interact the centrality measure with the adoption dummy. The treatment group in this case is given by the firms linked to an adopting supplier and the exposure to the treatment is given by the supplier centrality in the network. Figure 1 presents the event study by weighting the adoption dummy by the centrality of the supplier. Results show that spillovers are somewhat stronger when suppliers centrality increases.

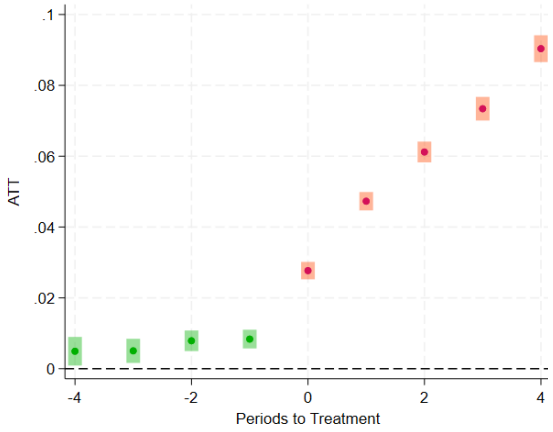
5.2. Other Performance Measures

For a comprehensive assessment of adoption on growth it is useful to examine also its impact on other performance measures. Figure 3 presents the same type of event study analysis with multiple cohorts of adopters to assess the impact on employment, wages, import and the gender employment ratio. We use the gender ratio as a measure of development, as the latter may be associated with female labor force participation. Standardized coefficient estimates are presented in Tables 12 to 15 in Appendix A.1 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 impact of knowledge spillovers on growth, 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.

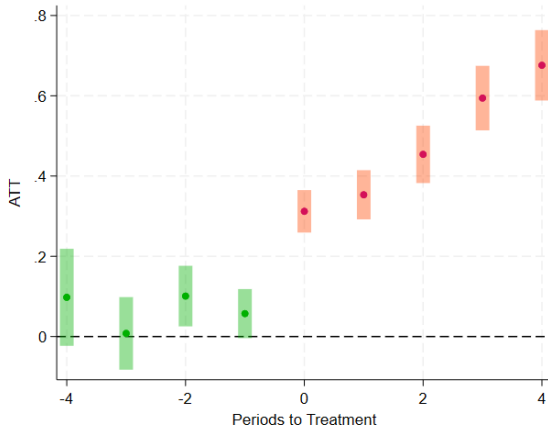
14 Weights are the B2B transactions across firms.



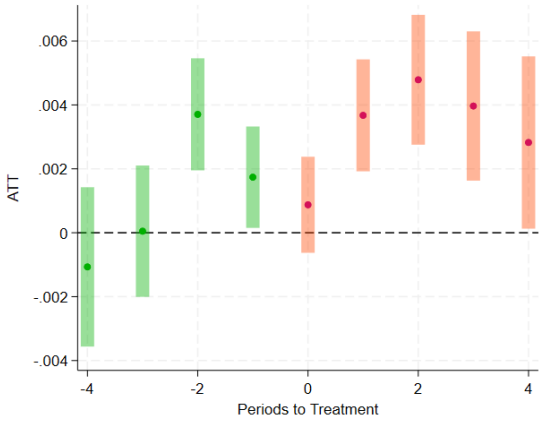
(a) Employment



(b) Average Wage



(c) Imports



(d) Female-Male Ratio

Figure 3: Event Study, First Time Adoption 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: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ are employment, wages, import or gender ratio of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.

Wages, imports and employment increase significantly after the event. The magnitudes are economically meaningful. We observe for instance a 6% increase in employment. Results are solid, since the plots show no significant pre-trends (see also Tables 14 and 15 in Appendix A.1). Spillover to wages occur through rent sharing, and those to employment and other demand components occur through demand externalities. In sum, knowledge spillover have a significant impact on the whole economy, and as such they can significantly boost growth.

5.3. 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. Past literature has also examined the role of technological change versus capital deepening for growth (see Kumar and Russell (2002)). We therefore re-assess this question and re-estimate our baseline specification for the case in which the first time adopter purchases tangible capital.

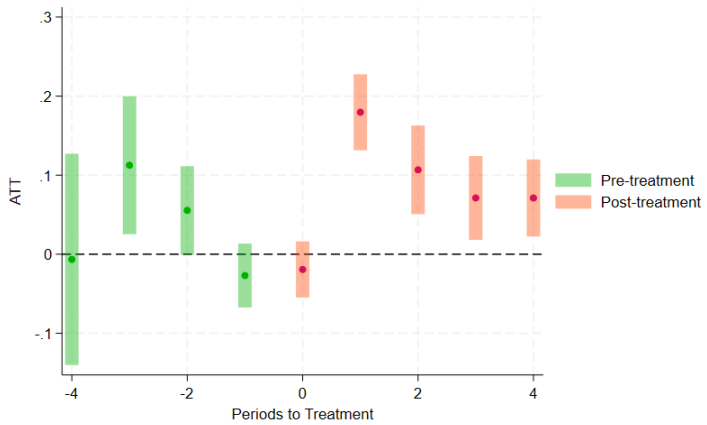


Figure 4: Event study of a first time capital deepening by the supplier

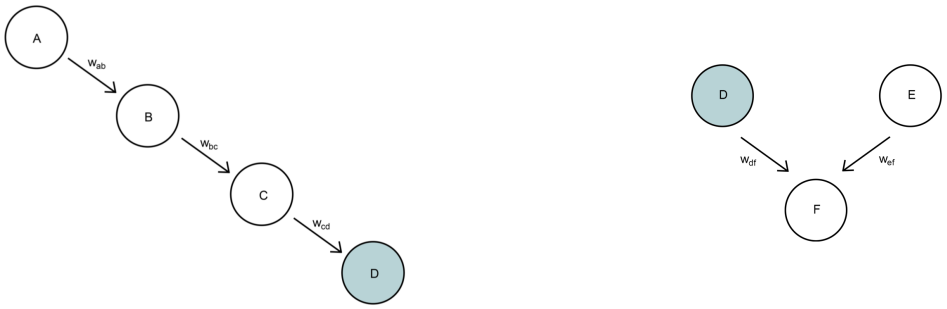
Notes: The figure plots the estimated average treatment effect of the event study with multiple periods Callaway and Sant'Anna (2021) with a four year window. The event is defined as the first-time capital deepening by the supplier. Econometric specification is: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is productivity of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ 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.

