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Pilar Beneito, Maria Garcia-Vega,
Oscar Vicente-Chirivella and Guillaume Wilemme

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Robots and Firms' Labor Search: The Role of Temporary Work Agencies

Pilar Beneito[1], María García-Vega*[2], Óscar Vicente-Chirivella[3] and Guillaume Wilemme[4]

[1]Universitat de València and ERICES
[2]University of Nottingham
[3]Universitat de València
[4]University of Leicester

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Abstract

We study the impact of industrial robots on the use of labor intermediaries or temporary work agencies (TWAs) and firm productivity. We develop a theoretical framework where new technologies increase the need for quality match workers. TWAs help firms to search for workers who better match their technologies. The model predicts that using robots increases TWA use, which increases robots' productivity. We test the model implications with panel data of Spanish firms from 1997 to 2016 with information on robot adoption and TWA use. Using staggered difference-in-difference (DiD) estimations, we estimate the causal effects of robot adoption on TWAs. We find robot adopters increase the probability of TWA use compared to non-adopters. We also find that firms that combine robots with TWAs achieve higher productivity than those who adopt robots without TWAs.

Keywords: Robots, job-worker matching, temporary work agencies, firm productivity.

JEL Codes: O33, J23, L22

*García-Vega: corresponding author. School of Economics, University of Nottingham, University Park, Nottingham NG7 2RD, United Kingdom and GEP (email: maria.garcia-vega@nottingham.ac.uk)

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1 Introduction

'It is essential to have good tools, but it is also essential that the tools should be used the right way.'

Wallace D. Wattles, *The Science of Getting Rich* (1910).

The introduction of automation-oriented technologies, such as robots, has transformed employment and production methods during the last decades. There is evidence of the effects of robots on wage inequality and within-firm employment (Acemoglu and Restrepo, 2022; Aghion et al., 2020, 2021; Bessen et al., 2020; Leone, 2023b), as well as on prices, sales and production scale (Koch et al., 2021; Stiebale et al., 2020). Studies have shown that automation technologies displace workers, but also increase productivity and might raise the need for robot adopters to hire new workers (Acemoglu et al., 2020; Aghion et al., 2021; Autor, 2015; Graetz and Michaels, 2018), including specialized employees to manage and work with this technology (Dixon et al., 2021; Bonfiglioli et al., 2020; Faia et al., 2022; Humlum, 2021). However, less is known about whether robot adoption influences firms' labor search strategies to find suitable employees and generates within-firm differences in job arrangements. In this paper, we study the impact of robots on employment outsourcing through intermediary agencies or temporary work agencies (TWAs) and their consequences on firm productivity.

Our argument is that TWAs can be an attractive labor recruitment channel for firms adopting robots due to their ability to provide good matches between jobs and workers in a timely manner. The purpose of TWAs is to hire suitable workers to supply them to a user firm.[1] TWAs have been associated with low-skill occupations, low wages and low firm productivity (Drenik et al., 2023; Hirsch and Mueller, 2012). However, TWAs can also facilitate access to a large pool of potential employees, including medium and high-skill employees, as well as screening candidates' skills. For example, Autor (2001) argues that, in the US, the large majority of TWAs offer free computer training to screen workers' abilities. In this way, TWAs assess workers, which allows them to provide information to the user firm about workers' skills, abilities and suitability for the job. Consistent with the screening role of TWAs, García-Pérez and Muñoz-Bullón (2005) find that, in Spain, high-skilled workers hired through TWAs make faster transitions to permanent jobs. Neugart and Storrie (2006) also highlight the importance of the

[1] A triangular relationship is established in which, on the one hand, the agency signs a contract with the worker ('employment contract'), and on the other hand, the agency signs another contract with the user firm ('contract of provision'), establishing the job conditions including an approximate duration of the contract.

matching efficiency of agencies.[2,3]

Robot adopters might need to change their recruitment strategies and increasingly rely on alternative job search channels to fulfill new job requirements. The reason is that by displacing existing jobs while creating new ones, automation technologies generate skill mismatches (Bughin et al., 2018). With the rapid and widespread adoption of these technologies, firms face increased competition to find qualified workers (Faia et al., 2022). The 'war for talent' to successfully implement these technologies is becoming a challenge for firms worldwide. In this line, CEOs increasingly identify automation-related skill gaps as a priority challenge for their organizations (McKinsey Global Survey, 2022).[4] TWAs can help robot adopters in the search for workers who better match their technologies in a flexible and cost-effective way. In this paper, we investigate this possibility.

We develop a theoretical model that formalizes our argument and test its main predictions. We model a firm's choice of labor search channels when the quality of the worker-firm match is imperfectly observed *à la* Pries (2004). We assume that new production technologies raise the stakes for firms to find the right worker for the job. Firms can use TWAs as a search channel or search by themselves on the labor market. They can also decide to offer a permanent or temporary contract upon meeting workers. Firms can use work agencies to better select job applicants (inspection good) and can use temporary contracts to learn without a strong employment commitment (experience good). Our theory emphasizes that new technologies and TWAs are complementary.

We provide two main testable implications. The first is that the adoption of new technologies increases the probability of TWA use as a recruitment channel. The second is that firm-level productivity increases with the combination of new technologies and TWA use. We test the model implications using firm-level panel data from Spanish firms for the period 1997 to 2016 for which we have firm-level information on robot adoption and TWA use.

[2]Neugart and Storrie (2006) augment the equilibrium unemployment model as developed by Pissarides and Mortensen with temporary work agencies.

[3]For example, one of the largest TWAs operating in Europe, Randstad, uses as one of its advertising slogans: *'(our) technology is designed to bring you closer to the work you want and employers closer to the talent they seek.' https://www.randstad.com.sg/relevate/*. Thus, they advertise themselves as specialized providers of 'high-quality matches' between firms and workers. A visit to the websites of these firms reveals, for instance, the intensive use of AI-based search technologies to maximize the efficiency of employer-employee matches.

[4]The McKinsey Global Survey (2022), based on interviews with CEOs from major US and EU firms, reports that 70% of them expect a growing demand for new skills as a result of their automation efforts and that finding the appropriate workers for the new technologies is a top ten priority for their successful implementation.

Using staggered difference-in-difference (DiD) estimations (Callaway and Sant'Anna, 2021), we find that the adoption of robots significantly impacts the likelihood of firm TWA use, with estimates ranging from around six to nearly nine percentage point increase, depending on the specification. These results are robust to different estimation techniques, the introduction of alternative technologies (such as computers or software), foreign acquisition, or the violation of the stable unit treatment value assumption. We also rule out potential mechanisms, such as the need to adjust the labor force to the demand and sectoral volatility. This suggests that the peaks or troughs of the business cycle or demand volatility do not drive the use of TWAs induced by robots. Furthermore, we do not find that robot adoption intensifies the use of temporary workers.

Then, using two-way fixed effects (TWFE) DiD estimations combined with matching techniques to deal with potential endogeneity, we explore the productivity effects of robots, TWAs, and their combined effect. In line with previous studies, we find that robots increase firm productivity by around 10.4%. What is novel in our study is that we find that by combining robots with TWAs as recruitment channel, firms further raise their productivity by around 8.4%. This suggests that there are complementarities between the adoption of robots and TWAs, as our model shows. This result is robust to alternative specifications and estimation techniques, including a staggered DiD methodology.

Our paper makes a number of contributions to several strands of the literature. First, we contribute to the literature that analyses the impact of automation technologies on firms' production processes and workforce organization (Acemoglu et al., 2020; Aghion et al., 2021; Bonfiglioli et al., 2020; Dauth et al., 2021; Koch et al., 2021; Leone, 2023a,b). Beyond the net employment effects or the induced changes in labor skill composition and its effects on productivity, as in Faia et al. (2022), we highlight that the successful implementation of automation technologies depends on the quality of the job-worker match. Our contribution is that we formalize how the quality of the match between technologies and workers depends on the choice of the optimal recruitment channel. We show that robots induce changes in job arrangements by increasing TWA use, which enhances robots' productivity.

Our paper also contributes to the literature on labor search channels, especially from the firms' perspective. Firms use different search channels to find different workers profiles (Holzer, 1987). Carrillo-Tudela et al. (2022) show that this differentiated use of search channels explains an important part of the labor market sorting. Bilal and Lhuillier (2021) study the outsourcing of labor as an alternative to searching for in-house workers. They find that more productive firms benefit more from outsourcing and use this channel more frequently. The same pattern emerges in our paper concerning TWAs. This explains why firms adopting robots rely more on TWAs. Our paper therefore sheds new light on the rise of TWAs since the 1990s. Robots increase TWAs-use because TWAs are an effective labor search channel that improves their productivity. TWAs have common elements to alternative search channels studied in the literature. Pissarides (1979) models public employment agencies as intermediaries that firms can use to find workers. Several other papers emphasize the role of referrals in screening workers efficiently and creating better matches (see, among others, Montgomery, 1991; Galenianos, 2013; Brown et al., 2016; Dustmann et al., 2016, and, for a survey, Topa, 2011). We propose that TWAs offer a similar matching advantage than these alternative searching channels and that the stakes of a good match increase with robot adoption.

We also contribute to the determinants and effects of temporary work arrangements (Drenik et al., 2023; Bertrand et al., 2021; Bilal and Lhuillier, 2021; Hirsch and Mueller, 2012; Litwin and Tanious, 2021). We distinguish, theoretically and empirically, between temporary employees hired through an agency or through the market. We emphasize the importance of TWAs associated with robots in their role as agencies instead of the temporary nature of the contracts they supply. That we do not find an increase in the share of temporary workers after robot adoption, supports the idea that TWAs provide matching advantages due to their role as market intermediaries.

The rest of the paper is organized as follows. In Section 2, we present the theoretical model and the main testable implications. In Section 3, we describe the institutional framework related to TWAs in Spain. In Section 4, we present the data, we provide the estimation results of robots on the probability of TWA use and the effect of TWAs and robots on firm productivity. Section 5 concludes.

2 The model

The model describes how new advanced technologies, which enhance productivity when combined with capable workers, affect the firms' use of TWAs and temporary contracts. We build a matching model in which firms and workers learn over time about match quality *à la* Pries

(2004) and Pries and Rogerson (2005). Conditional on their production technology, firms choose between searching for a worker by themselves or outsourcing the search process to a work agency. At any time after matching, firms and workers can choose to upgrade the temporary contract into a permanent one or, conversely, terminate the match.[5]

2.1 The setup

We consider a continuous-time stationary model. Time is discounted at the rate r. Firms produce with constant returns to scale in labor, hence the standard normalization that a firm has only one job to fill. Once the job is filled, the worker utilizes the technology provided by the firm to produce. The maximum level of production, called efficiency of labor, is denoted ξ. However, the technology requires specific skills so only certain workers are competent to use the firm's technology. Whether a worker has the required skills is interpreted as the quality of the match. The share of workers that are competent to produce with the firm's technology is denoted π.

Our key assumption is that new technologies enhance productivity but require a worker with more specific skills. In the model, adopting new technologies corresponds to both an increase in labor efficiency ξ and a decrease in the share of competent workers π.

Workers are ex-ante homogeneous and their measure is normalized to one. The productivity of a job occupied by a worker is equal to labor efficiency ξ only if the worker is fully operational. Job productivity can be lower than ξ for three reasons. First, a worker in a temporary relationship produces a fraction $\tau < 1$ of a worker in a permanent relationship.[6] Second, the worker may not be operational, which is captured by a match-specific factor z. This factor is equal to 0 or 1, and the match is said to be of good quality when $z = 1$. The factor remains constant throughout the match but it is imperfectly observed by both the firm and the worker. In the absence of additional information, a firm and a worker suppose that they will form a good match with (prior) probability π. A nonoperational worker, or bad match, does not produce anything. Third, the job can turn unproductive for exogenous reasons, at the rate λ.

Agents make the following decisions. Firms with vacant jobs choose a search channel. Once

[5] Faccini (2014) also adopts the framework of Pries (2004) and Pries and Rogerson (2005) with temporary and permanent contracts, but the firm does not choose the contract in his model.

[6] In the model, this is the reason why a firm could offer a permanent contract at the hiring stage. See Caggese and Cuñat (2008) for a similar assumption. This is a simplification for other mechanisms explored in the literature, such as investment in firm-specific human capital (Autor, 2003).

a firm and a worker meet, they jointly decide whether to match or not. If they match, they can separate at any time or transform a temporary contract into a permanent one.

Search channel and inspection. The labor market is frictional. A firm with a vacant job chooses between searching for a worker alone on the market or with a temporary work agency. Firms on the regular labor market meet workers at the Poisson rate q_R and do not have any additional information about match quality. Firms that use the services of a temporary work agency have to pay a fixed cost of C before meeting workers. A work agency proposes candidates at a rate q_A that is higher than the meeting rate on the regular market, $q_A \geq q_R$. A work agency also offers additional information about match quality before the firm and the worker decide to match. With that information, the firm and the worker update their beliefs and infer the (posterior) probability μ that the worker is competent. Given a prior π, the posterior is a draw from a distribution of probability density function $f(\mu|\pi)$ on the support $[0, 1]$. The function $f(\mu|\pi)$ is differentiable over π. Work agencies propose workers that have the same quality on average as those the firms can find by themselves on the market, $\int_0^1 \mu f(\mu|\pi) d\mu = \pi$ for any π.[7] We also assume that a raise in the prior π increases the probability of a good match in the sense of first-order stochastic dominance, $\int_0^z \frac{\partial f}{\partial \pi}(\mu|\pi) d\mu \leq 0$ for any z and π.

After deciding on matching, firms and workers bargain the match surplus such that workers receive a share φ between 0 and 1. We denote $\Omega(\mu)$ the joint value of a match whose probability to be good is μ. The value of a vacancy for a firm is V_R when searching alone on the regular market and V_A with a work agency. The worker's value of unemployment is U. The firm's choice of a search channel is defined by $V = \max\{V_R, V_A - C, 0\}$. The Bellman equations of V_R and V_A are:

$$rV_R = q_R(1 - \varphi) \max\{\Omega(\pi) - U - V_R, 0\}, \tag{1}$$

$$rV_A = q_A(1 - \varphi) \int_0^1 \max\{\Omega(\mu) - U - V_A, 0\} f(\mu|\pi) d\mu. \tag{2}$$

When a firm searches on the regular market, it meets a worker at rate q_R, expecting them to be competent with probability π. The firm then receives a share $1 - \varphi$ of the surplus

[7] We could assume that work agencies have also a matching advantage, by better finding the right workers for the firms, or that they train workers (Autor, 2001). We could also assume that firms observe a signal on the regular market as long as the signal is less precise than with a work agency. Both assumptions would not affect our findings.

