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

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May 2023

Abstract

We study the impact of industrial robots on the use of labour intermediaries or temporary work agencies (TWAs) and how TWAs affect firm productivity. We develop a theoretical framework where the adoption of new technologies increases the need for a quality match between jobs and workers. In the model, TWAs help firms in the search for workers who better match with their technologies. The model predicts that the use of modern technologies, such as robots, increases the likelihood that firms outsource workers through TWAs. Firm productivity can increase due to better quality matches. 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 causal effects of robot adoption on TWAs using staggered difference-in-difference (DiD) estimations. We find that firms that adopt robots increase the probability of using TWAs by seven percentage points as compared to non-adopters. Using DiD matching techniques, we also find that firms that combine robots with TWAs achieve higher productivity than those who simply adopt robots. This suggests that TWAs increase the matching quality between new technologies and labour.

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

JEL Codes: O33, J23, L22

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We would like to thank Alejandro Graciano, Richard Kneller, Richard Upward, Jose Luis Moraga and Abel Lucena for their very helpful comments along with seminars participants at the University of Leicester, V-KISS Workshop (Valencia), University of Granada, Universidad Complutense de Madrid, University of Illes Balears and OFCE. We also thank the comments received at the International Industrial Organization Conference, IIOC-2023, held in Washington. P. Beneito, M. García-Vega and O.Vicente-Chirivella acknowledge financial support from Grant PID2021-124266OB-I00 funded by MCIN/AEI/ 10.13039/501100011033 and by "ERDF A way of making Europe" and Grant TED2021-130232B-I00 funded by MCIN/AEI/ 10.13039/501100011033 and the "European Union NextGenerationEU/PRTR". P. Beneito also acknowledges the financial support of the Ministry of Universities of Spain, Grant PRX21/00071, to visit the School of Economics at the University of Nottingham, during which this project was initiated. We also thank the Fundación SEPI, Spain, for providing the data. Declarations of interest: none.

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 positive effects of robots on wage inequality and within-firm employment (Acemoglu and Restrepo, 2022; Aghion et al., 2021, 2020; Bessen et al., 2020), 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 production scale and might raise the need of robot adopters to hire new workers (Acemoglu et al., 2020; Aghion et al., 2021; Autor, 2015), including specialized employees to manage and work with these technologies (Bonfiglioli et al., 2020; Faia et al., 2022; Humlum, 2021). However, less is known about how firms search for the needed employees after adopting new automated technologies and whether robot adoption generates within-firm differences in job arrangements. In this paper, we study the effect of robot adoption on the search strategies of firms to find suitable employees who fit with their preferred technology. We focus on the effect of robots on employment outsourcing through intermediary agencies or temporary work agencies (TWAs) and its consequences for firm productivity.

Our argument is that TWA can be an attractive labour recruitment channel for companies adopting robots due to their ability to provide good matches between jobs and workers in a timely way. The purpose of TWAs is to provide a user company with workers hired by the TWA.[1] Traditionally, TWAs have been associated with low skill occupations, wages and 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 on the candidates' skills. For example, Autor (2001) argues that the majority of US TWAs offer free computer skills training with the objective to be able to screen their workers' abilities. In this way, TWAs can assess workers and provide information to their client firms about workers quality and suitability for the job. Neugart and Storrie (2006) likewise

[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 company ("contract of provision"), establishing the job conditions including an approximate duration of the contract.

highlight the importance of the 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 in a timely manner (Faia et al., 2022). The "war for talent" to successfully implement these technologies is becoming a challenge for companies worldwide. In this line, CEOs increasingly identify automation-related skill gaps as a priority challenge for their organizations (MacKinsey Survey 2022).[4] TWAs can help robot adopters in the search for workers who better match with 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 labour search channels when the quality of the worker-firm match is imperfectly observed *à la* Pries (2004). We assume that new 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 labour 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 temporary work agencies are complementary.

We provide two main testable implications. The first is that the adoption of new technologies increases the probability of using TWAs as recruitment channel. The second is that firm-level productivity increases with the combination of new technologies and the use of TWAs. 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 of robot adoption and use of TWAs.

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

[3] One of the largest TWAs operating in Europe, Randstand, uses as one of its advertising slogan: *"(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 specialised providers of 'high-quality matches' between firms and workers. A visit to the websites of these companies reveals, for instance, the intensive use of AI-based search technologies to maximise the efficiency of employer-employee matches.

[4] The McKinsey Global Institute's Survey (2022), based on interviews to CEOs from major U.S. and EU companies, 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) estimation (Callaway and Sant'Anna, 2021), we find that robot adoption increases the probability that firms use TWAs by around seven percentage points. These results are robust to excluding the Great Recession years, which suggests that the use of TWAs induced by robots is not driven by the peaks or troughs of the business cycle. Then, using two-way fixed effects (TWFE) DiD estimation combined with matching techniques and an instrumental variable (IV) strategy 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 10.2%. In contrast, TWAs have a negative impact on firm productivity. However, we find that by combining robots with TWA as a recruitment channel, firms further raise their productivity by around 8.5%. This suggests that there are complementarities between the adoption of robots and TWAs, as our model shows.

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). Beyond the net employment effects or the induced changes on labour 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 study 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 the use of TWAs with consequences for firm productivity.