Figure 4 reports the results for the impact of the capital acquisition on the productivity of the firms linked to the adopter. The acquisition of tangible capital too leads to some increase in firms' productivity, but the effects are much smaller. The productivity of directly connected firms increases by 7.1%. Additionally, the spillovers on firms that 2, 3 or 4 links away from the adopter are insignificant.

Note that pre-trends are still insignificant here, a fact that reassuringly confirms the robustness of our econometric design. In sum, robot adoption has distinct and more potent effects than classical capital deepening.

5.4. Horizontal Spillovers through Rivalry

A key challenge in identifying the technological spillovers across firms is to disentangle them from other forms of complementarities. Countervailing complementarities may indeed produce opposing effects. While learning and knowledge spillovers may have positive effects on firms' productivity, market competition may have ambiguous effects. On the one side, a competitor adopting a technology first may steal customers, and reduce firms' revenues. This, in turn, may have adverse effects on productivity and other performance variables through rent sharing and demand externalities. On other side, previous literature (Eaton and Kortum



(a) Vertical Diffusion **(b) Vertical Diffusion**

Notes: **Figure 5**. 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.

(2001) or Akcigit et al. (2018)) noted that rivalry may result in positive spillovers to the extent that it forces the firm, competing with the adopter, to improve its performance, in order to escape competition. Therefore, whether spillovers from a competitor are positive or negative is ultimately an empirical question.

Previous literature has addressed this identification problem by instrumenting the two opposing complementarities through measures of firm exposure in both the technological and the market space (see Jaffe (1986) or more recently Bloom et al. (2013)). Our VAT dataset provides information on whether the adopter is linked to the firms through vertical relations, supplier or customer, or through horizontal ones. In the second case the dataset also provides information on whether the adopter shares a customer base with the firm, and hence is a competitor. We exploit this information for a novel identification strategy that does not rely on instrumental variables. Specifically, we estimate our baseline specification

for the case in which the adopter shares the same customer base. From the point of view of the input-output network, we can represent the difference between the vertical diffusion, considered earlier, and the horizontal diffusion, considered now, through the example depicted in Figure 5. If the adoption event allowed the rival to steal customers, we expect the effect on firms' performance measures to be negative on impact. This does not exclude that peer pressure to compete and innovate may set in over time.

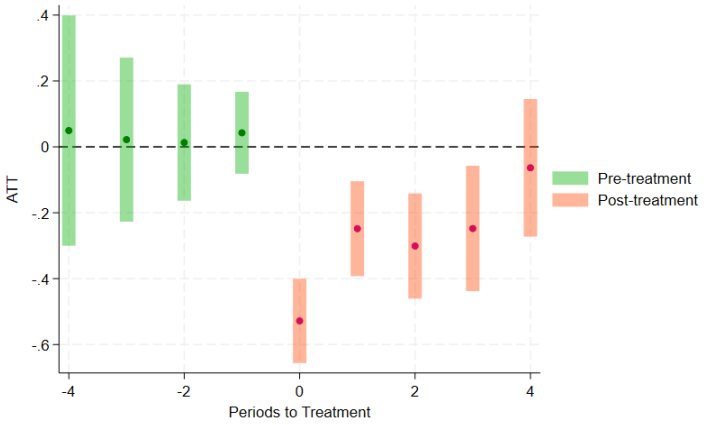


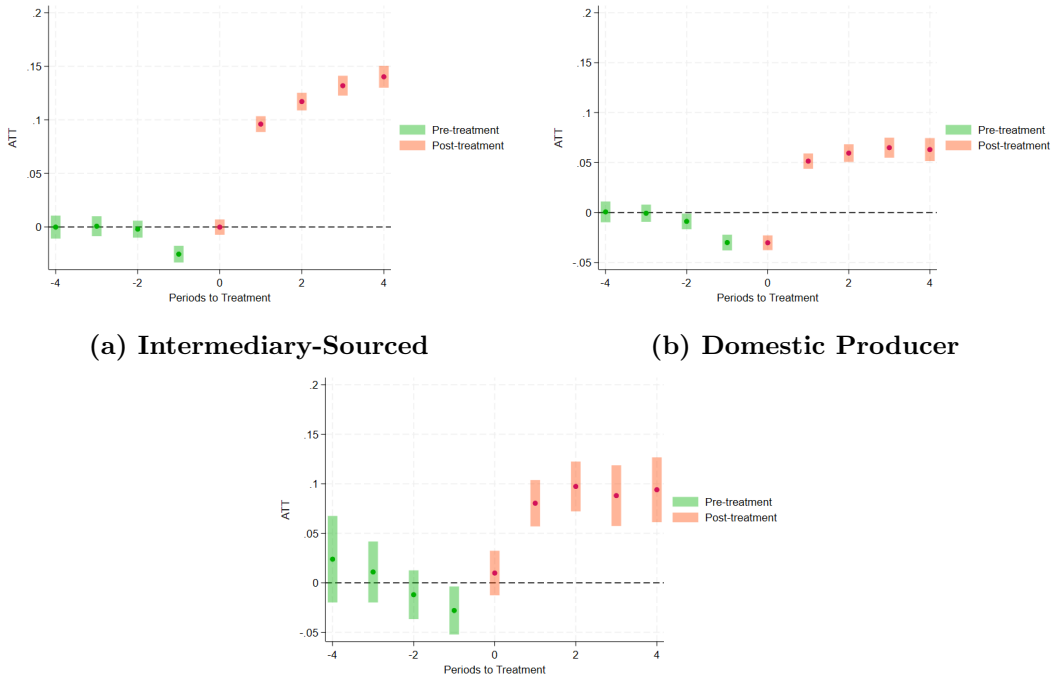
Figure 6: Horizontal Diffusion

Notes: The figure plots the event study of first time robot adoption of the supplier that shares the same customer portfolio. Impact on firm productivity. 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: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \lambda_{ht} + \epsilon_{i,t}$, where $y_{t,i}$ is productivity of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ 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.