$\Omega(\pi) - U - V_R$ if there is a match. A match is formed only if the surplus is positive. When a firm searches with a work agency, it meets a worker at rate q_A, expecting them to be competent with probability μ randomly drawn.[8]

Note that the search channel only affects the value of the match Ω through the information that is learned about match quality. The value only depends on the posterior probability that the match is good. This is because we abstract from any differences between an agency worker and a directly hired temporary worker once the job starts, including pay differences. In particular, firms can propose permanent contracts to agency workers, as they do to temporarily employed workers. Our assumption is supported by existing regulations that prevent unfair competition of agency work with respect to standard employment (see for instance the principle of equal treatment in the European Union's Directive on Temporary Agency Work, 2008/104/EC).

Contract and experience. Firms can employ workers on a temporary or permanent contract. There is no commitment to the type of contract before finding a worker. Firms and workers choose the best contract upon meeting. A temporary contract expires at the rate δ while a permanent contract never expires.[9] Upon expiration, the firm and the worker can stay together if they accept a permanent contract. Otherwise, the firm loses its vacancy and the worker becomes unemployed. A firm can also propose a permanent contract to its temporary workers at any time at no cost, whether they are directly employed or indirectly through an agency. The match incurs a red-tape cost of F when it separates before the expiration date but at no cost after expiration. The dismissal cost is assumed to be the same for directly hired permanent workers, directly hired temporary workers and agency workers.[10] Temporary relationships have the advantage of avoiding the payment of the dismissal fee if the firm waits until the expiration of the contract. They have the drawback of being less productive by τ.

[8] Although characterizing the labor market equilibrium is not necessary for our analysis, it would not be difficult to endogenize the worker's value of unemployment and the matching rates q_R and q_A.

[9] This assumption captures an essential feature of temporary contracts while avoiding modeling fixed-term contracts. See Wasmer (2001) for a similar assumption and see Cahuc et al. (2016) for a model with fixed-term contracts.

[10] The modeling of a dismissal cost as a red-tape cost is common in the literature (Faccini, 2014; Pries and Rogerson, 2005; Cahuc et al., 2016). The simplification that the dismissal cost is the same for any temporary worker is for exposition purposes only. Our results remain unchanged if the firing cost of an agent worker F_A and of a directly-hired temporary worker F_T are lower than F as long as they remain above $\frac{rU}{r+\delta}$. In that case, the firm will not fire agency workers and temporary workers at equilibrium.

Assumption 1 *The dismissal cost is such that*

$$\frac{rU}{r+\delta} < F < U.$$

Under this assumption, the dismissal cost is high enough that firms with unproductive matches prefer to wait for the expiration of the temporary contract instead of immediately dismissing the worker. The cost is not too high to prevent firms from dismissing permanent workers that are unproductive.

Once matched together, a firm and a worker learn by experience the quality of the match. At the Poisson rate β_0, the pair observes a signal $z+\varepsilon$ when the match quality is z. The noise ε is a random draw from a uniform distribution on $[-\frac{1}{2\beta_1}, \frac{1}{2\beta_1}]$, with $0 < \beta_1 \leq 1$. The noises drawn throughout the duration of the match are time-independent. We then define $\beta = \beta_0\beta_1$. Such modeling of the signals provides a simple characterization of dynamic learning. If the probability that the worker is competent is μ, the firm-worker pair learns for sure that the match is good at the Poisson rate $\beta\mu$. At the rate $\beta(1-\mu)$, the pair learns that the match is bad. A firm and a worker may decide to change the employment contract or to break the match upon receiving such new information. The efficiency of learning by experience is captured by β.

For our analysis, we do not need to be explicit about the way wages are formed. We only assume that workers receive a share φ of the surplus upon matching and that the pair achieves efficient contracting that maximizes joint surplus. This means that the choice of contract and the choice to terminate the relationship are efficient. The joint value of a match whose probability of being good is μ is $\Omega_T(\mu)$ under a temporary contract and $\Omega_P(\mu)$ under a permanent contract. The choice of a contract upon matching is $\Omega(\mu) = \max\{\Omega_T(\mu), \Omega_P(\mu)\}$.

Assumption 2 *The productivity penalty for temporary workers is such that*

$$\tau\lambda F < \left(1-\tau+\frac{\lambda}{r+\delta}\right) rU.$$

Under Assumptions 1 and 2, a firm never proposes a temporary contract to a worker of known productivity. Either the worker is productive enough to be offered a permanent job, or they are not offered a job. Assumption 2 is satisfied when the temporary job penalty τ is low enough or when the rate of turning unproductive λ is high enough, making temporary jobs less profitable than permanent jobs. We write the Bellman equations under these two assumptions, which lead to simple decisions about the continuation of a match. The appendix contains all the corresponding proofs.

The joint value of a match in a permanent contract is, for any μ in $]0,1]$,

$$r\Omega_P(\mu) = \xi\mu + \beta\mu\left[\Omega_P(1) - \Omega_P(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right)\left[U - F - \Omega_P(\mu)\right]. \tag{3}$$

In a permanent contract, the expected productivity is $\xi\mu$. At the rate, $\beta\mu$, the firm and the worker learn that the match is good and the joint value jumps to $\Omega_P(1)$. At the rate $\beta(1-\mu)+\lambda$, they discover that the job does not produce anything because the match is bad or because the job has turned unproductive. In that case, the firm and the worker prefer to separate. When a separation occurs, the match incurs the cost F, the firm receives nothing and the worker receives the value of unemployment U.

The joint value of a match in a temporary contract solves, for any μ in $]0,1[$,

$$\begin{aligned} r\Omega_T(\mu) = {} & \tau\xi\mu + \beta\mu\left[\Omega_P(1) - \Omega_T(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right)\left[\Omega_T(0) - \Omega_T(\mu)\right] \\ & + \delta\left[\max\left\{\Omega_P(\mu), U\right\} - \Omega_T(\mu)\right] \end{aligned} \tag{4}$$

and defining by continuity $\Omega_T(0) = \Omega_T(0^+)$. The match produces on expectation $\tau\xi\mu$. At rate $\beta\mu$, the match proves to be good and the firm upgrades the worker into a permanent contract. At the rate $\beta(1-\mu)+\lambda$, the job turns out to be unproductive. In that case, the firm and the worker wait for the job to expire. At the rate δ, a temporary job expires and so the pair chooses whether to stay together in a permanent contract or to separate at no cost.

2.2 Optimal contract and search channel

Proceeding by backward induction, we first characterize the optimal decision of a firm when meeting a job applicant. The firm decides whether to hire the worker or not, and whether to propose a permanent contract or not. This decision is based on the posterior probability μ that the worker is suitable for the job.

Proposition 1 *Consider a firm, with a vacant job of value $V \geq 0$, that has just met a worker of posterior probability μ.*

The firm and the worker form a match if and only if the odds ratio $\frac{1-\mu}{\mu}$ *satisfies*

$$\frac{1-\mu}{\mu} \leq H(\xi, V), \tag{5}$$

where H *is a continuous function.* $H(\xi, V)$ *is piecewise-linear increasing in* ξ*, and decreasing in* V*.*

Conditionally on matching, the worker is offered a permanent job if and only if

$$\frac{1-\mu}{\mu} \leq \frac{(1-\tau)\xi - \lambda\left(F - \frac{rU}{r+\delta}\right)}{(\beta+\lambda)\left(F - \frac{rU}{r+\delta}\right)}. \tag{6}$$

The proof and the exact definition of H are in the appendix. This proposition implies that the solution to the optimal matching decision, max $\{\Omega_P(\mu), \Omega_T(\mu), U+V\}$, can be represented as a partition of the plan $\left(\xi, \frac{1-\mu}{\mu}\right)$ into three areas. The borders between the three areas are straight lines in the plan because of the linearity in ξ.

Figure 1 illustrates this partition when $V = 0$. When the quality of the match is good enough, meaning $\frac{1-\mu}{\mu}$ close to 0, then the firm either offers a permanent contract or no contract at all. For values of labor efficiency ξ high enough, there is always a middle range of posterior probabilities μ such that hiring the worker on a temporary basis is best.

The choice between temporary and permanent contracts does not depend on the reservation value of the firm, but the decision to match does. An increase in the reservation value expands the 'No contract' area. This mechanism leads the firm to be pickier in matching when searching with a work agency, providing that $V_A \geq V_R$.

Proposition 2 *Consider the choice of a search channel when a share* π *of workers have the required skills for the firm's technology, with* $0 < \pi < 1$*. There exists a threshold labor efficiency* $\Xi(\pi) > 0$ *such that searching with an agency is optimal if* $\xi > \Xi(\pi)$*. If the discount rate is low enough,* $q_A \geq q_R >> r$*, then this threshold is unique.*

The proof is in the appendix and relies on the fact that V_A increases in ξ faster than V_R. This proposition implies that the solution to the optimal search channel problem, max$\{V_R, V_A - C\}$ can be represented as a partition of the plan $(\xi, \frac{1-\pi}{\pi})$ into two areas. Figure 2 illustrates this partition in the case $q_A > q_R >> r$.

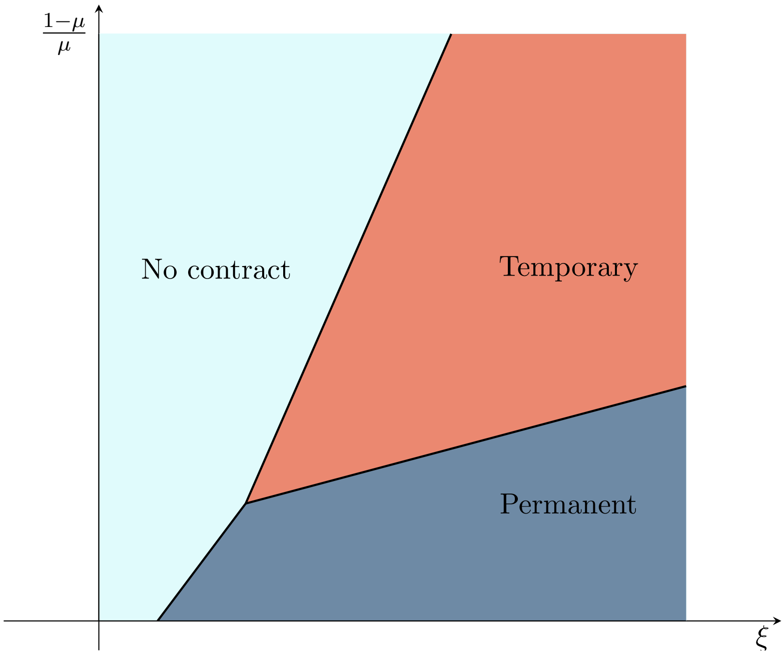

Figure 1: Optimal contract upon meeting

Note: A firm and a worker, with labor efficiency ξ and probability of good match μ, optimally choose the best contract depending on their location in the plan.

When labor efficiency is so low that no job is profitable, the firm does not use the services of a work agency because $V_A - C = -C < 0 = V_R$. As labor efficiency increases, the gains from having a better match increase as well. This is a complementarity effect between labor efficiency and match quality. At the limit when labor efficiency tends towards infinity, it is always optimal to rely on temporary work agencies.

When the prior probability of a good match is either close to zero or one, work agencies do not provide a strong informational advantage in screening workers. When the probability of a good match is low, the firm does not use work agencies because jobs are not productive enough, $\Xi(0) = \infty$. When the probability of a good match is high, the use of an agency depends on its access to the labor market. If agencies propose applicants at the same rate as the market, $q_A = q_R$, then the firm will not search with an agency, $\Xi(1) = \infty$. Alternatively, if $q_A > q_R$, then the firm will use a work agency if labor efficiency is high enough, $\Xi(1) \in \mathbb{R}$, to be worth the cost C.

Propositions 1 and 2 summarise the optimal decision of firms when searching for a worker. Proposition 2 tells whether the firm will search alone or with an agency. Proposition 1 tells whether the firm offers a permanent contract or prefers a temporary arrangement.

Figures 3 and 4 illustrate the decisions of two firms opening a job with different labor

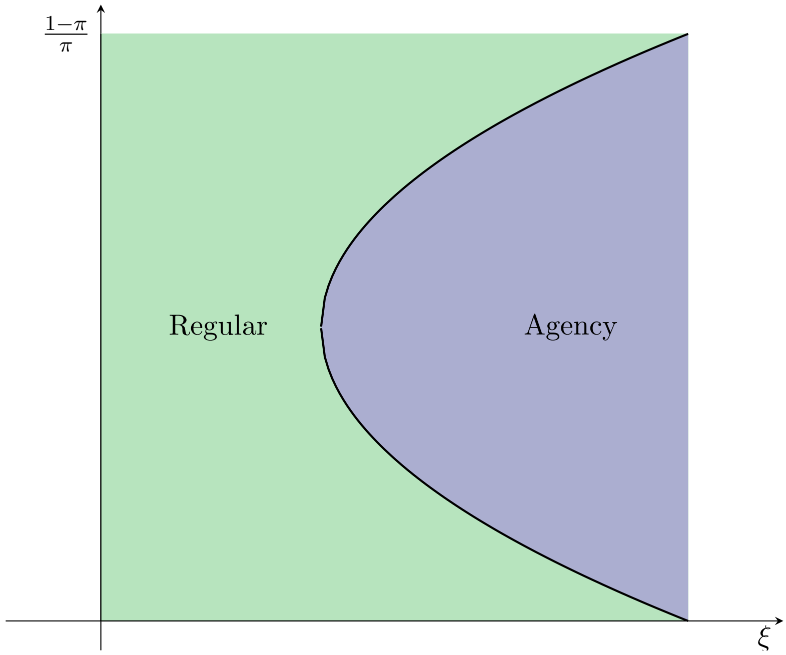

Figure 2: Optimal search channel channel
Note: A firm with labor efficiency ξ and prior π optimally chooses between searching alone on the regular market or through a work agency on its location in the plan.

efficiency ξ and prior π. The job in the first firm is represented by $\star$ in Figure 3. For these job characteristics, it is optimal for the firm to search for a job on the regular market. Since the firm searches on the regular market, no information about the match will be learned before matching. In other words, the posterior will be equal to the prior, $\mu = \pi$. If the Y-axes have the same scales on the two figures, then the firm can be represented by a point on Figure 4 at the exact same location as on Figure 3. Depending on the location of the point, the firm will choose to offer a permanent, temporary, or no contract at all. In the situation depicted, the firm will offer a temporary contract.

The job in the second firm is represented by $\bullet$ in Figure 3. The firm optimally searches with a work agency. In Figure 4, the $\bullet$ symbol shows the situation in which the firm meets a worker of posterior $\mu = \pi$. However, the posterior probability μ is in general different from π. Conditional on π, the match draws a value μ from the distribution $f(\mu|\pi)$. The dashed vertical segment shows all the possible values of μ that are acceptable for both the firm and the worker to stay together. The highest value of $\frac{1-\mu}{\mu}$ on that segment gives the reservation strategy in terms of posterior. Jobs above this point generate a negative surplus. The intuition is that the firm can be picky and wait for the work agency to propose candidates that have a high probability to suit the job. The minimum acceptable probability, or reservation probability, is therefore higher with an agency than on the regular market. When the posterior is large enough, or $\frac{1-\mu}{\mu}$ close to 0, the firm offers a permanent contract to the worker it has met with the work agency.