Our paper also contributes to the literature on labour search channels, especially from the firms' perspective. Firms use different search channels depending on the profile of workers they are looking for (Holzer, 1987). Carrillo-Tudela et al. (2022) show that this differentiated use explains an important part of labour market sorting. Bilal and Lhuillier (2021) study the outsourcing of labour as an alternative to searching for in-house workers. They find that more productive firms benefit more from outsourcing and rely more on this channel. The same pattern emerges in our paper with regard to TWAs, which explains why firms adopting productivity-enhancing technologies like robots rely more on TWAs. Our paper therefore sheds new light on the rise of TWAs since the 1990s. Not only does technological progress make TWAs more efficient in matching firms and workers (Neugart and Storrie, 2006), it also makes the firms' use of TWAs more profitable. The use of TWAs has a lot in common with 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 suggest that TWAs offer a similar matching advantage to firms 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 who can be hired through an agency or directly through the market. Our results indicate that firms that adopt robots increase their likelihood to use TWA, but not the share of temporary workers, which suggests the importance of TWAs to provide matching advantages. These findings complement the observation by Bertrand et al. (2021) that innovating firms in India outsource labour to contractor firms to avoid firing costs.

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. In Section 5, we provide the estimation results of robots on the probability of TWA use and the effect of TWA and robots on firm productivity. Section 6 concludes.

2 The model

The model describes how new technologies, which enhance productivity when combined with competent workers, affect the firms' use of temporary work agencies 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 labour, hence the standard normalization that a firm has only one job to fill. Once the job is filled, the worker uses the technology provided by the firm to produce. The maximum level of production, called efficiency of labour, 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 labour 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 labour 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 $z = 1$. It remains constant throughout the match but it is imperfectly observed by both the firm and the worker. In 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 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.

[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 can 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).

Search channel and inspection The labour 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 labour 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 $[0, 1]$. 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, $\int_0^1 \frac{\partial f}{\partial \pi}(\mu|\pi) d\mu \leq 0$ for any μ and π.

A firm and a worker that decide to match bargain the match surplus such that workers receive a share φ. 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 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 $\Omega(\pi) - U - V_R$ if there is a match. 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 through the information

[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 observes a signal on the regular market but less precise than a work agency. Both assumptions would not affect our findings.

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

that is learned about match quality. The value only depends on the posterior probability that the match is good. This is because we assume no differences for a firm to directly hire a temporary worker or to indirectly contract with a worker through an agency. 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 is unemployed. A firm can also propose a permanent contract to its temporary worker 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.[10] The dismissal cost is assumed to be the same for directly-hired permanent workers, directly-hired temporary workers and agency workers.[11] Temporary relationships have the advantage to avoid 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.

Assumption 1 *The dismissal cost is such that*

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

Under this assumption, the dismissal cost is high enough so 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.

[9] This assumption captures an essential feature of temporary contracts while avoiding modelling 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 modelling of a dismissal cost as a red-tape cost is common in the literature (Faccini, 2014; Pries and Rogerson, 2005; Cahuc et al., 2016).

[11] This simplification 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.

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 define $\beta=\beta_0\beta_1$. 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 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 assumed that workers receive a share φ of the surplus upon matching and that the pair achieves efficient contracting that maximises 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 to be 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 proofs of simplification.

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

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

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 must pay F and the worker becomes unemployed.

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

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

and defining by continuity $\Omega_T(0) = \Omega_T(0^+)$. The match produces on expectation $\tau\xi\mu$. At rate $\beta\mu$, the match is 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 will 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 contract 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 labour efficiency high enough, there is always a range of posterior probabilities μ such that it is efficient to hire the worker on a temporary basis.

The choice between temporary and permanent contract 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 $V_A \geq V_R$.

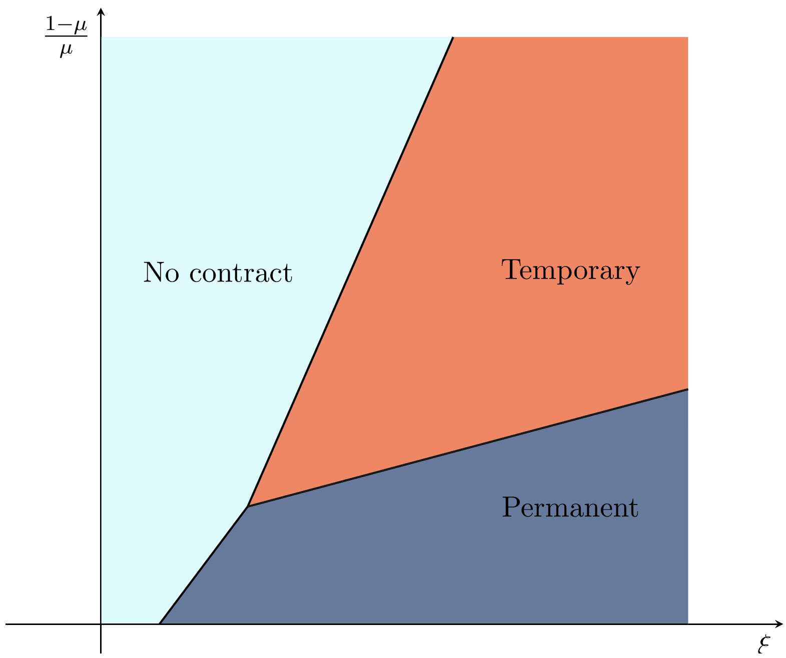

Figure 1: Optimal contract upon meeting

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

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 labour 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.

When labour 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 labour efficiency increases, the gains from having a better match increase as well. This is a complementarity effect between labour efficiency and match quality. At the limit when labour 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 labour 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 labour efficiency is high enough, $\Xi(1) \in \mathbb{R}$, to be worth the cost C.

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 $q_A > q_R$.