Results of the specification in which the adopter is a competitor are shown in Figure 6. In this case spillovers are negative, significant and sizable. Following the adoption event by a direct competitor, firms experience a 52 % decrease in their productivity, 30 % decrease after 2 years, 24 % decrease after 3 year. The measures rebound in the four years following the event, and this may be due to peer pressure forcing the firm to improve its performance. A strong aspect of our design is that the event study shows no pre-trend and a sharp decline on impact, a clear sign that the event was not anticipated, but truly unexpected. It is indeed very plausible that rivals, adopting new technologies, do so by hiding it to potential competitors until the time of the implementation.

5.5. Quality of Robots and Technological Support

The role of improvement in the quality of traded products for growth has been recognized in Grossman and Helpman (1991a) or Grossman and Helpman (1991b). Much less is known on the role of quality for technological change, and its impact on growth. Higher quality robots may boost firm productivity much more. The quality of robots is likely to differ between locally produced robots and those produced in more technologically advanced countries. We therefore exploit the information available in our dataset to distinguish robot acquisition by country of origin.



(a) Intermediary-Sourced **(b) Domestic Producer**

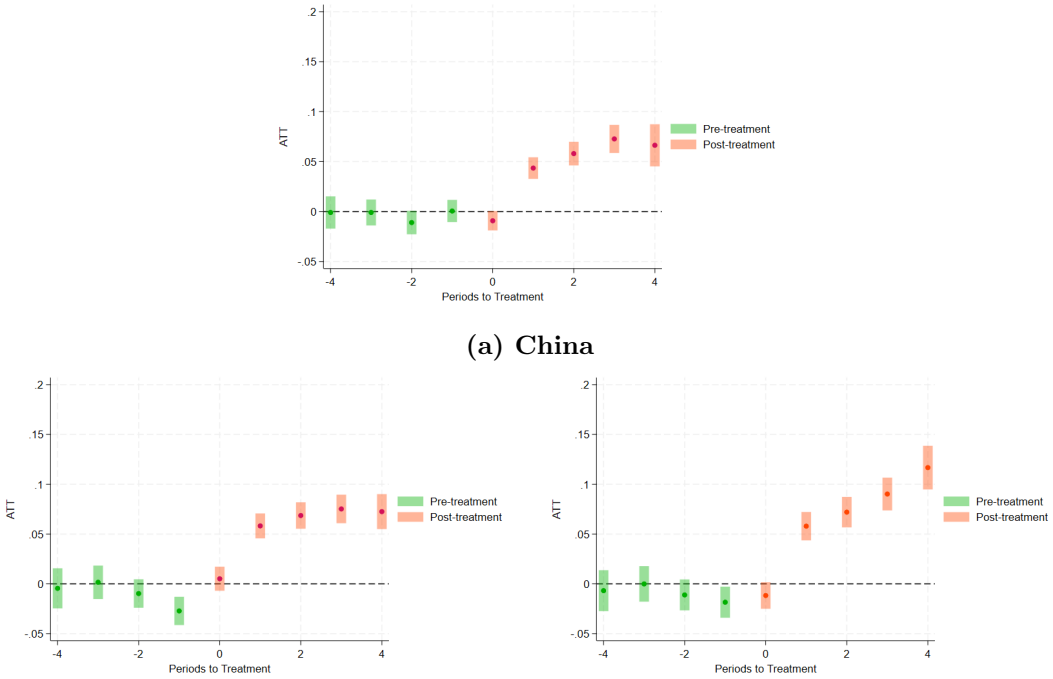
(c) Imported Robot

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: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is the productivity of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.

First, we repeat our event study analysis by distinguishing robots that have been produced locally or imported. Among the latter, we distinguish those imported by more technological advanced countries. To obtain such a country classification, we use robot prices, a variable also available in our datasets, as a proxy for quality. Figure 10 in Appendix C shows

that robots produced in Switzerland and Germany have on average higher prices than those produced in China. We then re-estimate our baseline specification alternatively for domestically produced robots and imported ones, also distinguishing the country of origin. We expect the spillovers from higher quality robots, hence those produced in Switzerland and Germany, to be stronger. To further assess the strength of the knowledge spillovers, we also distinguish between robot acquisition directly from the adopter or from intermediaries that provide also technical support.[15] Presumably, the latter may facilitate knowledge spillovers. We therefore re-estimate our baseline specification for the case in which robot acquisition is intermediated.[16]



(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: $y_{t,i} = \alpha + f_i + f_{st} + f_{rt} + \beta_{i,t} D_{i,j,t} + \epsilon_{i,t}$, where $y_{t,i}$ is the productivity of firm i linked to an adopter j, f_i is the firm fixed effect, f_{st} is the industry-year fixed effect and f_{rt} is the region-year fixed effect, $D_{i,j,t}$ is the dummy capturing the event that a firm j linked to firm i adopts the robot for the first time.

15 These intermediary-sourced robots can be purchased from agents, brokers, or distributors of firms that do not produce their robots in Turkey.