2.3 Testable implications

To bring the model closer to the data, we explicitly consider the choice of adopting new technologies. For a given firm, introducing new technologies shifts labor efficiency and prior probability from $\xi^\star$ and $\pi^\star$ to $\xi^\bullet$ and $\pi^\bullet$, with $\xi^\star < \xi^\bullet$ and $\pi^\star > \pi^\bullet$. The firm's problem now becomes the joint choice of a technology and a search channel, $\max\{V_R^\star, V_A^\star - C, V_R^\bullet, V_A^\bullet - C\}$, where $V_R^\star$ and $V_A^\star$ are the values of a vacancy with the first technology, and $V_R^\bullet$ and $V_A^\bullet$ with the second one.

If the technological shift is akin to a move from the $\star$ to the $\bullet$ on Figures 3 and 4, then the gains from using a temporary work agency are higher when firms use new technologies, $V_A^\bullet - V_R^\bullet \geq V_A^\star - V_R^\star$. In other words, there is complementarity between work agencies and new technologies. If that assumption is correct, there are two implications we can test empirically.

Implication 1 *The probability of relying on TWAs conditional on using new technologies is higher than the probability of relying on TWAs conditional on not using new technologies.*

Implication 2 *The combination of the new technology and the use of TWAs generates productivity gains.*

Finally, note that in the model, adopting the new technology increases TWA use but has an ambiguous impact on the share of temporary workers. The reason is that there are two effects of opposite sign. On the one hand, some firms adopting the new technology may now prefer to hire a temporary agency worker instead of a directly hired permanent worker. This may increase the share of temporary workers. On the other hand, some firms may already hire directly temporary workers and now rely on a TWA, as illustrated in the example, Figures 3 and 4. In that case, there is no change in temporary jobs created but the screening advantage of TWAs leads to a faster conversion of good jobs into permanent employment. This effect would reduce the share of temporary workers. Although it is not the main purpose of the paper, in the empirical analysis, we also explore the effect of the adoption of robots on the share of temporary workers.

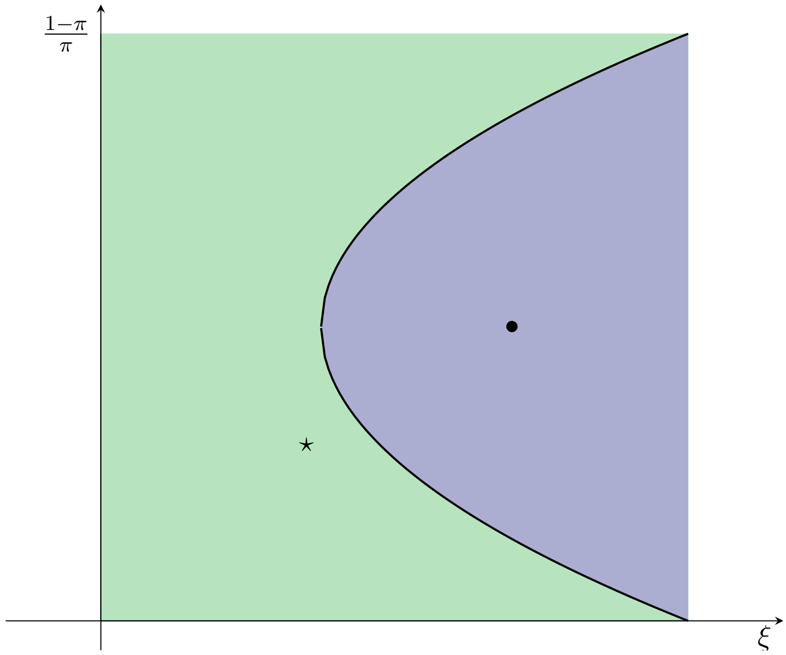

Figure 3: Recruitment channel in two examples

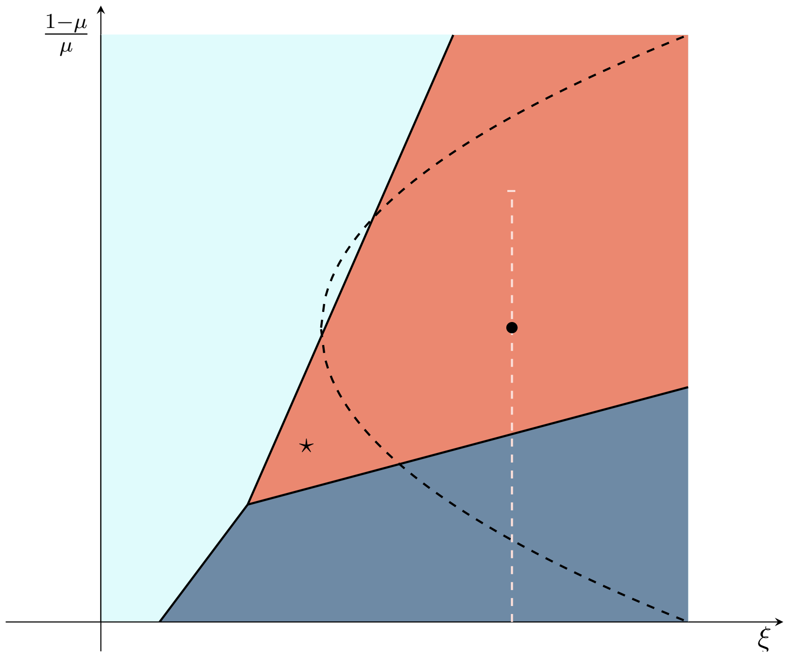

Figure 4: Contracting in two examples

3 TWAs in Spain

In Spain, TWAs were allowed to operate for the first time in 1994 (Law 14/1994), following the process of job market liberalization of the 90s in Europe (Countouris et al., 2016). A characteristic of Spanish law is that once the contract between the TWA and the user firm expires, the contract has to become permanent if the worker continues to work for the user firm (in the same way as temporary workers hired through the regular market). Initially, the Spanish law prohibited the use of agency workers for hazardous activities (such as mining or working with explosives), replacing workers on legal strikes and filling vacancies caused by recent layoffs at the user firm.[11] Subsequent reforms (Law 29/1999 and Law 35/2010) have deregulated the sector by allowing TWA employment contracts to be signed in the same cases and conditions as regular temporary contracts, and by weakening some of the original restrictions of the 1994 law (Carrasco et al., 2022). An important change introduced in 1999 was that, for an equivalent job, TWA workers have to receive the same salary as temporary workers hired directly by the user firm. As a consequence, from the point of view of the user firm, hiring a temporary worker through TWAs has an additional cost than hiring through the market (the same wage and a fee for the provision of the worker).[12]

The advantage of hiring through TWAs is that they have become highly competitive private companies specialized in the intermediation between firms and workers (de Blas et al., 2013). The official statistics from the Spanish Ministry of Labor (Estadística de Empresas de Trabajo Temporal, 2021) show that, in 2016, the percentage of high-skill workers hired by TWAs over the total of agency workers accounted for 15%, the percentage of medium-skilled workers by 54% and the percentage of low-skilled workers by 31%. TWAs supply labor to cover production peaks with flexible contracts, typically associated with low-skill work, but these numbers also reflect the importance of TWAs in providing workers for the high and medium-skill segment of the labor demand.

[11] The 1994 Spanish law also required that TWAs provide adequate training to their employees before they join the user firm and devote at least 1% of their total wage bill to training.

[12] In 2014 there was an amendment in the Spanish law (Act 18/2014) that allowed TWAs to act also as placement agencies. In other words, TWAs could also be intermediaries between the worker and the user firm without signing an employment contract with the agency.

4 Empirical section

4.1 Data and descriptive analysis

The data that we use in this paper is 'Encuesta sobre Estrategias Empresariales', ESEE (Survey of Entrepreneurial Strategies). This is a firm-level annual survey from 1990 covering around 1,800 Spanish manufacturing firms each year. It is sponsored by the Spanish Ministry of Industry and supplied by the SEPI Foundation. The dataset is representative of the Spanish manufacturing sector by industry and firm size. In its initial year, firms with 10 to 200 employees were randomly sampled, holding around 5% of the population of firms of that size in that year. All firms with more than 200 employees were requested to participate in the survey, obtaining a participation rate of about 70%. Since then, there has been annual incorporation of new firms to minimize attrition, so that the sample remains representative of the Spanish manufacturing sector.[13]

The dataset reports unique information on robot adoption and TWA use for the recruitment process. Our sample is an unbalanced panel of 3,743 firms and spans from 1997 - the first year with information on TWAs - to 2016. In the survey, besides accounting data, firms provide information on several output and input measures of their production process, including technology used and hire arrangements of their workforce. Most questions are asked every year, but in some cases, such as the use of robots and some skill composition indicators, the information is gathered every four years.[14]

For estimation purposes, the 4-year period between two ESEE response years is our time unit in the analysis, which we explain in detail in section 4.2.1. Since our identification strategy is a difference-in-differences estimation, we exclude from the sample firms that report the use of robots the first year we observe them in the survey. This renders a sample of 6,851 observations, with 700 firms adopting robots (first-time firms start reporting the use of robots, not having used them in the past), which we called 'robot adopters', and 3,043 never adopting robots, which we called 'non-adopters'. The large majority of firms continuously report the use of robots after adoption. Only 5% of firms are robot switchers - that is firms that stop reporting the use of robots in their production process. As robustness, we exclude switchers from the analysis to

[13]Details on EESE dataset and data access guidelines can be obtained at: `https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp` (last accessed 21 January 2023). Articles that have used this dataset are: Guadalupe et al. (2012), Doraszelski and Jaumandreu (2013), Doraszelski and Jaumandreu (2018), Koch et al. (2021), Kuzmina (2022) or Leone (2023b), among others.

[14]The ESEE full-response years in our time window (with information on robots) are: 1998, 2002, 2006, etc.

test the sensitivity of the results. The left side of Figure B1 in the Appendix depicts the steadily increasing adoption of robots in the Spanish manufacturing sector during our sample period.

The firms report yearly whether some of their employees are hired through a TWA. The dataset also provides information on the number of both temporary and non-temporary workers, so we can identify separately the use of temporary agency work from a hiring strategy based on temporary work. The right side of Figure B1 in the Appendix shows the evolution of the share of firms that use TWAs. During the first decade, this share increased by 13 percentage points, representing an increase of around 65% from the initial 20% in 1997. TWA use declined significantly between 2007 and 2009, which suggests that during the Great Recession firms adjusted employment through temporary workers. As a result, in 2009 the proportion of firms using TWAs was similar to that in 1997. During the last eight years of our sample, the growth of the share of firms using TWAs was steady, leading to the recovery of pre-crisis levels by 2016. The upward trend in the last years suggests an even greater increase in TWA use for the most recent out-of-sample years.

In Table 1, we display descriptive statistics of the main variables for the whole sample, for robot adopters before and after adoption, and for non-adopters during the sample period. On the top part of the table, we show the percentage of firms that use TWA and labor-related variables. In the rest of the table, we provide information on a set of variables that we use to evaluate the effects of TWAs and robots on firms' productivity, as well as other variables that we use in our analysis. Similar to Chen and Steinwender (2021), Koch et al. (2021) and Guadalupe et al. (2012) our measure of labor productivity is real value added per worker. We calculate value added as the sum of sales plus stock changes and other operating income, minus purchases and external services. We obtain firm-level prices directly from our dataset and with this information, we deflate the nominal variables. As robustness, we also use sales per worker as an alternative measure of productivity.

Table 1: Descriptive statistics

		All		**Robot adopters**				**Non adopters**	
				Before adoption		**After adoption**			
		(1)		(2)		(3)		(4)	
Variables	Obs.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
TWA(Yes/No)	6,851	0.209	0.406	0.339	0.473	0.382	0.486	0.155	0.362
Labor variables									
Total employment	6,851	3.803	1.324	4.557	1.302	4.757	1.370	3.500	1.181
High skill share	5,713	0.054	0.086	0.055	0.076	0.073	0.095	0.051	0.085
Medium skill share	5,655	0.072	0.126	0.069	0.110	0.078	0.114	0.071	0.130
Production workers share	5,737	0.695	0.194	0.696	0.188	0.677	0.187	0.698	0.197
Temporary share	6,851	0.159	0.213	0.190	0.218	0.130	0.174	0.157	0.217
Hours worked	6,816	11.282	1.310	12.030	1.292	12.223	1.369	10.985	1.167
Other variables									
Labor productivity	6,761	9.798	0.703	9.933	0.632	10.128	0.717	9.718	0.693
Real sales per hour	6,813	10.638	0.868	10.884	0.775	11.093	0.824	10.516	0.857
Capital	5,800	2.992	1.110	3.369	0.999	3.610	0.932	2.837	1.105
R&D intensity	6,832	0.244	0.538	0.342	0.613	0.393	0.628	0.200	0.499
Exports	6,847	0.587	0.492	0.731	0.443	0.793	0.404	0.525	0.499
Imports	6,837	0.575	0.494	0.733	0.442	0.798	0.401	0.508	0.499
Foreign ownership	6,851	0.122	0.327	0.193	0.395	0.218	0.413	0.092	0.290
N. Observations	6,851			973		832		5,046	

Notes: The table reports means and standard deviations (SD) of firm-specific variables for all firms, robot adopters before and after adoption and the control group of firms that never adopt robots during the sample period. The sample spans the years 1997-2016 and is restricted to firms that do not use robots in the first year they enter the sample. *Robot adopters* is a dummy variable that takes the value of one if a firm adopts robots, and zero otherwise. *TWA* is a dummy variable that takes the value of one if a firm hires temporary agency workers, and zero otherwise. *Total employment* is the logarithm of total personnel employed at the firm on December 31st. *High skill share* is the percentage of engineers and graduates over the total personnel of the firm on December 31st. *Medium skill share* is the percentage of graduates after a 3-year degree course over the total personnel of the firm on December 31st. *Production workers share* is the percentage of processing workers over the firm's total personnel on December 31st. *Temporary share* is the percentage of temporary staff employed at the firm on December 31st. *Hours worked* is the logarithm of hours effectively worked. *Labor productivity* is the logarithm of value added per hour effectively worked. Value added is calculated as the sum of sales, stock changes and other operating income, minus purchases and external services. *Real sales per hour* is the logarithm of sales per hour effectively worked. *Capital* is the logarithm of the deflated capital stock over the number of hours effectively worked. *R&D intensity* is the logarithm of R&D expenditures over sales. *Exports* is a dummy variable that takes the value of one if a firm is selling abroad, and zero otherwise. *Imports* is a dummy variable that takes the value of one if a firm is buying from abroad, and zero otherwise. *Foreign ownership* is a dummy variable that takes the value of one if more than 50% of the firm capital is foreign-owned.