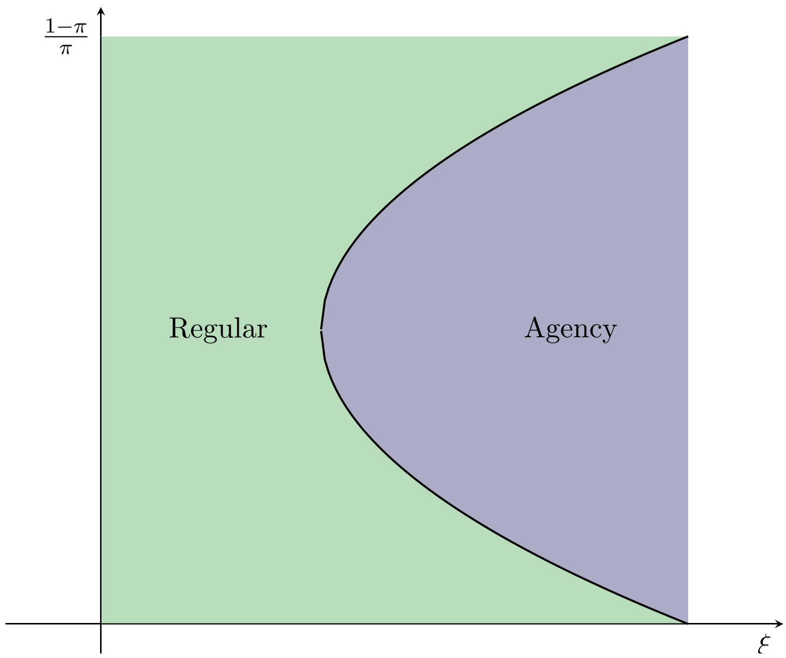

Figure 2: Optimal search channel channel

Note: A firm with labour efficiency ξ and prior π optimally chooses between searching alon on the regular market or through a work agency on its location in the plan.

Propositions 1 and 2 summarize 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 labour efficiency ξ and prior π. The job in the first firm is represented by $\star$ on 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 learn 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 $\bullet$ on Figure 3. The firm optimally searches with a work agency. On 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 labour 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,

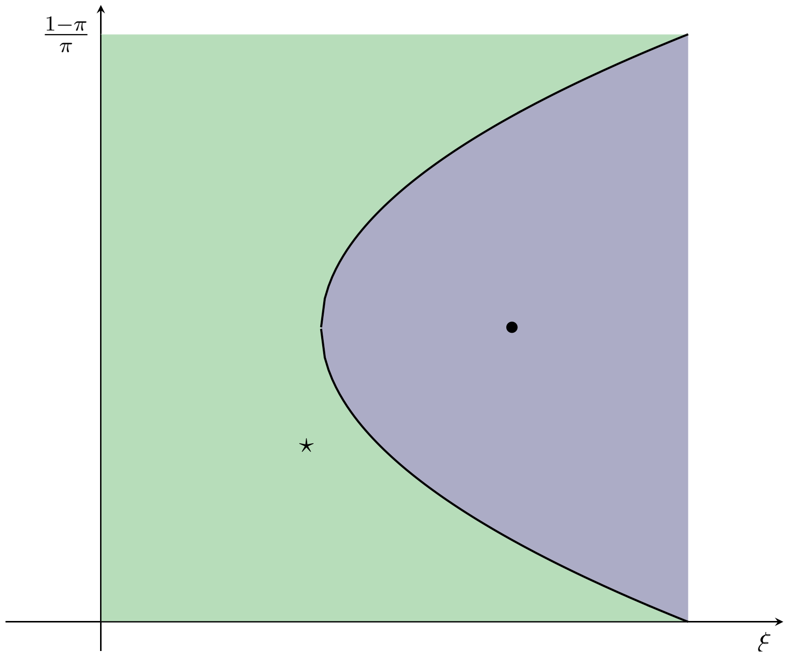

Figure 3: Recruitment channel in two examples

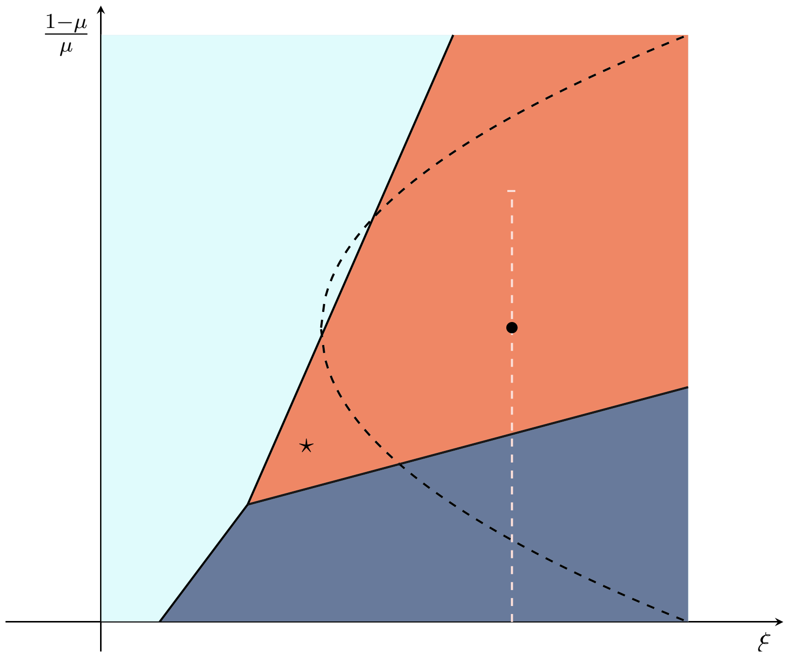

Figure 4: Contracting in two examples

$V_A^{\bullet} - V_R^{\bullet} \geq V_A^{\star} - V_R^{\star}$. 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 using agency workers conditional on using new technologies is higher than the probability of using agency workers conditional on not using new technologies.*

Implication 2 *Consider a regression of a measure of firm-level productivity on the use of work agency, the use of new technology and the interaction between the two. The coefficient of the interaction term should be positive.*

In the example illustrated by Figures 3 and 4, the firm with the $\star$ technology finds it optimal to search for a temporary worker on the regular market. This means adopting the new technology does not necessarily increase the share of temporary workers.