16 As noted before, when we estimate the impact of each of the options, we control for the remaining cases.

	Intermediary	Domestic	Imports
Four years before the event	-0.000	0.001	0.024
	(-0.02)	(0.12)	(1.07)
Three years before event	0.001	-0.001	0.011
	(0.16)	(-0.16)	(0.70)
Two years before event	-0.002	-0.009*	-0.012
	(-0.50)	(-2.23)	(-0.96)
One year before event	-0.025***	-0.030***	-0.028*
	(-6.38)	(-7.49)	(-2.26)
Adoption Supplier	-0.009	0.005	-0.012
	(-0.03)	(1.06)	(-0.86)
One year after event	0.096***	0.051***	0.080***
	(25.52)	(13.14)	(6.73)
Two years after event	0.117***	0.059***	0.097***
	(27.94)	(13.20)	(7.58)
Three years after event	0.132***	0.065***	0.088***
	(27.93)	(12.68)	(5.62)
Four years after event	0.140***	0.063***	0.094***
	(26.91)	(10.74)	(5.63)
Observations	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes

Table 5: Domestic 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, and region-year fixed effects at the NUTS1 level. The event is the suppliers robot acquisition depending on the robot acquisition of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

Results for the event study distinguishing between locally produced, imported robots and those purchased through an intermediary, are shown in Figure 7. The coefficient estimates, also over time, are reported in Table 5. First, once again the adoption event has significant long-lasting positive spillovers. Second, the spillovers are larger for imported robots, particularly for those acquired through intermediaries, thereby confirming that quality matters. Intermediated robot acquisitions lead, four years after the adoption, to a 14.0 % increase in firm productivity, while directly imported robots lead to a 9.3 % increase, and locally produced ones to a more modest 6.3 % rise.

	China	Germany	Switzerland
Four years before event	-0.001	-0.005	-0.001
	(-0.12)	(-0.44)	(-0.65)
Three years before event	-0.001	0.002	-0.000
	(-0.14)	(0.18)	(-0.01)
Two years before event	-0.011	-0.009	-0.011
	(-1.84)	(-1.33)	(-1.40)
One year before event	0.001	-0.027***	-0.018*
	(0.10)	(-3.75)	(-2.32)
Adoption Supplier	-0.009	0.005	-0.012
	(-1.86)	(0.83)	(-1.72)
One year after event	0.044***	0.058***	0.058***
	(7.88)	(9.12)	(7.97)
Two years after event	0.058***	0.069***	0.072***
	(9.60)	(10.13)	(9.22)
Three years after event	0.073***	0.075***	0.090***
	(10.12)	(10.28)	(10.74)
Four years after event	0.066***	0.073***	0.117***
	(6.16)	(8.11)	(10.43)
Obs.	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes

Table 6: 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. TThe estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level, and region-year fixed effects at the NUTS1 level. The event is the suppliers robot acquisition depending on the robot acquisition of the supplier. t-statistics are reported in parenthesis. $^{*}p < 0.05$,** $p < 0.01$,*** $p < 0.001$.

Lastly, figure 8 shows the results when robots are distinguished based on their country of origin. 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 6.6%, 7.3% and 11.7% respectively for Chinese, German and Swiss robots four years after acquisition from the supplier. In sum, quality matters.

6. Technology Diffusion

Growth is fostered by technology spillovers, but even more so by diffusion, which we measure through the impact of the adoption event on the likelihood that a firm adopts the new technology itself. To this purpose, we estimate a probit specification linking the probability that a firm adopts an industrial robot to the event that firms, linked to it through the supply chain, have adopted the technology. As before, we first lay now the baseline specification, and then entertain some variants in which we change the set of treated firms, or else the treatments. We will describe this in more detail for each of the ensuing experiments. The baseline specification also includes some controls for firms' characteristics. This is so since technology adoption is a decision, which is likely to involve other firms' characteristics. However, our goal is to measure only the extent of diffusion, that is, the impact that the technology adoption by connected firms alters the adoption probabilities of the treated firms. The baseline econometric specification reads as follows:

$$P(Adoption_{i,t} = 1) = \Phi\Big(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i\Big) \tag{9}$$

where $X_{i,t}$ is firms' characteristics which include firm TFPR, number of employees and capital, as well as te number of suppliers, a proxy for how connected is the firm. The index $j = supplier, customer, competitor$, m is the number of nodes in distance from the adopter, the index t is the year, and α_i is a firm-specific random effect. The dependent variable $Adoption_{i,t}$ 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. The specifications below distinguish whether robots are adopted by suppliers, central suppliers or customers. The exact variable is indicated in the labels of the first column in each of the following tables.

	Prob(Adoption(i,t))		
$TFP_{i,t-1}$	0.068***	0.055***	0.032**
	(6.06)	(4.64)	(2.67)
$NoSuppliers_{i,t-1}$	0.002***	0.001***	0.000***
	(38.99)	(29.61)	(6.78)
$Adoption_{Supplier,1,t-1}$		0.749***	0.534***
		(37.99)	(26.32)
$Capital_{i,t-1}$			0.034***
			(7.38)
$NoEmployees_{i,t-1}$			0.144***
			(21.15)
Obs.	1,047,727	1,047,727	1,047,727

Table 7: Probit Regression: Baseline

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ includes firm variables such as capital, number of employees, number of suppliers and TFP, $Adoption_{j,m,t-1}$ is an indicator for whether any of the firm's suppliers acquired a robot.

	Prob(Adoption(i,t))				
$TFP_{i,t-1}$	0.055***	0.079***	0.079***	0.078***	0.057***
	(4.64)	(6.61)	(6.71)	(6.61)	(4.73)
$NoSuppliers_{i,t-1}$	0.001***	0.002***	0.002***	0.002***	0.001***
	(29.61)	(34.47)	(35.23)	(35.64)	(28.59)
$Adoption_{Supplier,1,t-1}$	0.749***				0.659***
	(37.99)				(29.20)
$Adoption_{Supplier,2,t-1}$		0.522***			0.183***
		(25.66)			(7.37)
$Adoption_{Supplier,3,t-1}$			0.445***		0.045
			(22.44)		(1.82)
$Adoption_{Supplier,4,t-1}$				0.398***	-0.023
				(20.42)	(-0.93)
Obs.	1,047,727	1,047,727	1,047,727	1,047,727	1,047,727

Table 8: Probit Regression: Indirect Suppliers

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ are firm variables such as the firm TFPR and number of suppliers. $Adoption_{j,m,t-1}$ is the previous period adoption event of a supplier directly or indirectly connected.