Non-adopterss exhibit lower capital, R&D intensity, employment, skill share, and participation in international markets (exports and/or import activities) than robot adopters. Comparing robot adopters before and after adoption, the statistics suggest that TWA use increases slightly after adoption (0.339 vs. 0.382) as well as labor productivity, sales, employment, R&D intensity and internationalization. In the next sections, we describe the identification strategies that we follow to determine the causal impact of robots on TWA use, the consequences of their combined effect on firm productivity, and how we control for possible confounding factors.

Figure 5 shows the sectoral breakdown of the share of robot adopters, TWA use, temporary work share (temps over the total number of workers) and agency-work share (agency workers over temps). There is a positive relationship between robot adoption and TWA use. For example, the first and second panels of the figure show that 7 out of 10 sectors with the highest proportion of firms using robots are also the top sectors with the highest proportion of firms using TWAs. However, TWA use does not seem directly related to an increase in the share of temps. The third panel shows that 7 out of 10 sectors with the highest proportion of firms using TWAs rank among the 10 sectors with the lowest temps' share. For example, *Chemicals & Pharma* ranks first in terms of the proportion of firms using TWAs, but it is the last one in temps' share. Moreover, the fourth panel indicates that sectors with the highest proportion of temps coming from agencies are those with the lowest temps share. For example, the 4 sectors with the lowest temps share rank among the top 5 with the highest proportion of temps coming from agencies. This suggests that the use of TWAs and intensification of temps are not directly correlated.

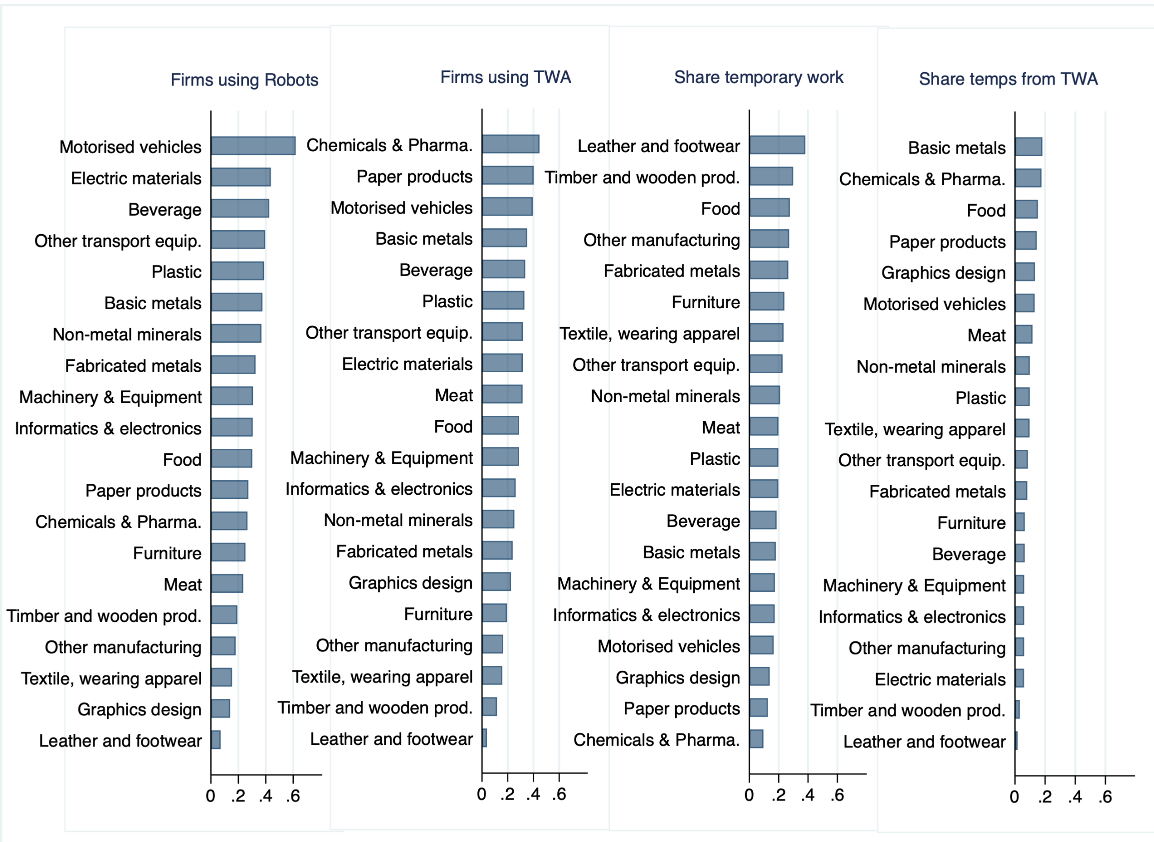

Figure 5: Industrial breakdown of robot adoption, TWA use, temporary work share and agency-work share.

Before explaining our econometric methodology, we first confirm that robots affect labor composition. We report a difference-in-difference of means between robot adopters and non-adopters. We present the results in Figure 6. On the left side of the figure, we include the firm's

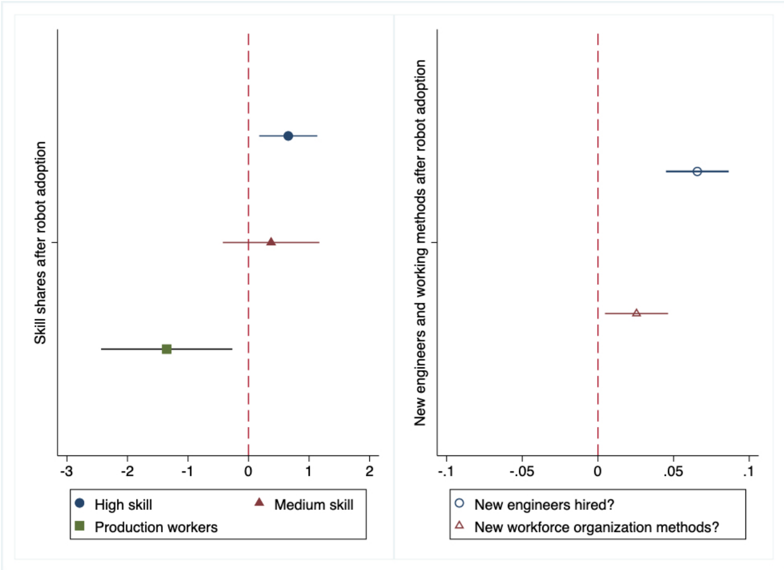

Figure 6: Left panel: Changes in firms' labor skill composition after robot adoption; Right panel: Changes in firms' answers to the following questions after robot adoption: i) Did the firm hire 'new' engineers during the year?; ii) Has the firm introduced new forms of workforce organization during the year? (canonical DID estimates).

share of production workers, medium-skilled workers and high-skilled workers. The figure shows that robot adopters reduce their share of production workers as compared to non-adopters. Robot adopters slightly increase their share of medium-skilled workers, although the effect is not statistically significant, and they significantly increase the share of high-skilled workers. On the right side of the panel, we explore with more detail the effects of robot adoption on firms' labor composition and consider two dummy variables that measure the hiring of new engineers and the introduction of new forms of workforce organisation.[15] After robot adoption, firms hire new engineers and are more likely to report having introduced new forms of workforce organization.

This preliminary analysis suggests that firms restructure their workforce towards higher skill levels, hire new engineers and introduce new forms of work organisation after robot adoption. This is consistent with previous empirical evidence (Koch et al., 2021). All these changes suggest that the adoption of robots is likely to induce the need for new worker profiles, which could also imply the use of new recruitment channels, such as TWAs.

[15] The variables account for a positive answer to the following two questions made to firms in the ESEE: 'Did the firm hire *new* engineers during the year?', and 'Did the firm introduce new forms of workforce organization during the year?'.

4.2 The effect of robot adoption on TWA use

4.2.1 Empirical strategy

To identify the causal impact of robot adoption on the probability of TWA use at the firm level, in our baseline specification, we use the staggered DiD estimation method proposed by Callaway and Sant'Anna (2021), CS-DiD henceforth. In the robustness section, we include additional estimation methods, including a standard two-way fixed effects (TWFE) DiD specification. Recent literature has raised concerns about the causal interpretation in standard TWFE DiD estimation if there is across firms variation in treatment timing and dynamic treatment effects (see, e.g., Borusyak et al., 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Athey and Imbens, 2022, among others). The CS-DiD methodology is a general framework for staggered DiD estimation that accounts for dynamic and treatment effect heterogeneity across different dimensions (groups or cohorts, calendar time, or events). This is appropriate for our research question because the effect of robots on firms' TWA use is likely to be dynamic (Koch et al., 2021), and the timing of robot adoption varies across firms. This methodology is designed for DiD setups where once units are treated, they remain treated in the following periods, as it is in the case of robot adoption.

The main building block of the CS-DiD method is the *group-time average treatment effect*. This is the ATT at a particular time period t for units who are members of a particular group or cohort g, where a cohort are the units that are first treated at the same point of time g:

$$ATT(g,t) = \mathbb{E}[TWA_t(g) - TWA_t(0)|G_g = 1] \tag{7}$$

In our setting, $TWA_t(g)$ denotes TWA use experienced at time t by firms that adopt robots for the first time in period g, while $TWA_t(0)$ denotes TWA use at time t by those firms that remain non-adopters in period g. In the survey, firms are asked about the use of robots in the production process every four years. We code positive responses to that question as 1 and negative responses as 0. If a firm's response changes from 0 in a given year to 1 four years later, we consider that first-time robot adoption took place during that 4-year period. Throughout our analysis, the subscript t refers to those 4-year periods. The TWA variable is constructed from the annual binary indicators of TWA use averaged over the 4 years of the corresponding period.

Therefore, our outcome measure indicates the frequency of TWA use during the period.[16]

The group-time $ATTs$ defined in equation (7) are weighted-based aggregated measures of the causal parameters of interest. Weights on each $ATT(g,t)$ vary depending on the aggregation scheme chosen (by group, by calendar period, by event, and/or total). The weights are all non-negative, and their sum is equal to one.[17]

The CS-DiD methodology allows for a conditional estimator by including covariate-specific pre-trends. That is the possibility that pre-trends hold after conditioning on some covariates. This conditional specification estimates a propensity score based on pre-treatment values of observable covariates.[18] Further, the CS-DiD estimation discards all left-censored observations, that is, those cases of firms that report using robots the first year they are observed in the dataset. We also check for robustness using not yet treated instead of never treated observations as the control group, which, as we show below, does not lead to appreciable changes in our results.

4.2.2 Baseline results

We present our main set of results in Table 2. In columns (1) and (2), we include all observations. In columns (3) and (4), we exclude switchers. At the top of the table, we present the ATT estimates, both for unconditional (columns 1 and 3) and conditional pre-trends estimation (columns 2 and 4).[19] For conditioning pre-trends, we include firm size (five intervals of the total number of employees) and previous experience using TWAs. That is, we assume that firms with similar size and TWA experience follow the same trend in TWA use in the absence of robot adoption.

The ATT estimate indicates a positive causal impact of robot adoption on the probability of TWA use. The estimate in column (1) suggests that the adoption of robots increases the likelihood of TWA use by 5.8 percentage points. The rest of the estimates are highly significant and of somewhat larger magnitude, ranging from 6.2 to 8.7 percentage points. As a compari-

[16]In the survey, the robot-response years are the years 1998, 2002, 2006, 2010, 2014 and 2016, which correspond to our periods of analysis.

[17]Table 1, p. 225 in Callaway and Sant'Anna (2021) provides expressions for the weights on each type of aggregation scheme of the $ATT(g,t)$.

[18]To allow for covariate-specific trends across groups in the CS-DiD setup the authors propose three different types of DiD estimands in their staggered treatment adoption setup. We use the default method of the '*csdid*' command in Stata (Rios-Avila et al., 2022), which corresponds to the Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (*drimp*).

[19]All inference procedures use robust and asymptotic standard errors clustered at the firm level, accounting for autocorrelation of the data.

Table 2: Robot Adoption treatment effects on firms' TWA use
Staggered DiD estimation

	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.058***	0.083***	0.062***	0.087***
	(0.020)	(0.021)	(0.023)	(0.023)
Event windows:				
-8, +4	0.026*	0.052***	0.020	0.042***
	(0.013)	(0.015)	(0.015)	(0.016)
-8, +8	0.035***	0.061***	0.032**	0.054***
	(0.015)	(0.017)	(0.016)	(0.017)
-8, +12	0.040***	0.066***	0.038**	0.061***
	(0.015)	(0.017)	(0.017)	(0.018)
-8, +16	0.042***	0.067***	0.039***	0.062***
	(0.015)	(0.017)	(0.017)	(0.018)
Pre-trends (Chi-sq)	0.775	1.207	0.775	1.061
(p-value)	[0.992]	[0.976]	[0.992]	[0.983]
N Obs.	6,851	6,851	6,447	6,447
Sample	All firms	All firms	Without switchers	Without switchers

Notes: *Uncond. PT* means unconditional parallel trends estimation; *Cond. PT* means conditional parallel trends estimation, where we include previous experience using TWA and firm size intervals. Columns (1) and (2) use all observations. Columns (3) and (4) discard switchers, that is robot adopters that stop reporting the use of robots (around 5% of cases). Estimation method: Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (drimp in csdid in Stata). Bootstrapped errors in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

son, for sample average probabilities of TWA use around 20%, the estimated ATT represents increases of more than one-third. The test provided at the bottom of the table shows that either unconditional or conditional, the data leads to no rejection of the null hypothesis of parallel pre-trends.

Table 2 also displays treatment effects aggregated using event-based weights within different event windows. Although smaller in magnitude, these estimates largely confirm the positive and significant effect of robots on TWA use. As compared to the 8-year period before treatment, the effects appear to be positive and increase in magnitude as the windows widen, with estimated impacts of around 4 to 6.7 percentage points towards the end of the period, depending on the specification.

Next, in Figure 7, we plot the dynamic average effect differentiating by period-specific es-

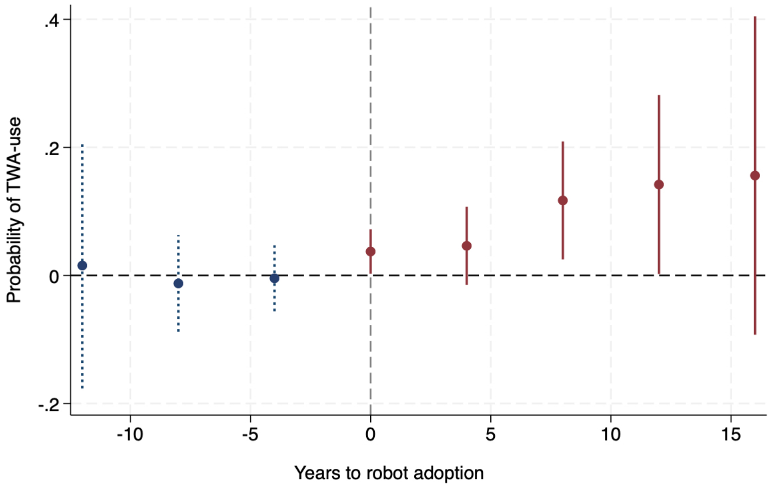

Figure 7: Event Study of the probability of using TWAs after robot adoption.

timates using the event study specification from column (1). All estimated coefficients for the pre-treatment period are close to zero and statistically insignificant. This confirms null differences in pre-trends between robot adopters and non-adopters in terms of TWA use, supporting our identification strategy. We find an increasing and positive effect after robot adoption up to ten years after treatment. This indicates a long-post treatment effect, which suggests that once firms start using robots there is a persistence of TWA use in the firms' hiring process.