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).[12] In Spain, once the contract signed between the TWA and the user company expires, if the worker continues to work for the user company her contract has to become permanent (the same as temporary workers hired through the regular market).[13] Initially, Spanish law prohibited the use of agency workers in the performance of particularly hazardous activities (mining activities, work related to explosives, etc.) and under certain situations, such as to replace workers on a legal strike and filling vacancies caused by recent layoffs at the user company.[14] However, subsequent reforms (Law 29/1999 and Law 35/2010) have contributed to the deregulation of this sector by allowing TWA employment contracts to be signed in the same cases and conditions which apply to 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 agency workers were to receive at least the same wage associated with their position as temporary workers hired directly by the company. This means that for user firms the cost of hiring a temporary worker through a TWA implies paying the wage and the fee to the TWA for the provision of the worker.[15]

In Spain, TWAs are becoming highly specialised and competitive private companies in the provision of intermediation services between companies and workers (de Blas et al., 2013).They can supply labour to cover production peaks with flexible contracts, but they also serve the high-skill segment of the labour demand. The official statistics from the Spanish Ministry of Labour (Estadística de Empresas de Trabajo Temporal, 2021) show that, in 2016, the percentage of high-skilled workers hired by TWAs over the total of agency workers accounted by 15%, the percentage of medium-skilled workers by 54% and the percentage of low-skilled workers by

[12] The origin of TWAs dates back to the 1940s in the United States and it was motivated by the lack of workers during the World War II. As workers went to fight in World War II, they left behind open positions. This made that businesses struggled to find suitable workers. The need to fill these positions incentivised the creation of TWAs (Lips, 1998). However, it was not until the late 1960s and early 1970s that the use of these agencies became popular.

[13] García-Pérez and Muñoz-Bullón (2005) find that the probability of getting a permanent job is higher for workers who use TWAs than for these hired directly through the user company. Moreover, this effect is especially important for high skill workers. The authors argue that the better job prospects of these workers are due to the role of TWAs to provide quality signals for the workers.

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

[15] 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 company without signing a employment contract with the agency.

31%.[16] Within the group of high-skilled workers, the percentage of workers with an undergraduate, a MSc or a PhD degree is 64%. This indicates the importance of high-skill workers hired through TWAs.

4 Data and descriptive statistics

4.1 Data

The data source used in this paper is the Encuesta sobre Estrategias Empresariales, ESEE, (Survey of Entrepreneurial Strategies) for the period 1997-2016. The ESEE is a firm-level annual survey covering around 1,900 Spanish manufacturing firms each year. It is sponsored by the Spanish Ministry of Industry and supplied by the SEPI Foundation. This dataset is representative of the Spanish manufacturing sector by industry and firm size. The initial year of the database is 1990. In that year, firms with 10 to 200 employees were randomly sampled, holding around 5% of the population of firms in that year. All firms with more than 200 employees were requested to participate, obtaining a participation rate of about 70% in the initial year. Since then, there have been annual incorporation of new firms to minimize attrition, so that the sample remains representative of the Spanish manufacturing sector.[17]

Our analysis exploits data spanning a period of two decades, from 1997 - first year with information on TWA use-, and 2016. It is an unbalanced panel of 4,725 firms, of which 1,670 report using robots at some point during the sample period, while 3,055 never did. The ESEE contains information that is suitable for our research question. In the survey, besides accounting data, firms provide information about several output and input measures of their production process, including details about the technology used and hire arrangements of their workforce. Importantly for us, this includes information on firms' robot adoption and use of TWAs. Most of the questions in the ESEE are asked to firms every year, but in some cases, such as the robot adoption indicator and some skill-composition indicators, the information is gathered every four years.

[16]Low-skilled includes workers with no education and those with completed primary education. Medium-skilled, workers with completed secondary education. Finally, high-skilled includes workers with vocational training studies and workers with an university degree, a Master's degree or a PhD.

[17]Details on EESE dataset and data access guidelines can be obtained at: http://www.fundacionsepi.es/investigacion/esee/en
/spresentacion.asp (last accessed 21 January 2023). Several papers have used this dataset. For example: Guadalupe et al. (2012), Doraszelski and Jaumandreu (2013), Doraszelski and Jaumandreu (2018), Koch et al. (2021) or Kuzmina (2022), among others.

The robot adoption variable that we use is a binary indicator that takes the value of one the first time the firm declares to use robots in its production process and the following years and zero otherwise. The ESEE provides information of this variable in the years 1998, 2000, 2004, 2010 and 2014.[18] Our measure of TWA is a yearly dummy variable that takes the value of one if in a given year a firm hires temporary agency workers and zero otherwise. The dataset also provides information on the number of both temporary and non-temporary workers, so that we can identify separately the use of temporary agency work from what would be just a labour hiring strategy based on temporary work.

4.2 Descriptive statistics

Tables B1 and B2 in the Appendix display some descriptive statistics on the main variables. The notes at the bottom of the tables provide definitions and additional details about the construction of the variables. Table B1 displays the percentage of firms adopting robots and using agency workers both for the full sample and for large and small firms.[19] For the full sample, the presence of robot adopters and TWA users is similar in numbers. There is a percentage of 30% of robot adopters and around 27% of TWA users. These numbers are though quite heterogeneous between large and small firms. While around 50% of large firms both adopt robots and make use of TWAs, this percentage is around 20% among small firms.

In Table B1 in the Appendix, we provide information on a set of variables that we use in Section 5.2 to evaluate the effects of TWAs and robots on firms' productiviy. As in Koch et al. (2021) and Guadalupe et al. (2012), in our baseline specifications, we consider labour productivity, measured as real value added per worker. The variable value added is calculated 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.