In the baseline specification, previous period adopters in the networks refer to suppliers.

Table 7 presents the results for each of the three adopter. Both firms characteristics and technology adoption by suppliers, significantly increase the probability of adopting a robot. The coefficient on the dummy for the suppliers' adoption is the largest. Moreover, the positive coefficient on the firms' characteristics indicate that more productive and larger firms are more likely to adopt the technology.

Speed of Diffusion and Influence of the Network. Next, we test the diffusion through the network by estimating 9 when the adopters are suppliers are distant 1, 2, 3, or 4 links. Table 8 reports the results. Diffusion, contrary to the spillovers, dissipates rapidly, becoming insignificant with the first indirectly linked adopter.

Capital Deepening. As before, we are interested in assessing the distinct impact of technology adoption from capital deepening. We do so by extending the probit model to include the variables capturing the acquisition of tangible capital from adopters located 2, 3 or 4 links upstream. Table 9 reports the results. Once again capital deepening has minimal, or even slightly negative effects.

	Prob(Adoption(i,t))				
$TFPR_{i,t-1}$	0.067***	0.067***	0.066***	0.067***	0.066***
	(5.94)	(5.92)	(5.90)	(5.92)	(5.90)
$NoSuppliers_{i,t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***
	(38.92)	(38.93)	(38.94)	(38.93)	(38.92)
$CapitalDeepening_{Supplier,1,t-1}$	-0.035				0.021
	(-1.41)				(0.43)
$CapitalDeepening_{Supplier,2,t-1}$		-0.042			-0.009
		(-1.68)			(-0.18)
$CapitalDeepening_{Supplier,3,t-1}$			-0.049*		-0.049
			(-1.98)		(-0.98)
$CapitalDeepening_{Supplier,4,t-1}$				-0.042	-0.012
				(-1.70)	(-0.24)
Obs.	1,047,727	1,047,727	1,047,727	1,047,727	1,047,727

Table 9: Probit Regression: Capital Deepening

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ are firm variables such as the firm TFPR and number of suppliers. $Adoption_{j,m,t-1}$ includes the number of suppliers and the event a previous period tangible capital acquisition by a directly or indirectly connected supplier.

Adopter's Centrality. The centrality of the adopter in the network may also influence

the probability that the firm adopts a robot. We therefore extend the probit specification in 9 by interacting the adoption event with the weighted out-degree centrality, where the weights correspond to the transaction amount reported in VAT filings. Results are shown in Table 10, which compares the results for the baseline regression in the first column with those of the interacted regression in the second and third columns. As expected, the centrality of the adopter tends to increase the impact of the adoption event on the diffusion.

	Prob(Adoption(i,t))		
$TFPR_{i,t-1}$	0.055***	0.054***	0.054***
	(4.64)	(4.50)	(4.50)
$NoSuppliers_{i,t-1}$	0.001***	0.001***	0.001***
	(29.61)	(29.15)	(29.15)
$Adoption_{Supplier,1,t-1}$	0.749***		0.037
	(37.99)		(0.31)
$Adoption_{Supplier,Central,t-1}$		0.756***	0.720***
		(38.67)	(6.11)
Obs.	1,047,727	1,043,472	1,043,472

Table 10: Probit Regression: Network Centrality

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ are firm variables such as the firm TFPR and number of suppliers. $Adoption_{j,m,t-1}$ includes the number of suppliers and the event that a supplier acquired a robot, interacted by the weighted out-degree centrality of the supplier in the network.

Innovation Race among Competitors and with Customers. Innovation races are likely activated in two cases. First, if a competitor adopts a new technology, the first impact effect may be the decline in revenues and productivity, as documented above. However, over time technology adoption by a competitor may incentivize firms to adopt themselves due to arms races. Columns 5 and 6 of Table 11 show that the adoption event by a competitor, or else a firm sharing the same customer base, increases the probability of adopting the technology by about 50%. For robustness appendix A.3 presents in table 17 a similar regression, but with different combinations of regressors: results are very similar.

A second instance in which innovation races may be activated is when a customer adopts an advanced technology: its suppliers are then compelled to maintain the relation. We test whether this is the case by extending the probit model to include a variable that captures

whether customers (or else downstream firms) have adopted a technology, as well as the firms' customer base. Table 11 presents the results. The coefficient of interest, namely the impact of robot adoption by customers, is positive, large and significant, confirming the positive spillovers from an innovation race.

	Prob(Adoption(i,t))				
$TFPR_{i,t-1}$	0.055***	0.032**	0.048***	0.038**	0.018
	(4.64)	(2.66)	(4.28)	(3.17)	(1.49)
$NoSuppliers_{i,t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***
	(29.61)	(26.16)	(24.21)	(20.74)	(17.57)
$Adoption_{Supplier,1,t-1}$	0.749***	0.581***		0.654***	0.505***
	(37.99)	(27.95)		(33.62)	(24.12)
$Adoption_{Customer,1,t-1}$		0.376***			0.343***
		(20.72)			(18.82)
$Adoption_{Competitor,1,t-1}$			0.670***	0.533***	0.510***
			(45.36)	(35.81)	(33.93)
Obs	1,047,727	1,047,727	1,047,727	1,047,727	1,047,727

Table 11: Probit Regression: Network

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ are firm variables such as the firm TFPR and number of suppliers. $Adoption_{i,m,t-1}$ is the previous period adoption event by either a supplier or a customer or a competitor, or else a firm sharing a customer base.