4.2.3 Robustness checks

Here, we compare the results obtained with our baseline specification (column 1 in Table 2) to four alternative DiD estimators. We present the results in Table B1 in the Appendix. We show the standard TWFE-OLS estimation (in column 1), the DiD design for multiple groups and periods of De Chaisemartin and d'Haultfoeuille (2020) (column 2), the interaction weighted estimator of Sun and Abraham (2021) (column 3), and the imputation method of Borusyak et al. (2021) (column 4).[20] To facilitate the comparison across estimates, we report again our CS-DiD baseline specification (column 5). We plot the dynamic effects in Figure B2 in the Appendix. The results indicate that our results are strongly robust to the five alternative specification methods. The point estimate of the ATT ranges from 4 percentage points in the TWFE-OLS estimation to 5.2 percentage points in the Borusyak et al. (2021) estimator. The latter estimator and the CS-DiD estimator are not only the most similar in terms of the estimated ATT value,

[20]We thank Kirill Borusyak for making available on his GitHub site a Stata do-file with all five estimation methods discussed here.

but also show virtually identical dynamic effects.

Next, we consider additional robustness checks that we present in Table B2 in the Appendix. First, in column (1), we include a placebo test where we randomized the timing of the robot adoption. The estimated ATT is not significant at standard statistical levels. This provides support evidence for our identification strategy based on the timing of robot adoption.

Second, it is possible that the adoption of robots coincides with the introduction of other technologies, such as computers. To address this issue and similar to Acemoglu et al. (2023), we construct a dummy variable that takes the value one when a firm's investments in computers or software in the past years were at least once among the top 5% of all investments in that year. Then, we exclude from our analysis these observations. We present this estimation in column (2). The estimated coefficient is very similar to these previously estimated, which suggests that the effects we are capturing come from the introduction of robots and not from adopting other technologies.[21]

Third, it is also possible that changes in ownership induce within-firm changes in labor organization and hiring strategies. In particular, firms acquired by foreign MNEs might be more likely to adopt robots in the production process (Leone, 2023b). To eliminate the effects of foreign ownership, we construct a dummy variable that takes the value one if a firm is foreign-owned (defined as having more than 50% of foreign ownership) or becomes foreign-owned during the sample period.[22] Then, we exclude these observations from our analysis. The estimations are presented in column (3). The results are consistent with our previous results, which suggests that our effects are not driven by foreign acquisition.

Fourth, another potential concern is that the control group of non-adopters might be negatively affected by the adoption of robots, which in turn might have an impact on their hiring decisions. We follow Acemoglu et al. (2023) who address the potential violation of the stable unit treatment value assumption (SUTVA) excluding observations in the control group that could be affected by the treatment. We consider that the potential spillover is likely to be sector and geographical-specific and therefore exclude from our analysis all observations in the control group that are in the same industry and region cluster as robot adopters. We present this estimation in column (4). The results are in line with the previous evidence.

[21] Our results are also robust to a threshold of 1% .

[22] For the definition of foreign ownership, we follow Guadalupe et al. (2012), Javorcik and Poelhekke (2017) or Koch and Smolka (2019).

4.2.4 Ruling out possible confounding mechanisms

Our analysis considers that firms increase TWA use after robot adoption because robots increase labor efficiency but, at the same time, it becomes harder to find well-matched workers. Here we check for alternative mechanisms that could drive the positive relationship between robots and TWA use.

Intensification in the use of temporary workers. As discussed in Section 2.3, the theoretical model predicts an ambiguous effect of robot adoption on the share of temporary workers. Here we study the effect of robots on the share of temporary contracts (defined as the ratio of temporary workers over the total number of workers) at the firm level. It is possible that the higher likelihood of using TWA after robot adoption may be due to the more intensive use of temporary contracts following the adoption of robots. For example, firms adopting robots might want to increase their temporary workforce to raise flexibility and adjust their production more accurately to their demand volatility. Another possibility is that firms adopting robots are following a cost-reducing strategy and increasing their proportion of temporary workers through agencies because these workers might be easier to fire.

To study this possible mechanism, we estimate the effect of robots on the share of temporary contracts (defined as the ratio of temporary workers over the total number of workers) at the firm level. The estimated ATT equals 0.0009, with standard error equal to 0.0076 (p-value is 0.897), and the pre-trends test has a p-value equal to 0.475. This result suggests that robot adoption does not affect the firm share of temporary contracts. In Figure 8, we disentangle the ATT in different pre and post-adoption periods. Both before and after the adoption of robots the estimated coefficients are negligible and not statistically significant. This suggests that the optimal proportion of temporary workers in the production process does not change after the adoption of robots, i.e., the increased use of agencies is not a result of an increased demand for workers due to their temporary status.

The above evidence uses information on the number of temporary workers. We further explore the intensification of the use of temporary workers studying the number of hours worked by temporary workers. In Table B3 in the Appendix, we show the effect of robot adoption on the number of effective hours worked by different types of workers. First, we show the effect of robots on the logarithm of the number of hours of temporary workers hired through TWAs (column 1). The estimate is positive and significant, which indicates that after robot adoption

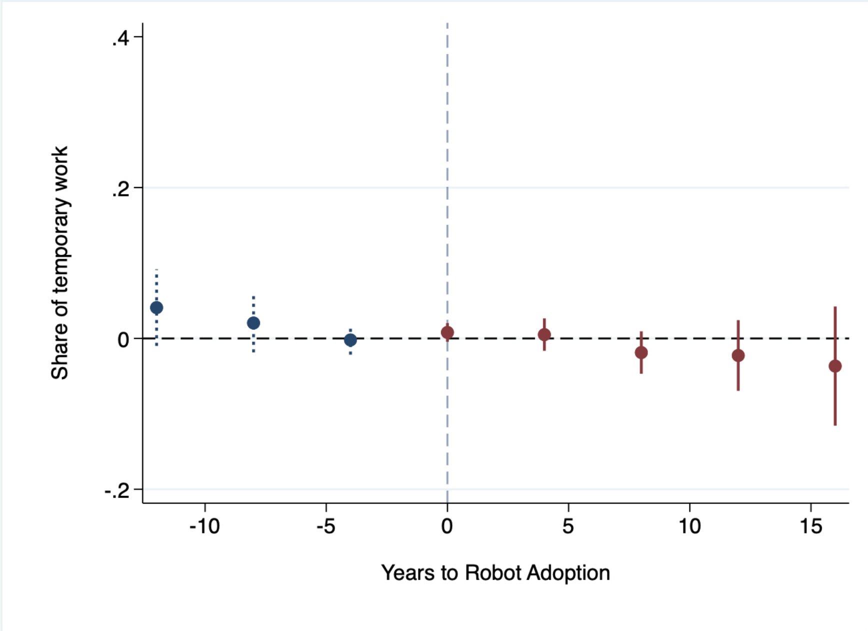

Figure 8: Is it just an intensification on the use of temps? Event Study.

the number of hours worked by TWA workers increases. As in Acemoglu et al. (2023) and Koch et al. (2021), we find an increase in total employment - measured as the logarithm of the total number of hours worked in the firm (column 2). Furthermore, we find an increase in the ratio between hours worked by temporary workers hired through TWAs and the total number of hours (column 3). However, the proportion of hours of temporary workers (column 4) remains constant after robot adoption. This again supports the idea that firms are not intensifying the use of temporary workers after the adoption of robots.

TWA use after robot adoption and demand adjustments. Another possible explanation for the increase in the use of agencies after the adoption of robots is that hiring through agencies allows firms to adjust their labor force to the potential variability of the demand. We evaluate the importance of this mechanism by exploring, first the years of the Great Recession, second sectors with high volatility, and third firms that experience high economic performance.

The Great Recession and the Spanish Sovereign Debt Crisis (from 2008 to 2014) were a period that affected very negatively the Spanish economy (Almunia et al., 2021). As shown in Figure B1 in the Appendix, at the beginning of the crisis the use of TWAs fell sharply, suggesting that firms may have adjusted employment by laying off temporary workers. If the TWA use induced by robot adoption was mostly driven by the need for production adjustments due to demand changes, then we would expect that our results would be very sensitive to the

Table 3: Robot Adoption ATT on firms' TWA use.
Staggered DiD estimation - Excluding Great Recession years

	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.070***	0.073***	0.074***	0.087***
	(0.022)	(0.023)	(0.027)	(0.026)
Pre-trends (Chi-sq)	0.285	0.979	0.285	0.979
(p-value)	[0.997]	[0.964]	[0.997]	[0.964]
N Obs.	5,234	5,234	4,951	4,951
Sample	All firms	All firms	Without switchers	Without switchers

Notes: Years 2008 to 2013 - both included- are out of estimation. Notes: *Uncond. PT* refers to unconditional parallel trends estimation; *Cond. PT*: conditional parallel trends estimation (previous experience using TWA and firm's size interval). Columns (1) and (2) use all observations. Columns (3) and (4) discard all the observations coming from switchers, that is robot adopters that at some point stop using robots. Estimation method: Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (drimp in csdid in Stata). Bootstrapped errors in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

recession years. In contrast, if an important reason for the use of TWAs is driven by the search for well-matched workers, the use of TWAs after robot adoption would be less affected by the adjustments taken during the Great Recession.

Table 3 replicates our baseline results without the years of the recession. The estimates are of similar magnitude as those of our previous estimations, ranging from 7 to 8.7 percentage points increase in the probability of TWA use. All the estimated coefficients are highly significant. This suggests that the main effect on the use of TWAs after the adoption of robots that we capture in the DiD estimation is not driven by the adjustment to the recession.

Second, we explore whether the effects are driven by sectors characterized by greater demand volatility, where the need for firing and scaling up or down quickly is important due to unforeseen market circumstances. To study this possible mechanism, we exclude from our analysis firms in sectors with high volatility. To obtain the volatility measure, we follow Czarnitzki and Toole (2011). We calculate the standard deviation of sales per employee and divide it by the average level of sales per employee to obtain a measure that is comparable across firms of different sizes. The sectoral measure is the average across all firms in a given industry. We reduce the potential endogeneity of the volatility by considering the pre-sample period (from 1990 to 1995).

Then, we construct a dummy variable that takes the value one for firms that are among the top 10% of sectoral volatility. Table B4 in the Appendix replicates our baseline results without firms in sectors with high volatility. The estimates are significant and larger than the baseline estimations and range from 0.068 to 0.104. This suggests that the increase in TWA use after robot adoption is not related to adjustments to demand volatility.

Third, the higher likelihood of using TWA after robot adoption may be because market expectations are positive and firms just need to scale up their production. We explore this potential mechanism by studying the effects of robot adoption on TWA use excluding observations that experience large economic growth. To do that, we drop from our analysis observations in an industry with sales above the 90% percentile of the industrial distribution. The results presented in Table B5 in the Appendix are consistent with the previous estimations.

To summarize, so far, we have obtained a positive and significant effect of robot adoption on the probability of TWA use providing evidence in favor of our model's theoretical prediction that the use of robots tends to shift the hiring channel of firms towards TWAs. It does not seem that the reasons for this relationship are to adjust their production more accurately to their demand volatility or the need to adjust the labor force to the demand cycle. We also do not find an intensification of the share of temporary workers.

4.3 Robots and TWA use: Effects on firm productivity

4.3.1 Empirical strategy

In this section, we test the second prediction of our model, namely that using agencies combined with robot adoption increases firm productivity. To explore this effect, we study the complementarity between robot adoption and TWA use on firm productivity by estimating the following DiD equation at the firm level:

$$\begin{aligned} y_{it} &= \alpha + \gamma\ Robots_{it} + \delta\ TWA_{it} + \theta\ TWA_{it} \times Robots_{it} + \\ &\quad + \lambda\ Temps_{it} + \eta_t + \eta_i + \eta_{jt} + \eta_{rt} + u_{it} \end{aligned} \tag{8}$$

In equation (8), the variable y_{it} represents the labor productivity of firm i in period t, and it is constructed as the logarithm of the firm's value added deflated with firm-level deflators, available in our dataset, and divided by (effective) labor-hours.[23] $Robots_{it}$ is the post-treatment indicator variable for firm i in period t. To simplify notation, we refer to current-period robot adoption in equation (8), but in the estimations below we explore different time specifications of this variable. Specifically, as in Koch et al. (2021), we consider the effect of robot adoption in period t on a firm's productivity in the current period t, and also the effect of robot adoption in the previous period $t-1$. TWA_{it} is the indicator of TWA use in period t; $Temps_{it}$ stands for the firm's share of temporary workers and aims at partialling out the productivity impacts that may stem from the labor-contracting structure of firms; η_t includes a full set of time dummies; η_i stands for firm fixed effects; η_{jt} stands for sector-time effects; η_{rj} stands for region-industry effects (17 regions and 20 industrial sectors); and, finally, u_{it} is the error term of the equation.[24] By including fixed effects for individual firms, the productivity effects of robot adoption are identified through within-firm variation, i.e., firms switching from non-robot use to robot use over time. Standard errors are bootstrapped clustered errors at the firm level.

Our theory considers that TWAs provide better job matches (regardless of robot adoption). We expect a positive estimated coefficient of δ. Moreover, robot adoption raises the stakes of obtaining a good match. Therefore, our main term of interest is the interaction term $TWA_{it} \times Robots_{it_a}$, with the productivity effect captured by the parameter θ. A positive and significant estimate of θ would indicate, as our model predicts, that there is a positive complementarity between robots and TWAs. In other words, the use of TWAs increases robots' productivity; similarly, it would indicate that agency workers combined with robots have a productivity premium.

In our baseline specification, we use the static TWFE DiD strategy specified in equation (8) because we are interested not only in the treatment effect of robot adoption but also in its combined effect with TWA use. At the same time, we want to partial out the potential negative effect of temporary employment on productivity. The static DiD strategy provides a flexible framework to simultaneously estimate these effects and it also allows us to compare our estimates with previous results in the literature that used a similar empirical strategy (Koch et al., 2021). In the robustness section, we show staggered specifications to study the complementarity between robots and TWA use by comparing robot adopters that use TWAs

[23] As in section 4.2.1, subscript t refers to the 4-year periods ending in the year in which firms are asked in the survey about the use of robots. The remaining variables are annual variables averaged over those 4-year periods.