In Table B2, we report descriptive figures for TWA and non-TWA users as well as for robot adopters and non-robot adopters. On the left side of the table, we show that firms that use TWAs are more capital and R&D intensive, larger, more internationalised, have a higher percentage of high-skilled workers and have a higher percentage of foreign-owned firms than

[18]As explained in Section 5.2, in the productivity analysis section, we impute forward the information of the last available year to the missing years.

[19]Large firms are defined in the survey as those with more than 200 employees.

non-TWA users. Hence, firms differ in terms of relevant productivity-enhancing factors jointly with the use of TWA. The right side of Table B2 shows descriptive statistics for three group of firms: First, robot adopters before adoption, second, robot adopters after adoption and third, firms that never adopt robots in our sample period. Firms that never adopt robots exhibit lower values in important variables, such as capital and R&D intensity, employment, skill share, and participation in international markets (exports and/or import activities) than firms that adopt robots. After robot adoption the figures point to a higher frequency of TWA use as well as larger labour productivity on average. The differences found between TWA users and non-users as well as between robot adopters and non-adopters prevent us from giving to the observed differences in labour productivity a causal interpretation. Moreover, differences between robot adopters and non-adopters could also confound the impact of robots on TWA use. In the next sections, we describe the identification strategies that we follow in order to determine the causal effects of interest, namely, the impact of robots on TWA probability, and the impact of robots, TWA and their combined effect on productivity.

Next, we provide some description of the time trends and sectoral breakdown of robot adoption and TWA, as well as some evidence on the relationship between robots use and firms' skill labour composition in our data. Figure 5 shows the evolution of the share of firms that use TWAs in the manufacturing sector over the period 1997-2016. During the first decade, this share increased by 11 percentage points, representing an increase of more than 50% from the initial 20% in 1997. The use of TWAs declined significantly in 2008 and 2009, suggesting that firms have adjusted employment through temporary workers during the Great Recession. As a result, in 2009 the proportion of firms using TWAs was the same as in 1997. During the last eight years of our sample, the growth of the share of firms using TWAs was steady, leading to a full recovery of pre-crisis levels by 2016. The upward trend in the last years suggests an even greater increase in the use of TWAs for the most recent out-of-sample years.

Figure 6 shows the evolution of firms' adoption of robots in the Spanish manufacturing sector over the same period. As documented by Koch et al. (2021), there is a large heterogeneity in robot adoption in the Spanish industry by firm's size, so we depict the trends separately for small firms (those with up to 200 employees) and large firms (those with more than 200 employees).[20] The figure reveals that about 11% of small firms had adopted robots at the beginning of the

[20]Our Figure 6 replicates Figure 2, Panel (a), in Koch et al. (2021), p. 2559, for our period of analysis.

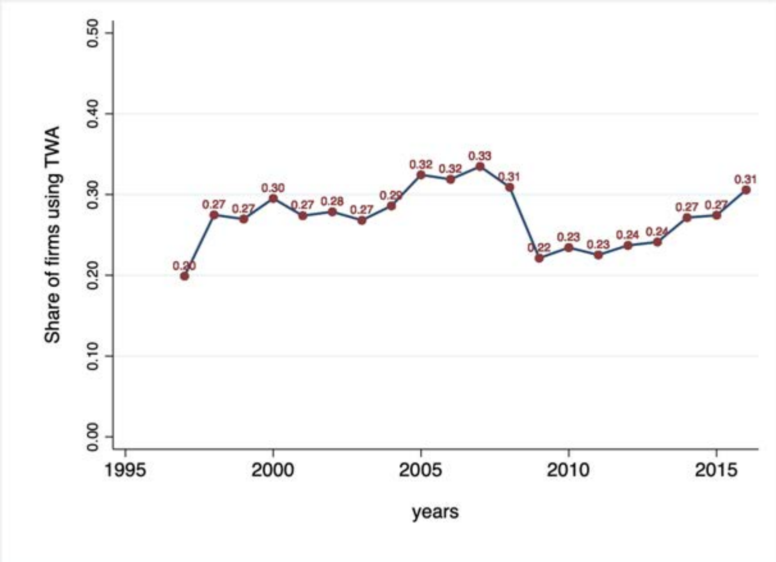

Figure 5: Share of Firms using TWA

period, while the percentage among large firms was almost three times as large, around 31%. The difference between these shares has grown over time, such that in 2016 about 63% of large firms use robots as compared to 25% among small firms.

Figure 7 shows the sectoral breakdown of the share of firms with robot adoption and TWA use. The figure also shows the sectoral distribution of the firms' temporary work share (temps over total number of workers) and agency-work share (agency workers over temps). The evidence from the table suggests that the use of TWA is not directly related with the intensification of temporary-contracts. The first and second panel of the figure show that 7 out of the 10 sectors with the highest proportion of firms using robots also top the ranking of sectors with the highest proportion of firms using agencies. This might suggests that a more intense use of TWA by firms could simply respond to a more intense use of temporary work by firms in those sectors. However, the third panel, shows that 7 out of the 10 sectors with the highest proportion of firms using TWA rank among the 10 sectors with the lowest share of temps over total employment. An extreme case is the sector of *Chemicals & Pharma*, which ranks the first in terms of the proportion of firms using TWA while the last in terms of the share of temps over total employment. Moreover, the last panel of the figure indicates that sectors where a higher proportion of temps come from agency are those with the lowest share of temporary work (7 of the 10 sectors with the lowest temps' share rank among the 10 with the highest proportion of temps coming from agency). Therefore, it seems that the use of TWA and intensification of temps may respond to different incentives and strategies on the part of firms.