7. Conclusion

We have studied how the adoption of a new technology by a firm affects its network of suppliers, customers and competitors, distinguishing between spillovers and diffusion. The latter refers to their probability of adopting the technology themselves; the former to changes in their performance that are independent of them actually adopting the technology.

Technology spillovers and diffusion are crucial for long-run growth, yet their identification is challenging due to the reflection problem. We have provided a novel identification through a within firm-to-firm network strategy measuring the responses of firms linked to a first-time robot adopter relative to the rest through a staggered event analysis.

Due to a unique match with employer-employee and customs data, we have been able

measure spillovers on several firm outcomes. Spillovers on productivity, employment, wages and imports are sizable, accumulate over time, persist over some distance from the adopter within the network, and are magnified by the adopter's centrality. The same applies to the probability that firms in the network also adopt when one of them does. In contrast, we detect minimal spillovers from capital deepening.

Spillovers are positive from suppliers, negative from competitors, and positive from customers. Quality matters as positive spillovers are stronger when the robot is imported from a technologically advanced country, and when it is acquired from an agency (intermediary or foreign affiliate of a multinational producer) that also provides technical support.

We have rationalized these findings in terms of learning from suppliers, market stealing by competitors and incentives to innovate from customers through the lens of a dynamic discrete choice model of technology adoption in a network with uncertainty and learning from peers that provides theoretical support to our main econometric specifications.

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A. Other regressions and Robustness Checks

A.1. Direct and Indirect Effects: 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	1,322,011	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 12: 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, and region-year fixed effects at the NUTS1 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	1,322,011	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 13: 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, and region-year fixed effects at the NUTS1 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	1,322,011	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 14: 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, and region-year fixed effects at the NUTS1 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	1,322,011	1,322,011	1,322,011	1,322,011
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 15: 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, and region-year fixed effects at the NUTS1 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.2. Alternative Productivity Measures

	Upstream 1	Upstream 2	Upstream 3	Upstream 4
Four years before the event	-0.002	0.001	0.003	-0.035*
	(-0.25)	(0.13)	(0.57)	(-2.38)
Three years before the event	-0.005	-0.006	-0.009*	-0.008
	(-0.80)	(-0.98)	(-2.10)	(-0.89)
Two years before the event	-0.002	-0.010*	-0.000	0.001
	(-0.29)	(-2.08)	(-0.09)	(0.08)
One year before the event	-0.006	-0.005	-0.016***	0.000
	(-1.22)	(-1.10)	(-4.43)	(0.07)
Year of the event	0.015***	-0.006	-0.007*	-0.017***
	(3.49)	(-1.51)	(-2.11)	(-3.44)
One year after the event	0.087***	0.047***	0.042***	0.034***
	(15.91)	(8.37)	(9.45)	(4.93)
Two years after the event	0.129***	0.086***	0.076***	0.062***
	(18.32)	(12.44)	(13.60)	(7.00)
Three years after the event	0.164***	0.114***	0.098***	0.083***
	(20.69)	(13.99)	(13.68)	(7.65)
Four years after the event	0.202***	0.150***	0.138***	0.113***
	(22.89)	(16.31)	(15.67)	(9.19)
Observations	1,335,098	1,335,098	1,335,098	1,335,098
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes

Table 16: Spillovers on Productivity: Levinsohn-Petrin

Notes: The table reports aggregated treatment effect parameters on the productivity based on levinsohn and petrin approach, with clustering at the firm-level. The estimation incorporates fixed effects for sector-year, categorized at the one-digit industry level, and region-year fixed effects at the NUTS1 level. The event is the suppliers' robot acquisition depending on the distance of the supplier. t-statistics are reported in parentheses. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

A.3. Other Probit Regressions

	Probability of Adoption				
$TFPR_{i,t-1}$	0.055***	0.032**	0.048***	0.038**	0.018
	(4.64)	(2.66)	(4.28)	(3.17)	(1.49)
$No.Suppliers_{i,t-1}$	0.001***	0.001***	0.001***	0.001***	0.001***
	(29.61)	(26.16)	(24.21)	(20.74)	(17.57)
$AdoptionSupplier_{i,t-1}$	0.749***	0.581***		0.654***	0.505***
	(37.99)	(27.95)		(33.62)	(24.12)
$AdoptionCustomer_{i,t-1}$		0.376***			0.343***
		(20.72)			(18.82)
$AdoptionCompetitor_{t-1}$			0.670***	0.533***	0.510***
			(45.36)	(35.81)	(33.93)
Obs.	1,047,727	1,047,727	1,047,727	1,047,727	1,047,727
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 17: Probit Regression: Network

Notes: The table shows the results of the following probit regression: $P(Adoption_{i,t} = 1) = \Phi(\beta_0 + \beta_1 X_{i,t-1} + \beta_2 Adoption_{j,m,t-1} + \alpha_i)$, $X_{i,t-1}$ are firm variables such as the firm TFPR and number of suppliers. $Adoption_{i,m,t-1}$ is the previous period adoption event by a supplier, a customer or a competitor. The variable competitor refers to robot acquisition in a rival firm that is connected horizontally.

B. Data Construction

This section outlines the steps taken to construct the dataset used in this study. The dataset combines a variety of sources, including firm-to-firm transactions, administrative records, employer-employee data, customs data, and a list of local robot producers. All data used in this study obtained from Turkey's Ministry of Industry and Technology and accessed directly on-site.

Step 1. Firm-Level Setup: This paper combines various firm-level datasets from 2007 to 2019, starting with the firm registry data. This administrative firm data categorizes sectors according to the four-digit NACE Rev.2 classification, consistent with European Union sector identifiers.

This dataset enables the use of industry-year fixed effects in the regressions. Additionally,

the firm registry data includes each firm's location, allowing us to identify regions based on NUTS1 definitions and construct region-year fixed effects accordingly.