[24] As in Guadalupe et al. (2012) the productivity variable, as well as the TWA use and temporary share measures are deviated from the industry mean, within 5-size firms' size intervals.

with robot adopters that do not use TWAs.

An estimation concern is that robot adopters might be more productive than non-adopters before adoption (Graetz and Michaels, 2018; Koch et al., 2021). To address this issue, we apply a balancing method before estimating equation (8). We use the entropy balance reweighting algorithm of Hainmueller (2012), implemented following Hainmueller and Xu (2013). The main advantage of the entropy balance in comparison to other balancing algorithms such as p-score, is that the data in the control group can be reweighted to exactly match several distributional moments of the covariates in the treatment group. This ensures that the treatment and control groups are similar not only in terms of average characteristics but also at higher moments of the distribution. This further reduces concerns that changes in productivity following robot adoption may be due to pre-existing differential productivity trends between robot adopters and non-adopters.

The identifying assumption is that by balancing the pre-treated and control samples on observable characteristics relevant to both productivity and robot adoption, productivity would not systematically differ between robot adopters and non-adopters in the absence of robot adoption. We balance the treated and control samples in terms of both the mean and the variance of the following variables: TWA use, real sales, sales growth, labor productivity, labor productivity growth, capital-, skill- and R&D intensity, indicators for an exporter, importer and foreign ownership, share of firms within each industry and year dummies. The final DiD analysis is conducted for the firms with common support. A weight is assigned to each firm based on the entropy balance. In Table B6 in the Appendix, we present the balancing test for the entropy balance. Looking at firm characteristics before matching, we see that robot adopters before adoption are more productive than non-adopters, also more R&D intensive and have more sales. After matching, the mean and variance values of all covariates, for robot and non-robot adopters, are equal in observed characteristics. Therefore, the algorithm balances the samples and solves the potential selection bias.

4.3.2 Baseline results

Table 4 displays the main results. In columns (1) and (2), we explore the effect of robots on firm productivity considering different lags of robot adoption. In column (1), we show both current and lagged robot adoption. The results in column (1) indicate that the estimated effect for current period adoption is very small and insignificant at standard statistical levels, while the lagged effect is positive and significant. Firm productivity increases by 10.4 percent over the 4-year period following the period of robot adoption. In column (2), we obtain the same result when we only include lagged robot adoption. This estimated effect compares quite closely to the productivity effects estimated by Koch et al. (2021).[25] In column (3), we include the TWA use variable and the share of temporary workers. The estimated coefficient for the share of temporary workers is negative and significant at standard levels. This negative productivity effect is in line with the idea that temporary workers are on average less productive than permanent workers (Lisi and Malo, 2017). Conditional on the share of temporary work, the use of TWAs has a differential positive impact on productivity, with an estimated value equal to 8.9 percent. In column (4), we estimate the complementarity between robots and TWA use by including the interaction term. The estimated coefficient is positive and significantly different from zero, suggesting gains in productivity equal to 8.4 percent. This latter result confirms our theoretical prediction that firms introducing robots will be able to achieve greater productivity gains if they can employ well-suited employees to the needs of the new technology, a possibility facilitated by the use of recruitment agencies.

4.3.3 Robustness checks

In Table B7 in the Appendix, we present several robustness checks. First, we use an alternative measure of productivity. We repeat the analysis using real sales per worker instead of value added as a measure of firm productivity. The main findings remain. We find a positive complementarity between robot adoption and TWA use, a positive direct effect of both robot adoption and TWA use and a negative effect of the temporary work share. Second, we use p-score as an alternative balancing method. Similar to Guadalupe et al. (2012), we combine the TWFE approach with the p-score reweighting estimator in the spirit of DiNardo et al. (1996). We first conduct industry-specific probit regressions for robot adoption with the same covariates that we have used for the entropy balance. The DiD analysis is conducted for the firms with common support and for which the balancing property on the average values of covariates is satisfied within each industry. The results are consistent with previous estimations in terms of the effects of robots, TWA use and complementarity effects.

[25] Their estimates lie between 16.1 percent and 10.5 percent, depending on the specification (their Table 2 on page 2573).

Table 4: Productivity of Robots and TWA use (DiD estimation with re-weighting)

	(1)	(2)	(3)	(4)
$Robots_t$	-0.026			
	(0.016)			
$Robots_{t-1}$	0.104***	0.104***	0.100***	0.086***
	(0.022)	(0.012)	(0.012)	(0.014)
TWA			0.089***	0.067***
			(0.009)	(0.011)
$Robots_{t-1} \times TWA$				0.084**
				(0.029)
$Temps$			-0.165***	-0.164***
			(0.019)	(0.018)
Observations	2,550	2,550	2,550	2,550
R-squared	0.839	0.839	0.841	0.841
Industry-year effects	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes

Notes: The outcome variable is labor productivity of firm i in period t, and it is constructed as the (log of) firm's value added deflated with ESEE annual firm-level deflators and divided by (effective) labor hours. $Robots_t$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters that report for the first time using robots in the current ESEE response year; $Robots_{t-1}$ is similarly defined for firms reporting robot use for the first time in the previous ESEE response year; TWA is the indicator of TWA use in period t; $Temps$ stands for the firm's share of temporary workers during that period. All the variables other than robots are sample averages over the years between two consecutive ESEE response years (i.e., over 4-year periods denoted by t). Bootstrapped standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01.

For robustness purposes, we further present estimations for the complementarity of robots and TWA using the staggered CS-DiD methodology. As indicated before, a drawback of this methodology in our context is that it does not allow us to simultaneously study the effect of robots while including additional variables of interest such as agency or the robot-agency interaction term. To study the complementarity between robot adoption and TWA use on firm productivity with the staggered methodology we proceed as follows. We restrict our sample to robot adopters and compare the productivity of robot adopters that combine robot adoption with TWA use to robot adopters without TWA use. We experiment with different intervals of TWA use (two, four and six-year intervals) after robot adoption, obtaining similar results. For example, for robot adopters with TWA use four years after adoption, the estimated ATT is equal to 0.133, with standard error equal to 0.042 (p-value is 0.002), and the pre-trends test has a p-value equal to 0.481. This indicates that TWA increases the productivity of robot adopters and supports our complementarity prediction. In Figure B3 in the Appendix, we show the dynamics of the estimated effect. The dynamic pattern shows a positive effect that lasts up to eight years. This suggests that firms that adopt robots with TWA use have higher productivity than those without TWA use. The positive effect lasts up to eight years after robot adoption.

Finally, for completeness, in Table B8 in the Appendix, we repeat the additional robustness checks that we include in Section 4.2.3. In particular, in column (1), we exclude switchers -firms that stop reporting robots after adoption- from our analysis. The results are consistent with previous estimations. In column (2), we run a placebo test, where we randomly assign the timing of the robot adoption. In this case, the estimated coefficients for both robots and the interaction between robots and TWA use are very small and insignificant at standard levels. This suggests that the productivity effects we found come from robot adoption and its interaction with TWA use. In column (3), we address the issue of alternative investments at the time of robot adoption by excluding from our regression observations with high investments in computers or software in the past years - measured as the top 5% of all investments in that year. The results are robust to the exclusion of these other investments.[26] In column (4), we address the possible effect of foreign ownership by excluding from the sample firms that are either foreign-owned or that become foreign-owned during our sample period. Dropping these firms from our analysis does not change our results. In column (5), we address the potential issue of the violation of the STUVA by excluding control observations in the same industry and region as firms with robot adoption. Differently from our previous regressions where we control from possible spillovers (Table B2, column 4), in this regression, we only exclude control observations after the first time we observe, within a region-industry cluster, a robot adoption. We do that to ensure that we have enough control observations in our sample. Similar to the baseline result, we find a positive effect of robots and TWA use on firm productivity, a positive complementarity between robots and TWA use and a negative effect for the share of temporary workers.

5 Summary and concluding remarks

This paper studies for the first time, theoretically and empirically, the effects of robot adoption on the use of TWAs and the combined effect of robots and TWAs on firm productivity. This is important for understanding the relationship between robots and labor arrangements within

[26]The results are also robust to a threshold of 1% and to the exclusion of observations with high expenditures in machinery.

firms. We develop a theoretical framework where the adoption of new production technologies increases firm productivity, but it also increases the need for a higher quality match between jobs and workers. In the model, TWAs are market intermediaries that provide a signal to the firms about the appropriateness of the workers to the new technologies. Moreover, TWAs can provide workers in a faster way than if the firm goes directly to the job market. As a consequence, after the adoption of robots firms have incentives to change their search strategies increasing their likelihood to use TWAs. The model also predicts that firms that adopt new technologies can increase their productivity with the use of TWAs due to the better and faster quality match between workers and technologies.

We test the model implications with panel data of Spanish firms from 1997 to 2016 with information on robot adoption and use of TWAs. We estimate the causal effects of robot adoption on TWAs using staggered difference-in-difference (DiD) estimations. We find that firms that introduce robots increase the probability of using TWAs by six to nearly nine percentage points, depending on the specification. We further find that firms that combine robots with agency workers achieve additional productivity gains beyond the productivity effects of robot adoption. This suggests that TWAs increase the matching quality between new production technologies and labor.

This paper contributes to the understanding of the effects of robots at a broader level. Our results highlight the challenges of introducing robots for the reorganization of the labor force. Our findings suggest that automated technologies have consequences on firm searching strategies and outsourcing heterogeneity of the labor force. We consider that further understanding of the role of job market intermediaries and new technologies, as well as possible policy interventions of public agencies are promising avenues of future work.

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A Mathematical appendix

A.1 The Bellman equations

Consider permanent contracts first. If a firm accepts a match of bad quality, its value solves

$$r\Omega_P(0) = \lambda \left[\max\left\{\Omega_P(0), U - F\right\} - \Omega_P(0)\right], \tag{9}$$

Under Assumption 1, $U - F > 0$ and so $\Omega_P(0) = \frac{\lambda}{r+\lambda}(U - F)$. If a firm accepts a match of posterior $\mu > 0$, its value solves

$$r\Omega_P(\mu) = \xi\mu + \beta\mu\left[\Omega_P(1) - \Omega_P(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right)\left[\max\left\{\Omega_P(0), U - F\right\} - \Omega_P(\mu)\right]. \tag{10}$$

From the previous equation, we observe that $\Omega_P(0) < U - F$. Any match separates when it turns unproductive or if match quality turns out to be bad. Hence we obtain equation (3).

Consider now temporary contracts. If a firm accepts a match of bad quality, it can wait until the contract expiration to avoid the dismissal cost. The corresponding Bellman equation is

$$r\Omega_T(0) = \lambda \left[\max\left\{\Omega_T(0), U - F\right\} - \Omega_T(0)\right] + \delta\left[\max\left\{\Omega_P(0), U\right\} - \Omega_T(0)\right]. \tag{11}$$

Under Assumption 1, $\Omega_T(0) = \frac{\delta U}{r+\delta} > U - F$. This means the firm prefers to wait for the expiration of the contract when the job is unproductive. If a firm in a good match prefers to keep a temporary relationship, its value solves

$$r\Omega_T(1) = \tau\xi + \lambda\left[\max\left\{\Omega_T(0), U-F\right\} - \Omega_T(1)\right] + \delta\left[\max\left\{\Omega_P(1), U\right\} - \Omega_T(1)\right]. \tag{12}$$

If a firm accepts a match of posterior μ in $]0,1[$, its value solves

$$\begin{aligned} r\Omega_T(\mu) = {}& \tau\xi\mu + \beta\mu\left[\max\left\{\Omega_T(1), \Omega_P(1)\right\} - \Omega_T(\mu)\right] + (\beta(1-\mu)+\lambda)\left[\max\left\{\Omega_T(0), U-F\right\} - \Omega_T(\mu)\right] \\ & + \delta\left[\max\left\{\Omega_P(\mu), U\right\} - \Omega_T(\mu)\right]. \end{aligned} \tag{13}$$

To obtain equation (4), we will show that $\Omega_T(1)$ is always lower than $\Omega_P(1)$ or U. We will show this result by contradiction. Suppose $\Omega_T(1) \geq \max\left\{\Omega_P(1), U\right\}$. We find

$$(r+\lambda)\left[\Omega_P(1) - \Omega_T(1)\right] = (1-\tau)\xi - \lambda\left(\omega_0 - U + F\right) - \delta\left[\max\left\{\Omega_P(1), U\right\} - \Omega_T(1)\right], \tag{14}$$

$$(r+\lambda)\left[U - \Omega_T(1)\right] = rU - \tau\xi + \lambda\left(U - \omega_0\right) - \delta\left[\max\left\{\Omega_P(1), U\right\} - \Omega_T(1)\right], \tag{15}$$

with the parameter $\omega_0 = \Omega_T(0) = \frac{\delta U}{r+\delta}$. It must be that

$$\begin{cases} (1-\tau)\xi - \lambda(\omega_0 - U + F) \leq 0 \\ rU - \tau\xi + \lambda(U - \omega_0) \leq 0 \end{cases} \tag{16}$$

Combining the two inequalities, we find

$$-\tau\lambda(\omega_0 - U + F) + (1-\tau)\left(rU + \lambda\left(U - \omega_0\right)\right) \leq 0, \tag{17}$$

which contradicts Assumption 2.

We therefore obtain equation (4) as a simplification of (13).

A.2 Proposition 1

We introduce the parameter $\omega_1 = \Omega_P(1) = \frac{\xi + \lambda(U-F)}{r+\lambda}$. Now define, for any μ in $]0,1[$,

$$r\Omega_T^U(\mu) = \tau\xi\mu + \beta\mu\left[\omega_1 - \Omega_T^U(\mu)\right] + (\beta(1-\mu)+\lambda)\left[\omega_0 - \Omega_T^U(\mu)\right] + \delta\left[U - \Omega_T^U(\mu)\right], \tag{18}$$

$$r\Omega_T^P(\mu) = \tau\xi\mu + \beta\mu\left[\omega_1 - \Omega_T^P(\mu)\right] + (\beta(1-\mu)+\lambda)\left[\omega_0 - \Omega_T^P(\mu)\right] + \delta\left[\Omega_P(\mu) - \Omega_T^P(\mu)\right], \tag{19}$$

so that $\Omega_T(\mu) = \max\left\{\Omega_T^U(\mu), \Omega_T^P(\mu)\right\}$.