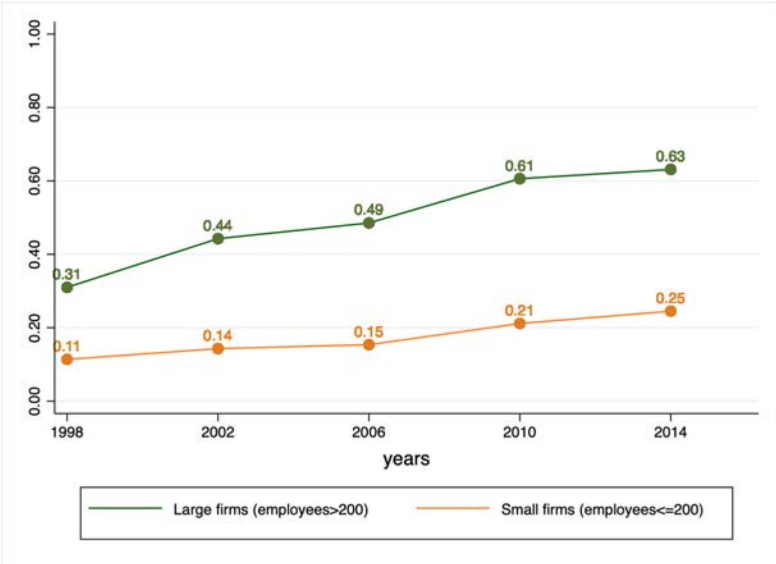

Figure 6: Share of Firms using Robots

Before explaining our empirical methodology, we first confirm that robots affect labour composition. We report a difference-in-difference of means between firms that adopt robots and those that do not adopt robots. We present the results in Figure 8. In the Figure, we include the firms' shares of high-skill workers, medium-skill workers, production workers, and temporary workers. Moreover, we also consider two dummy variables that measure the hiring of new engineers and new forms of workforce organization.[21] The left-side panel shows that, as compared to non-adopters, robot adopters increase the share of high-skill workers after robot adoption. The increase is around one percentage point in magnitude which, as a proportion over the average share of high-skill workers in firms, account for increases of around 20% and 11% for small and large firms, respectively. Robot adopters reduce the share of production workers by somewhat less than one percentage point, which represents a small though statistically significant effect. The impacts in terms of medium skill workers and temps' share are near zero and negative, respectively, and not statistically significant in any of the two cases. This last result suggests that an intensification of the temporary-contracts strategy on the part of firms does not seem to be among the main changes induced by robot adoption. The right-side panel in Figure 8 further reveals that firms hire new engineers (the data does not clarify if 'new' means here 'more' or 'different') and are more likely to report having introduced new forms of workforce organization. This preliminary analysis highlights that firms restructure

[21] 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?".

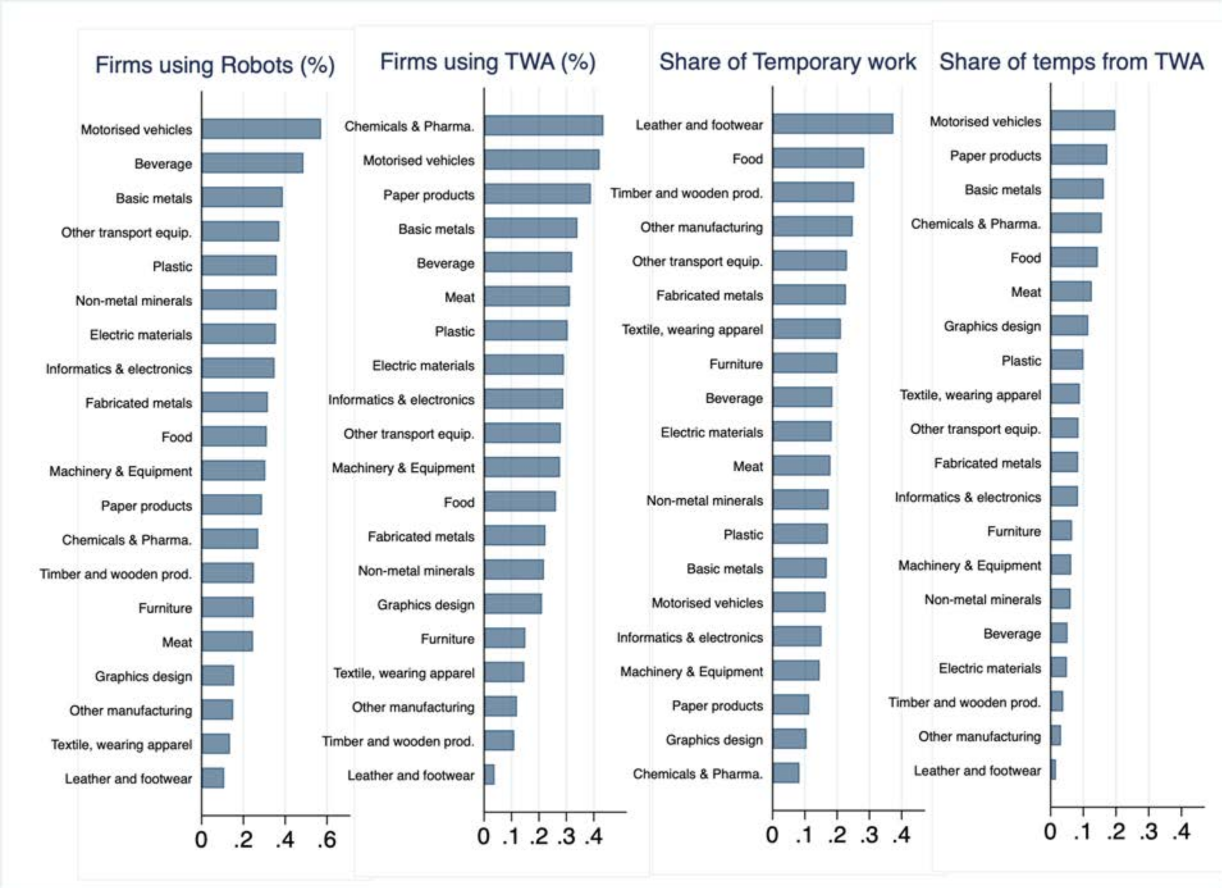

Figure 7: Industrial breakdown of robot adoption, TWA use, temporary work share and agency-work share.

their workforce towards higher skill levels, hire new engineers and introduce new forms of work organisation after robot adoption (see also 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 TWA.