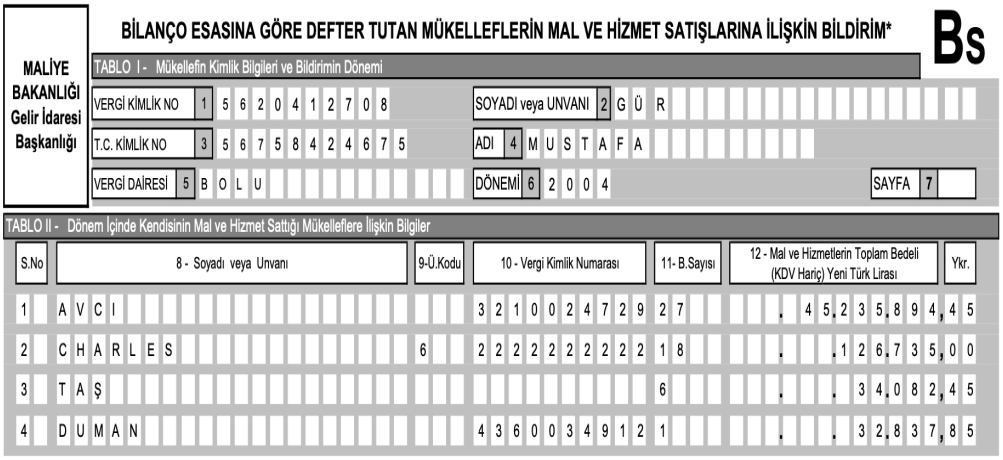


Figure 9: Forms for VAT Statements

Notes: This figure illustrates the VAT statements submitted by firms, including tax identifiers, the names of both the supplier and the customer, and the transaction amount.

Step 2. Building the Production Network: In Turkey, each firm is obligated to report their sales to 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 these 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.

By relying on each bilateral statement shown in Figure 9, we identify the customer and supplier of each firm. Each year, we aggregate transactions by supplier and customer identifiers, allowing us to track firm-to-firm linkages and transaction values annually. Using this information, we estimate the number of suppliers, number of customers, and each firm's domestic sales and purchases. 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.

We also calculate firms' network centrality using this data, focusing on weighted out-degree centrality as a measure of supplier importance or influence within the production network. In a supply chain, out-degree centrality represents the number of firms a given firm supplies. The weighted aspect captures the transaction value relative to the firm's total output. Therefore, higher-centrality suppliers have a greater influence on downstream firms.

Step 3. Balance Sheet to Performance Measures: To track performance measures, this paper also merges the dataset with balance sheet information, from which we extract sales and capital data. We track the firm's capital deepening over time using the capital variable from the balance sheets.

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 change within the firm if it imports an industrial robot with the reported six digit HS-code "847950" from this dataset.

Table 18 shows the annual count of firms that invested in industrial robots for the first time, distinguishing between purchases from the domestic market and imports.

Year	Domestic Producer	Intermediary-Sourced	Imported
2007	222	599	79
2008	155	431	90
2009	102	305	73
2010	207	388	72
2011	248	487	84
2012	184	448	91
2013	266	492	82
2014	291	699	89
2015	257	580	102
2016	268	519	83
2017	298	664	76
2018	275	486	94
2019	171	352	76

Table 18: First-time robot adopters

Notes: This table presents the number of firms adopting robots for the first time, categorized by whether the purchase was made from a domestic producer, an agent, or through import.

Step 4. Employer-Employee: The employer-employee dataset provides information on the salary and gender of each employee, as well as the companies where each employee works. We aggregate the employee count for each firm, calculate the average wage paid by each firm per year, and determine the gender ratio of its workforce. This dataset provides aggregated values for employee count, average wage, and gender ratio. Finally, we merge these datasets for each firm-year combination. The final dataset excludes firms that do not have balance sheet or social security data.

Step 5. Estimation of Firm productivity: Productivity estimation in this study follows the methodology of Ackerberg et al. (2015) at the firm-level. Before estimating productivity, we deflate all physical variables. We begin by using the logarithm of sales as a proxy for output, which is derived from the firms' balance sheets. We then include the logarithm of the number of employees as a free variable in the model, with the employee count estimated from the employer-employee dataset. The firm's reported capital is used as the state variable from the balance sheet.

For the total factor productivity calculation, we select the cost of intermediate inputs as

the proxy in the production function. However, this cost is not directly available in the datasets. To estimate the intermediate input purchases for each firm, we combine its domestic market purchases with its total intermediate input imports.[17] This approach allows us to use intermediate inputs as a proxy for productivity shocks which can control for unobserved fluctuations in productivity.

We also control for time fixed effects and use firm identifiers. Time fixed effects is employed to control for trends that affect all firms equally within a given year. Meanwhile, the firm identifiers control for firm-specific heterogeneity by ensuring that each firm's TFP is estimated relative to its own history, rather than being compared across firms.

By applying the methods from Ackerberg et al. (2015), we address simultaneity bias in production function estimation. This approach results in a more robust estimate of productivity, better reflecting firm-level productivity by controlling for the endogeneity of input choices across firms and years.

Other Descriptive Statistics. Tables 19 and 20 present other summary statistics.

Category	Mean	Std. Dev.	Min	Max
All Types of Robots				
Upstream 1: Automation	0.08	0.27	0	1
Upstream 2: Automation	0.12	0.33	0	1
Upstream 3: Automation	0.14	0.34	0	1
Upstream 4: Automation	0.14	0.35	0	1
Intermediary-Sourced				
Upstream 1: Automation	0.06	0.24	0	1
Upstream 2: Automation	0.09	0.29	0	1
Upstream 3: Automation	0.11	0.31	0	1
Upstream 4: Automation	0.11	0.31	0	1
Imported				
Upstream 1: Automation	0.02	0.15	0	1
Upstream 2: Automation	0.04	0.20	0	1
Upstream 3: Automation	0.04	0.20	0	1
Upstream 4: Automation	0.05	0.21	0	1

Table 19: Summary Statistics of Automation Across Upstream Categories

17 Intermediate imported inputs are identified in customs dataset based on the HS-code of the product by using the BEC (Broad Economic Category) codes.