The values $\Omega_P(\mu)$, $\Omega_T^U(\mu)$ and $\Omega_T^P(\mu)$ are all linear in μ. It follows that:

$$\Omega_P(\mu) = (1-\mu)\Omega_P(0^+) + \mu\Omega_P(1), \tag{20}$$

$$\Omega_T^U(\mu) = (1-\mu)\Omega_T^U(0^+) + \mu\Omega_T^U(1^-), \tag{21}$$

$$\Omega_T^P(\mu) = (1-\mu)\Omega_T^P(0^+) + \mu\Omega_T^P(1^-), \tag{22}$$

where

$$\Omega_P(0^+) = \frac{\beta+\lambda}{r+\beta+\lambda}(U-F) \qquad \text{and} \qquad \Omega_P(1) = \omega_1, \tag{23}$$

$$\Omega_T^U(0^+) = \omega_0 \qquad \text{and} \qquad \Omega_T^U(1^-) = \frac{\tau\xi + \beta\omega_1 + \lambda\omega_0 + \delta U}{r+\beta+\lambda+\delta}, \tag{24}$$

$$\Omega_T^P(0^+) = \omega_0 - \frac{\delta}{r+\beta+\lambda+\delta}(U - \Omega_P(0^+)) \qquad \text{and} \qquad \Omega_T^P(1^-) = \frac{\tau\xi + (\beta+\delta)\omega_1 + \lambda\omega_0}{r+\beta+\lambda+\delta}. \tag{25}$$

Given the value of the vacancy V, a match is accepted if $\Omega_P(\mu) \geq U+V$ or $\Omega_T^U(\mu) \geq U+V$ or $\Omega_T^P(\mu) \geq U+V$. For the first condition, $\Omega_P(\mu) \geq U+V$ if and only if

$$\frac{1-\mu}{\mu} \leq \frac{\Omega_P(1) - U - V}{U + V - \Omega_P(0^+)}.$$

We can find similar inequalities for the two other conditions. We therefore define

$$H(\xi, V) = \max\left(\frac{\omega_1 - U - V}{U+V-\Omega_P(0^+)}, \frac{\Omega_T^U(1^-) - U - V}{U+V-\omega_0}, \frac{\Omega_T^P(1^-) - U - V}{U+V-\Omega_T^P(0^+)}\right). \tag{26}$$

Since ω_1, $\Omega_T^U(1^-)$ and $\Omega_T^P(1^-)$ are linear and increasing in ξ, the function $H(\xi, V)$ is piecewise-linear and increasing in ξ.

We now show the second part of Proposition 1. Fix ξ. Define μ_T^U and μ_P as solutions to $\Omega_T^U(\mu_T^U) = U$ and $\Omega_P(\mu_P) = U$. We will consider separately the two cases $\mu_T^U \leq \mu_P$ and $\mu_T^U > \mu_P$.

Suppose $\mu_T^U \leq \mu_P$. For any μ in $\left[\mu_T^U, \mu_P\right]$, we have $\Omega_T^U(\mu) \geq \Omega_T^P(\mu)$ and $\Omega_T^U(\mu) \geq U \geq \Omega_P(\mu)$. This result means that a temporary job is preferred on $\left[\mu_T^U, \mu_P\right]$. For $\mu > \mu_P$, we have that $\Omega_T^P(\mu) \geq \Omega_T^U(\mu)$ and so a permanent job is preferred if and only if $\Omega_P(\mu) \geq \Omega_T^P(\mu)$. Using

$$(r+\beta+\lambda+\delta)\left(\Omega_P(\mu)-\Omega_T^P(\mu)\right)=(1-\tau)\xi\mu+(\beta\,(1-\mu)+\lambda)\left[U-F-\omega_0\right], \tag{27}$$

we find the condition in Proposition 1.

Suppose $\mu_T^U > \mu_P$, then $\Omega_P(\mu) \geq \Omega_T^U(\mu)$ for any accepted match. Using Assumption 1, we can show that $\Omega_P(0^+) \leq \Omega_T^P(0^+)$ and $\Omega_P(1) \geq \Omega_T^P(1^-)$. This implies that the slope of $\Omega_P(\mu)$ in μ is higher than the slope of $\Omega_T^P(\mu)$. We also find at the threshold μ_P that $\Omega_P(\mu_P) \geq \Omega_T^P(\mu_P) = \Omega_T^U(\mu_P)$. Hence, for any accepted match, $\Omega_P(\mu) \geq \Omega_T^P(\mu)$. This result means that a permanent job is always proposed and the second inequality in Proposition 1 is always satisfied.

A.3 Proposition 2

A.3.1 Existence

When $\xi = 0$, then $V_A = V_R = 0$ and so $V_A - C < V_R$. When $\xi = \infty$, we show below that $V_A - C < V_R$. We introduce $\tilde{V}_A$ as solution to

$$r\tilde{V}_A = q_A(1-\varphi)\int_0^1 \left(\Omega(\mu) - U - \tilde{V}_A\right) f(\mu|\pi)d\mu. \tag{28}$$

We want to a lower bound to $V_A - V_R$ that tends towards infinity when ξ goes to infinity. We decompose $V_A - V_R = V_A - \tilde{V}_A + \tilde{V}_A - V_R$.

First,

$$\tilde{V}_A - V_R \geq \frac{q_R(1-\varphi)}{r+q_R(1-\varphi)}\left(\int_0^1 \Omega(\mu)f(\mu|\pi)d\mu - \Omega(\pi)\right). \tag{29}$$

Equations (20), (21) and (22) imply that $\Omega(\mu)$ can be decomposed as

$$\Omega(\mu) = \begin{cases} \Omega_T^U(\mu) \text{ if } \mu < \mu_1 \\ \Omega_T^P(\mu) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \Omega_P(\mu) \text{ if } \mu_2 \leq \mu \end{cases}, \tag{30}$$

with $0 \leq \mu_1 \leq \mu_2 \leq 1$. We differentiate this function and find:

$$\frac{\partial \Omega}{\partial \mu}(\mu) = \begin{cases} \Omega_T^U(1^-) - \Omega_T^U(0^+) \text{ if } \mu < \mu_1 \\ \Omega_T^P(1^-) - \Omega_T^P(0^+) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \Omega_P(1) - \Omega_P(0^+) \text{ if } \mu_2 \leq \mu \end{cases} . \tag{31}$$

Notice that $\Omega_P(0^+) \leq \Omega_T^P(0^+) \leq \Omega_T^U(0^+)$ and $\Omega_P(1) \geq \Omega_T^P(1^-) \geq \Omega_T^U(1^-)$. Therefore $\frac{\partial \Omega}{\partial \mu}(\mu)$ is increasing in μ and $\Omega(\mu)$ is convex in μ. With Jensen's inequality and inequality (29), we find that $\tilde{V}_A - V_R \geq 0$.

Define π_A such that $V_A = \Omega(\pi_A) - U$, which implicitly depend on π and ξ. We have

$$rV_A = q_A(1-\varphi) \int_{\pi_A}^{1} \left(\Omega(\mu) - U - V_A\right) f(\mu|\pi) d\mu. \tag{32}$$

Second,

$$V_A - \tilde{V}_A = -\frac{q_A(1-\varphi)}{r + q_A(1-\varphi)} \int_0^{\pi_A} \left(\Omega(\mu) - U - V_A\right) f(\mu|\pi) d\mu. \tag{33}$$

Let $G(\mu|\pi)$ be the complementary cumulative distribution function of the posterior, i.e. $G(\mu|\pi) = \int_\mu^1 f(x|\pi)dx$. Integrating by parts, we obtain

$$V_A - \tilde{V}_A = \frac{q_A(1-\varphi)}{r + q_A(1-\varphi)} \int_0^{\pi_A} \frac{\partial \Omega(\mu)}{\partial \mu}(\mu)(1 - G(\mu|\pi)) d\mu. \tag{34}$$

Therefore, we find $V_A - V_R \geq \frac{q_A(1-\varphi)}{r+q_A(1-\varphi)} \int_0^{\pi_A} \frac{\partial \Omega(\mu)}{\partial \mu}(\mu)(1 - G(\mu|\pi))d\mu$. The right-hand side tends towards infinity when ξ tends towards infinity.

Since $V_A - C - V_R$ is continuous in ξ, the intermediate value theorem implies the existence of $\Xi(\pi)$ when $0 < \pi < 1$.

A.3.2 Uniqueness

The unicity of $\bar{\xi}(\pi)$ derives from the monotonicity of $V_A - V_R$ in ξ. We show that $\frac{\partial V_A - V_R}{\partial \xi} > 0$ for any π and ξ. Define π_R such that $V_R = \Omega(\pi_R) - U$. We differentiate equations (1) and (2).

$$\frac{\partial V_R}{\partial \xi} = \frac{q_R(1-\varphi)}{r + q_R(1-\varphi)} \frac{\partial \Omega}{\partial \xi}(\pi) \text{ if } \pi > \pi_R, \text{ and 0 otherwise,} \tag{35}$$

$$\frac{\partial V_A}{\partial \xi} = \frac{q_A(1-\varphi)}{r + q_A(1-\varphi)G(\pi_A|\pi)} \int_{\pi_A}^{1} \frac{\partial \Omega}{\partial \xi}(\mu) f(\mu|\pi) d\mu. \tag{36}$$

When $\pi < \pi_R$, we have $\frac{\partial V_A}{\partial \xi} > 0 = \frac{\partial V_R}{\partial \xi}$. We will show the result when $\pi > \pi_R$. Given $q_A \geq q_R >> r$, the partial derivatives simplify:

$$\frac{\partial V_R}{\partial \xi} = \frac{\partial \Omega}{\partial \xi}(\pi), \tag{37}$$

$$\frac{\partial V_A}{\partial \xi} = \int_{\pi_A}^{1} \frac{\partial \Omega}{\partial \xi}(\mu) \frac{f(\mu|\pi)}{G(\pi_A|\pi)} d\mu. \tag{38}$$

We now show that $\frac{\partial \Omega}{\partial \xi}(\mu)$ is convex in μ. The parameters μ_1 and μ_2 in equation (30) depend on ξ, but we can use the envelope theorem to find that

$$\frac{\partial \Omega}{\partial \xi}(\mu) = \begin{cases} \mu \frac{\partial \Omega_T^U}{\partial \xi}(1^-) \text{ if } \mu < \mu_1 \\ \mu \frac{\partial \Omega_T^P}{\partial \xi}(1^-) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \mu \frac{\partial \Omega_P}{\partial \xi}(1) \text{ if } \mu_2 \leq \mu \end{cases} \quad \text{hence } \frac{\partial^2 \Omega}{\partial \mu \partial \xi}(\mu) = \begin{cases} \frac{\partial \Omega_T^U}{\partial \xi}(1^-) \text{ if } \mu < \mu_1 \\ \frac{\partial \Omega_T^P}{\partial \xi}(1^-) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \frac{\partial \Omega_P}{\partial \xi}(1) \text{ if } \mu_2 \leq \mu. \end{cases} \tag{39}$$

Since $\frac{\partial \Omega_T^U}{\partial \xi}(1^-) < \frac{\partial \Omega_T^P}{\partial \xi}(1^-) < \frac{\partial \Omega_P}{\partial \xi}(1)$, we conclude that $\frac{\partial^2 \Omega}{\partial \mu \partial \xi}(\mu)$ is increasing in μ. Therefore $\frac{\partial \Omega}{\partial \xi}(\mu)$ is convex in μ.

We apply Jensen's inequality to the right-hand side of equation (38):

$$\frac{\partial V_A}{\partial \xi} \geq \frac{\partial \Omega}{\partial \xi} \left(\int_{\pi_A}^{1} \mu \frac{f(\mu|\pi)}{G(\pi_A|\pi)} d\mu \right). \tag{40}$$

Notice that $\int_{\pi_A}^{1} \mu \frac{f(\mu|\pi)}{G(\pi_A|\pi)} d\mu = \mathbb{E}[\mu|\mu > \pi_A] > \mathbb{E}[\mu] = \pi$. Notice also that the function $\frac{\partial \Omega}{\partial \xi}$ is increasing in μ. Therefore, we find that

$$\frac{\partial V_A}{\partial \xi} > \frac{\partial \Omega}{\partial \xi}(\pi) = \frac{\partial V_R}{\partial \xi}. \tag{41}$$

This inequality proves that, for a given π, there cannot be two values of ξ such that $V_A - C = V_R$.

$\Xi(\pi)$ is therefore unique.

B Appendix: Additional descriptive statistics and figures

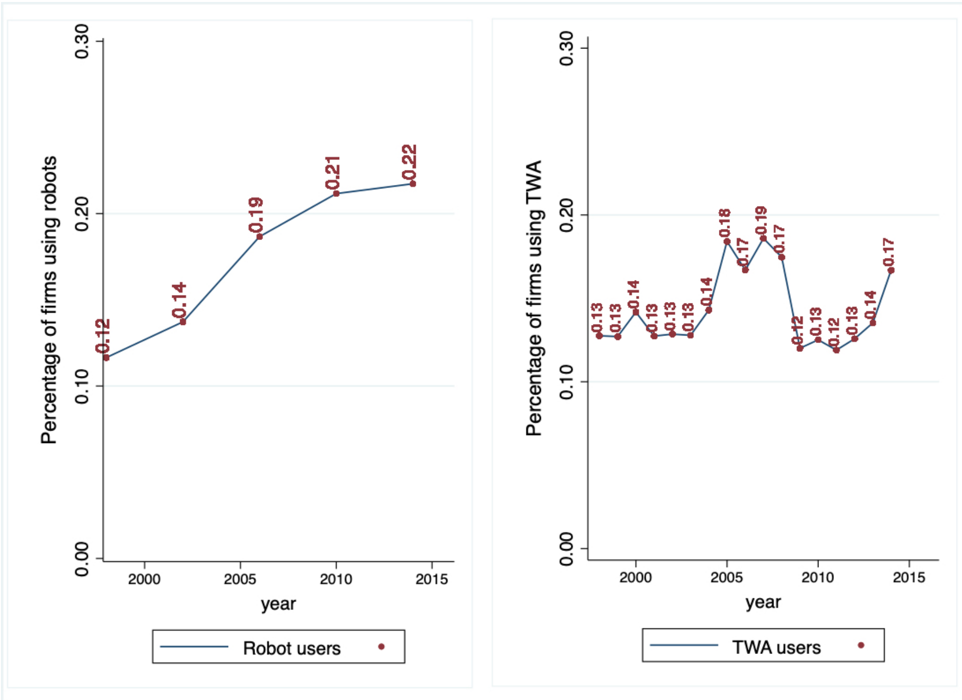

Figure B1: Share of firms using TWA and robots

Table B1: Robot Adoption ATT on firms' TWA use. Staggered DiD estimation - Results with five DiD estimators

	OLS-TWFE (1)	DeCh.-d'H.(2020) (2)	Sun-Ab.(2021) (3)	Borusy. (2021) (4)	Call-Sant.(2021) (5)
Total ATT	0.040*** (0.015)	0.046*** (0.016)	0.040*** (0.015)	0.052*** (0.017)	0.058*** (0.020)
Pre-trends[a]	0.940 [0.421]	0.005 (0.016) -0.022 (0.063)	-0.002 [0.222]	0.402 [0.897]	0.775 [0.992]
N.Obs	6,851	6,851	6,851	6,851	6,851

Notes: [a] Pre-trends tests p-values in squared brackets; in the case of column (2), standard errors of the pre-period differences are provided in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01. Column labels: (1) TWFE OLS estimation; (2) De Chaisemartin and d'Haultfoeuille (2020); (3) Sun and Abraham (2021); (4) Borusyak et al. (2021); (5) Callaway and Sant'Anna (2021), column 1 of Table 2. The estimates in the table are graphically shown in Figure B2.