5 Empirical strategy

5.1 The effect of robot adoption on firms' TWA use: staggered DiD

Our strategy to identify the causal impact of robot adoption on the probability of TWA use by firms is based on the staggered DiD estimation method proposed by Callaway and Sant'Anna (2021), CS-DiD henceforth. A recent line of the literature has pointed out the issues of causal interpretation in standard two-way fixed effects (TWFE) DiD estimation when there exists 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,

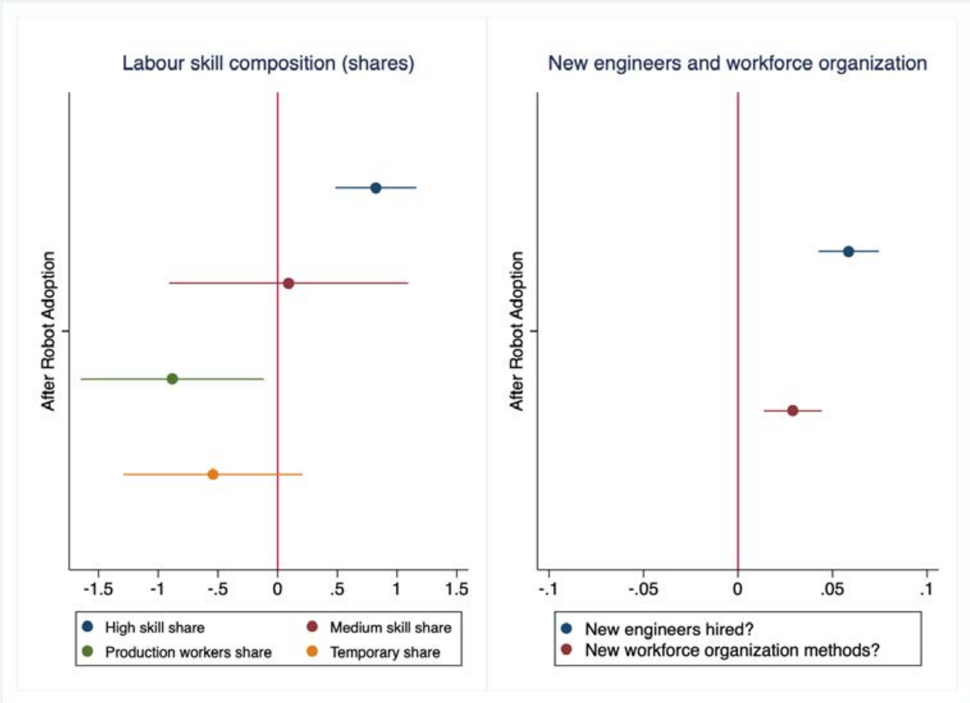

Figure 8: Left panel: Changes in firms' labour skill composition and temporary work share after Robot Adoption; Right panel: Changes in firms' answers to the following questions after Robot Adoption: i) Did the firm hire 'new' engineers during the year?; ii) Has the firm introduced new forms of workforce organization during the year? (standard DID estimates).

2021; Athey and Imbens, 2022, among others)). The effect of robots on firms' TWA use would be a challenging case for TWFE DiD, as the effect of robot adoption is likely to be dynamic (Koch et al., 2021) and the timing of robot adoption varies across firms. The Callaway and Sant'Anna (2021)'s proposal is a general and flexible framework for staggered DiD estimation that accounts for dynamic effects and treatment effect heterogeneity across different dimensions (groups or cohorts, calendar time or events). It is designed for DiD setups such that once units are treated they remain treated in the following periods, as it is the case of robot adoption.[22]

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

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

The group-time $ATTs$ are then weighted-based aggregated measures of the causal parameters of interest. Weights on each $ATT(g,t)$ vary depending on the aggregation scheme chosen (by

[22]In Section 5.1.1 below we check the robustness of our results to several of the estimation methods proposed by the recent subject literature.

group, by calendar period, by event, and/or total), are all non-negative, and sum to one.[23]

The CS-DiD proposal further allows for covariate-specific pre-trends, that is, for the possibility that pre-trends are hold only after conditioning on covariates. For example, in our case, the distribution of observed covariates such as firm' size, labour skill composition, productivity or previous experience using TWA could be quite different between firms that adopt robots and firms that do not. When the use of TWA (in the absence of robots) depends on these covariates, a conditional parallel trends becomes more plausible than an unconditional parallel trends assumption. The conditional estimator is based on the estimation of a propensity score based on pre-treatment values of observable covariates.[24] Finally, the comparison or control group can be composed by the 'never-treated' firms or, alternatively, by the 'not yet-treated' ones, provided the parallel trends assumption holds.