Year	Number of Firms
2007	56,747
2008	69,930
2009	72,745
2010	84,108
2011	92,862
2012	100,874
2013	108,335
2014	112,820
2015	119,778
2016	122,425
2017	131,379
2018	134,611
2019	136,376

Table 20: Number of Firms by Year

C. Robot Prices

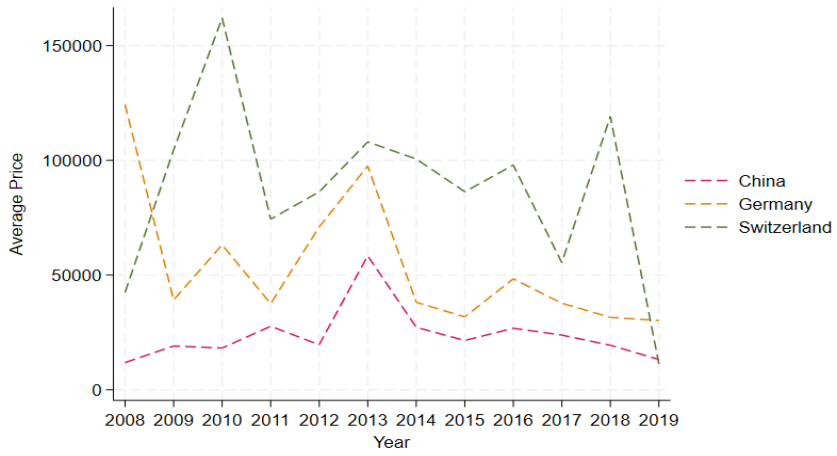


Figure 10: Robot Prices

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

In this study, we use robot prices as a proxy for robot quality. For each industrial robot, we estimate the prices of robots purchased from various countries. Figure 10 displays the average robot prices estimated at the firm-level from different countries, including China, Germany, and Switzerland. According to Figure 10, the most expensive robots are those imported from

Switzerland, while robots imported from China are the least costly. The significant price differences among these sources allow us to use price variation as a proxy for robot quality.

C.1. Model Appendix

Monopolistic Competition with non-Homothetic Aggregators. Under monopolistic competition the average action refers to the average of the continuum of competitors, under other competition structure it entails a finite number of competitors. To make a specific example, suppose that firm i competes in a market with a finite number of firms N, whose output is aggregated through a Dixit-Stiglitz aggregator with elasticity ρ: $y_t^i = \left(\frac{p_t^i}{[\sum_{i=0}^{N_t} (p_t^i)^{\frac{\rho-1}{\rho}} di]^{\frac{\rho}{\rho-1}}} \right)^{-\rho} (y_t^c)$, where y_t^c is aggregate output. In this case firms' sales are: $\chi_t^i (\tilde{f}^i)^\rho$, where $\tilde{f}^i$ is the same production function used before, $z_{h,t}^i f(k_t^i, \mathbf{x}_t^{ij}, n_t^i)$, and evaluated at the optimal input levels and χ is the marginal cost or the inverse of the mark-up. In presence of non-homothetic preferences or Bertrand competition, elasticities and mark-ups depend on the firm market shares. Specifically, the firms' first order condition to prices are: $\frac{\partial \Pi_t^i}{\partial p_t^i} = y_t^i + (p_t^i - \frac{W_t}{z_t}) \frac{\rho y_t^i}{p_t^i} [\xi^i - 1] = 0$. It follows that prices are: $p_t^* = \frac{(1-\xi_t^i)\rho}{(1-\xi_t^i)\rho - 1} \frac{W_t}{z_t}$ and mark-ups are $\mu(\xi^i) = \frac{(1-\xi^i)\rho}{(1-\xi^i)\rho - 1}$, The latter depends on the market shares $\xi = (\frac{p^i}{p^c})^{1-\rho}$.

Proof Lemma 3. The optimization problem reads as follows:

$$h = \text{argmax}_{[1,.....,H]} [\tilde{V}_{h,t}^i (z_{h,t}^i, k_{h,t}^i, \tau_t^i) + \gamma_{h,t}^i] \tag{C.1}$$

The probability of choosing m in the discrete choice problem (C.1) satisfies: $F(\tilde{V}_{h,t}^i + \gamma_{h,t}^i \geq \tilde{V}_{h',t}^i + \gamma_{h',t}^i) \, \forall m' \neq m \cup m' \in M$, where $F(.)$ is the cumulative density of the Gumbel shock. Taking expectations with respect to the current period shocks and evaluating at the optimal choice yields:

$$E_{\boldsymbol{\phi}} V_{ih,t}(z_{h,t+1}^i, , k_{h,t}^i, \tau_{h,t}^i, \boldsymbol{\gamma_{t+1}}) = E_{\boldsymbol{\gamma}} \max_{h_t} \left[\tilde{V}_{h,t}^i (z_{h,t}^i, k_{h,t-1}^i, \tau_{h,t-1}^i) + \gamma_{h,t}^i \right] \tag{C.2}$$

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

$$E_\gamma \max_{h_t} \left[\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}) + \gamma^i_{h,t} \right] = \ln \left(\sum_{h_t} \exp(\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1})) \right) \tag{C.3}$$

Combining equations (C.1) and (C.3) yields the following closed-form solution for the technology choice probabilities:

$$\theta^i_{h,t}(h|z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}) = \frac{\exp(\tilde{V}^i_{h,t}(z^i_{h,t}, k^i_{h,t-1}, \tau^{ij}_{h,t-1}))}{\sum_h \exp(\tilde{V}^i_{ht}(z^i_{h,t}, k^i_{h,t-1}, \tau^i_{h,t-1}))}. \tag{C.4}$$