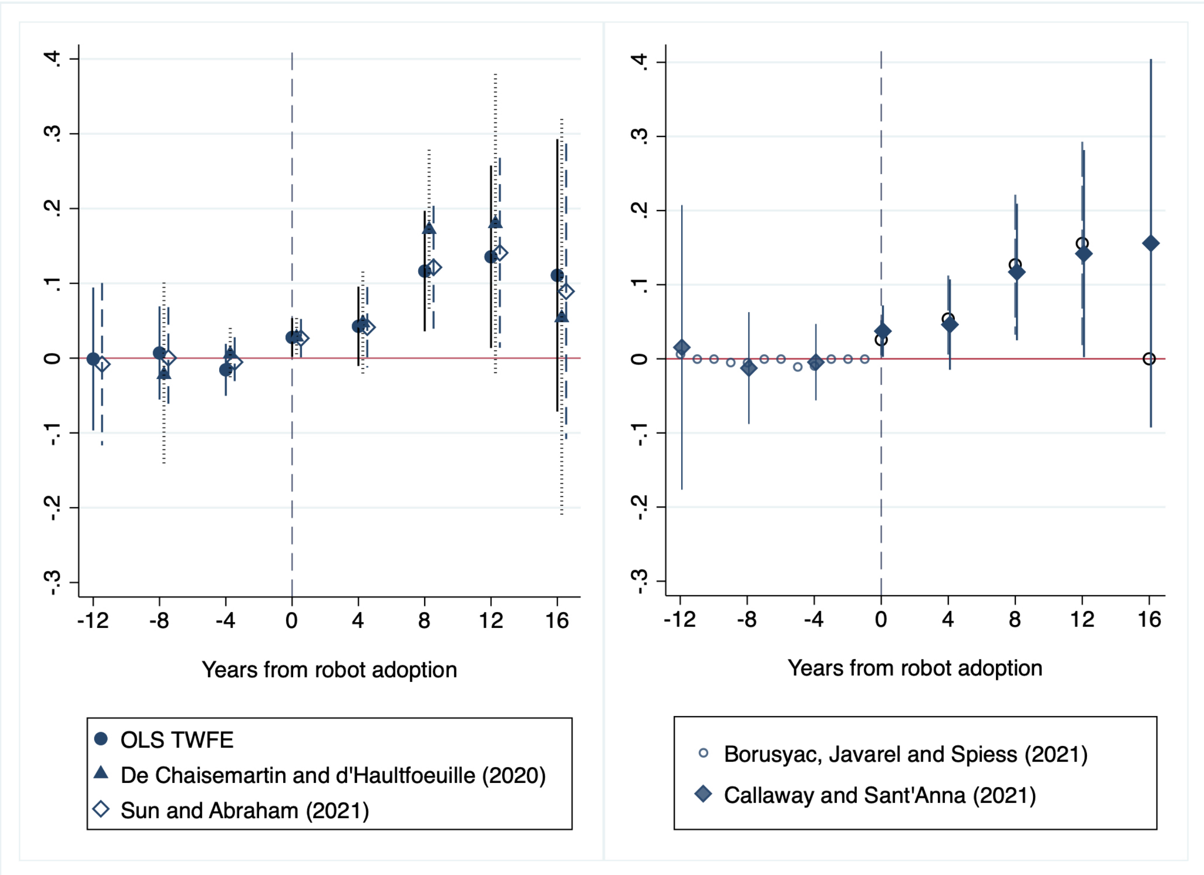

Figure B2: Probability of using TWAs after robot adoption using five DiD estimators. The plot displays the point ATT estimates and the 95% confidence interval corresponding to results provided in Table B1.

Table B2: Robustness checks. Staggered DiD estimation

	Placebo	Control for computers	Control for foreign MNEs	SUTVA
	(1)	(2)	(3)	(4)
Total ATT	-0.059	0.057**	0.057**	0.066***
	(0.066)	(0.021)	(0.021)	(0.022)
Pre-trends (Chi-sq)	186.6	0.651	5.73	0.748
(p-value)	[0.000]	[0.995]	[0.454]	[0.993]
N Obs.	2,512	6,358	5,581	2,515

Notes: In column (1), we construct a placebo test, where we assign randomly the timing of the robot adoption. In column (2), we exclude observations with high investments in computers or software in the past years (defined as at least top 5% of all investments in that year. In column (3), we exclude observations that are foreign-owned or become foreign-owned during our sample period (measured as having more than 50% foreign ownership). In column (4), we exclude observations in the control group that are in the same industry and region as the firms that adopt robots. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

Table B3: The effect of robot adoption on number of hours by different type of workers. Staggered DiD estimation

	Temps TWA	Total hours	Temps TWA over total	Temps over total
	(1)	(2)	(3)	(4)
Total ATT	0.414***	0.069**	0.011***	0.0062
	(0.140)	(0.029)	(0.003)	(0.0063)
Pre-trends[a]	7.382	8.596	6.400	9.092
	[0.286]	[0.197]	[0.379]	[0.168]
N.Obs	1,670	6,170	6,416	6,411

Notes: [a] Pre-trends tests p-values in squared brackets. * p-value<0.10 ** p-value<0.05 *** p-value<0.01. *Temps TWA* is the logarithm of the total number of effective hours worked by temporary workers hired through TWAs. *Total hours* is the logarithm of the total number of effective hours worked in the firm. *Temps TWA over total* is the ratio between the total number of hours worked by temporary workers hired through TWAs over the total number of effective hours worked in the firm. *Temps over total* is the proportional hours worked by temporary workers.

Table B4: Robot Adoption ATT on firms' TWA use. Staggered DiD estimation - Excluding observations in sectors with high volatility

	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.068**	0.074**	0.084**	0.104***
	(0.022)	(0.023)	(0.028)	(0.027)
Pre-trends (Chi-sq)	1.384	1.558	1.384	1.558
(p-value)	[0.966]	[0.955]	[0.966]	[0.955]
N Obs.	5,134	5,134	4,808	4,808
Sample	All firms	All firms	Without switchers	Without switchers

Notes: We exclude firms in sectors with high volatility (top 10%). To obtain the volatility measure, we follow Czarnitzki and Toole (2011). We calculate the standard deviation of sales per employee and divide it by the average level of sales per employee. The sectoral measure is the average across all firms in a given industry and is calculated during the pre-sample period (from 1990 to 1995). *Uncond. PT* refers to unconditional parallel trends estimation; *Cond. PT*: conditional parallel trends estimation (previous experience using TWA and firm's size interval). Columns (1) and (2) use all observations. Columns (3) and (4) discard all observations coming from switchers, that is robot adopters that at some point stop using robots. Estimation method: Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (drimp in csdid in Stata). Bootstrapped errors in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

Table B5: Robot Adoption ATT on firms' TWA use. Staggered DiD estimation - Excluding observations with high economic performance

	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.053**	0.061**	0.047*	0.069**
	(0.021)	(0.023)	(0.025)	(0.025)
Pre-trends (Chi-sq)	0.898	1.805	0.898	1.805
(p-value)	[0.989]	[0.936]	[0.989]	[0.936]
N Obs.	5,991	5,991	5,664	5,664
Sample	All firms	All firms	Without switchers	Without switchers

Notes: We exclude observations within an industry and year with sales larger than the 90% percentile. Notes: *Uncond. PT* refers to unconditional parallel trends estimation; *Cond. PT*: conditional parallel trends estimation (previous experience using TWA and firm's size interval). Columns (1) and (2) use all observations. Columns (3) and (4) discard all the observations coming from switchers, that is robot adopters that at some point stop using robots. Estimation method: Sant'Anna and Zhao (2020)'s improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares (drimp in csdid in Stata). Bootstrapped errors in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

Table B6: Balancing test: Distributions of Covariates of Treated and Untreated Firms, Before and After Re-Weighting (Entropy Balancing)

	Before Matching				After Matching			
	Mean Treated	Mean Control	Var. Treated	Var. Control	Mean Treated	Mean Control	Var. Treated	Var. Control
TWA	0.584	0.483	0.243	0.249	0.584	0.584	0.243	0.243
Sales	0.324	-0.055	0.480	0.561	0.324	0.324	0.480	0.480
Sales growth	0.044	0.032	0.052	0.060	0.044	0.044	0.052	0.052
Productivity	0.221	-0.044	0.333	0.353	0.221	0.221	0.333	0.333
Productivity growth	0.034	0.025	0.219	0.234	0.034	0.034	0.219	0.219
Capital intensity	-0.182	-0.134	2.309	1.656	-0.182	-0.182	2.309	2.309
Skill intensity	0.262	-0.107	0.721	0.923	0.262	0.262	0.721	0.721
R&D intensity	2.742	-0.385	33.540	23.260	2.742	2.742	33.540	33.540
Export	0.779	0.529	0.172	0.249	0.779	0.779	0.172	0.172
Import	0.805	0.531	0.157	0.249	0.805	0.805	0.156	0.156
Foreign	0.232	0.110	0.178	0.097	0.232	0.232	0.178	0.178

Notes: The table reports the mean and variance of firm characteristics for the treated and control groups, after applying the entropy balance re-weighting algorithm of Hainmueller (2012). The weights assigned to treated and non-treated firms are constructed to equate the mean and variance of all covariates. *TWA* is the number of hours (in logs) worked by temporary agency workers. *Sales* is the firm's deflated sales deviation from the industry mean (in logs). *Sales growth* is the growth of firm's deflated sales (in logs). *Productivity* is the deviation of firm's deflated value added per hours worked (in logs) from the industry mean. *Productivity growth* is the growth of firm's deflated productivity. *Capital intensity* is the deviation of firm's deflated capital stock per hours worked (in logs) from the industry mean. *Skill intensity* is the deviation of firm's share of workers with a five-year university degree (in logs) from the industry mean. *R&D intensity* is the deviation of firm's deflated R&D expenditures relative to its deflated total sales (in logs) from the industry mean. *Export* is a dummy variable for positive exports. *Import* is a dummy variable for positive imports. *Foreign* is a dummy variable for foreign ownership (equal to one if the firm is foreign-owned by more than 50 percent and zero otherwise).

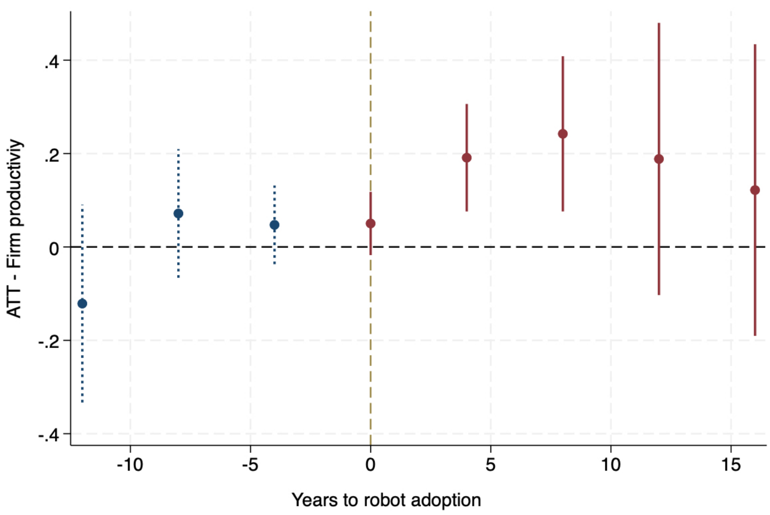

Figure B3: The plot displays the average treatment effect of the first time a firm adopts robots and uses TWAs. The control group are firms that adopt robots without TWA. Staggered estimation using CS-DiD methodology. We use the conditional pre-trends methodology, where we include as covariates previous firm productivity, previous firm's size (measured as firm size intervals) and previous share of temporary workers. We also show the 95% confidence interval.

Table B7: Robustness checks (DiD estimation with re-weighting)

	Sales per hour worked (1)	p-score (2)
$Robots_{t-1}$	0.081***	0.141***
	(0.015)	(0.020)
TWA	0.093***	0.137***
	(0.011)	(0.015)
$Robots_{t-1} \times TWA$	0.097***	0.190***
	(0.031)	(0.037)
Share temporary	-0.381***	-0.009
	(0.022)	(0.032)
Observations	2,551	2,584
R-squared	0.942	0.836
Entropy weights	Yes	No
Industry-year effects	Yes	Yes
Regional-year effects	Yes	Yes

Notes: In column (1) the outcome variable is the logarithm of real sales per (effective) hour worked of firm i in period t; In column(2) the outcome variable is the logarithm of firm's value added deflated with ESEE firm-level deflators and divided by (effective) labor; $Robots_{t-1}$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters that report for the first time using robots in the previous ESEE response year; TWA is the average of the binary indicator of TWA use averaged over period t; $Temps$ stands for the firm's average share of temporary workers during that period. In column (2), we use the p-score as an alternative weighting algorithm. Bootstrapped standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01.

Table B8: Additional robustness checks (DiD estimation with re-weighting)

	Without switchers	Placebo	Control for computers	Control for foreign MNEs	STUVA
	(1)	(2)	(3)	(4)	(5)
$Robots_{t-1}$	0.059***	0.005	0.074***	0.071***	0.086***
	(0.013)	(0.013)	(0.016)	(0.012)	(0.018)
TWA	0.082***	0.082***	0.051***	0.149***	0.067***
	(0.011)	(0.028)	(0.012)	(0.011)	(0.018)
$Robots_{t-1} \times TWA$	0.129***	0.009	0.081**	0.149***	0.077**
	(0.032)	(0.030)	(0.031)	(0.031)	(0.035)
Share temporary	-0.155***	-0.287***	-0.194***	-0.121***	-0.389***
	(0.020)	(0.023)	(0.027)	(0.018)	(0.029)
Observations	2,381	4,480	2,329	2,085	1,091
R-squared	0.842	0.809	0.828	0.845	0.835
Entropy weights	Yes	Yes	Yes	Yes	Yes
Industry-year effects	Yes	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes	No

Notes: In all columns, the outcome variable is the logarithm of firm's value added deflated with ESEE firm level deflators and divided by (effective) labor; $Robots_{t-1}$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters that report for the first time using robots in the previous ESEE response year; TWA is the average of the binary indicator of TWA use averaged over period t; $Temps$ stands for the firm's average share of temporary workers during that period. In column (1) we exclude switchers from our analysis (robot adopters that stop reporting robots after a first treatment). In column (2) we randomize the time of robot adoption. In column (3) we drop from our analysis observations with high investments in computers in the past years (defined as at least top 5% of all investments in that year). In column (4), we exclude observations that are foreign-owned or become foreign-owned during our sample period (measured as having more than 50% foreign ownership). In column (5), we exclude observations in the control group that are in the same industry and region as the firms that adopt robots. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.