We apply the CS-DiD method to assess the impact of firms' robot adoption on TWA use. For the CS-DiD to be implemented, all those observations that are left censored are discarded, that is, all those cases of firms that report using robots the first year they are observed in the ESEE. In addition, since firms in the ESEE are asked about the use of robots every four years, the treatment variable can only vary every four years in our sample data. We only include the years in which that question is made in the ESEE questionnaire (years 1998, 2000, 2004, 2010 and 2014) in our DiD estimation. As a result, we use a total of 6,447 observations in the DiD estimation, corresponding to 1,909 firms, of which 488 adopted robots for the first time at some point between 1997 and 2016, while 1,421 firms never adopted robots during this period.[25]

A positive answer to the use of robots in production in e.g. year 2010 may correspond to the adoption of robots happening up to three years earlier. Therefore, the reaction of firms in terms of use of TWA, a yearly-varying variable in the ESEE, could also have been triggered up to three years before the ESEE response year. Moreover, anticipation effects in estimation are plausible if firms were using TWA to recruit highly skilled workers, e.g. engineers or technicians,

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

[24]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), that 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*).

[25] A number of robot adopters declare not using robots in subsequent waves of the ESEE. We discard in estimation those observations with no-robots for firms that used robots before while we keep the observations with robots for these firms. The discarded observations amount to 4.2% of the estimation sample. In Section 5.1.1 Table and in Appendix C we show the sensitivity of our results to including/excluding observations coming from these firms.

who would be responsible for preparing the changes. To explore different possibilities in this temporal pattern, we construct alternative rolling averages of the binary indicator of TWA use centred around the year in which firms answer the question about robots. In the main text we show the results the average of the TWA binary indicator from years $t_0 - 3$ to t_0 (with t_0 being the year when firms answer about robots in the ESEE), for which we obtain the strongest evidence in favour of parallel pre-trends. Our outcome measure therefore indicates the frequency of years in which the firm used TWA during the corresponding 4-year period.[26]

Table 1 displays our main set of results. All inference procedures use clustered bootstrapped standard errors at the firm level, accounting for autocorrelation of the data. In columns 1 and 2 we show first the ATT estimates for the entire period using as control group never treated and not-yet treated firms, respectively. Pre-treatment trends are unconditional in columns (1) and (2), while in columns (3) and (4) they are conditional on the firms' experience using TWA previous to the robot adoption. That is, we assume in that latter case that only firms with the same previous experience using TWA would follow the same trend in TWA use in the absence of robot adoption. In both cases, either unconditional or conditional, the data leads to no rejection of the null of parallel pre-trends but the p-values are appreciably larger when conditioning the pre-trends (tests provided at the bottom of the table).[27] The total aggregated ATT renders an estimated causal impact of robot adoption on the probability of TWA use that is around 9 percentage points in both cases. This estimate is remarkably robust across specifications in Table 1. As a rough comparison, for sample average probabilities of TWA use around 27%, the estimated ATT represent an increase of near a third.

Table 1 also displays treatment effects aggregated under a different scheme. More specifically, we consider how the effect of robots depend on the amount of time elapsed since adoption. In this case the effects are aggregated using event-based weights within different windows that we define as labeled in the table. These estimates largely confirm the positive and significant effect of robots on firms' TWA use. As compared to the 8-year period before treatment, the effects appear to be positive and increasing in magnitude during the first years, with estimated impacts of around 5.7 percentage points four years after adoption increasing up to 6.5 percentage

[26] In Section 5.1.1 below and in Appendix C we explore alternative timings for the outcome variable.

[27] We also explore conditional pre-trends on a wider set of covariates, namely, industrial sector, skill composition and firm's size and age. Also in these cases the test leads to no rejection of the null of parallel pre-trends. Although the p-values of the test are smaller in those cases, the point estimates of the total ATT are similar in magnitude to the ones reported here and also statistically significant.

Table 1:
Robot Adoption treatment effects on firms' TWA use
Staggered DiD estimation

control units:	Never treated Uncond. PT (1)	Not-Yet treated Uncond. PT (2)	Never treated Cond. PT (3)	Not-Yet treated Cond. PT (4)
Total ATT	0.090***	0.086***	0.091***	0.089***
	(0.018)	(0.018)	(0.019)	(0.019)
Event windows:				
-8, +4	0.057***	0.053***	0.055***	0.054***
	(0.013)	(0.012)	(0.013)	(0.013)
-8, +8	0.0653***	0.063***	0.066***	0.064***
	(0.014)	(0.013)	(0.014)	(0.014)
-8, +12	0.073***	0.071***	0.072***	0.070***
	(0.014)	(0.014)	(0.015)	(0.015)
-8, +16	0.074***	0.071***	0.073***	0.072***
	(0.015)	(0.015)	(0.016)	(0.015)
Pre-trends (Chi-sq)	11.013	11.075	2.858	2.978
(p-value)	[0.356]	[0.3561]	[0.984]	[0.982]
N Obs.	6,447	6,447	6,447	6,447

Notes: Uncond.PT refers to uconditional parallel trends estimation; Cond.PT: conditional parallel trends estimation (previous experience using TWA). Estimation method: Sant'Anna and Zhao (2020) 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. .

points eight years after. Beyond the eight year after robot adoption, the effects tend to stabilise around 7 percentage points. Figure 9 plots graphically the results, where we have chosen to represent the results corresponding to column (3). The figure permits a visual inspection that confirms the nule differences pre-trends between robot adopters and non-adopters in terms of TWA use, as well as the dynamics of the post-treatment effects.

Finally, in Figure 10 we show the results we find when using as outcome variable the share of temporary contracts used by firms. As in the descriptive section above, our concern here relates to the possibility that the higher likelihood of using TWA may simply be due to a more intensive use of temporary contracts following the adoption of robots. The plot rules out this possibility, again supporting the idea that the underlying reasons for using TWA or temporary contracts are likely to be different.

5.1.1 Robustness checks

We perform robustness checks of the CS-DiD results along several lines. Firstly, we check the robustness of our results to excluding from the estimation sample the years of the Great Recession (from 2008 to 2014). As shown in Figure 5, in 2008 the use of TWAs fell sharply,

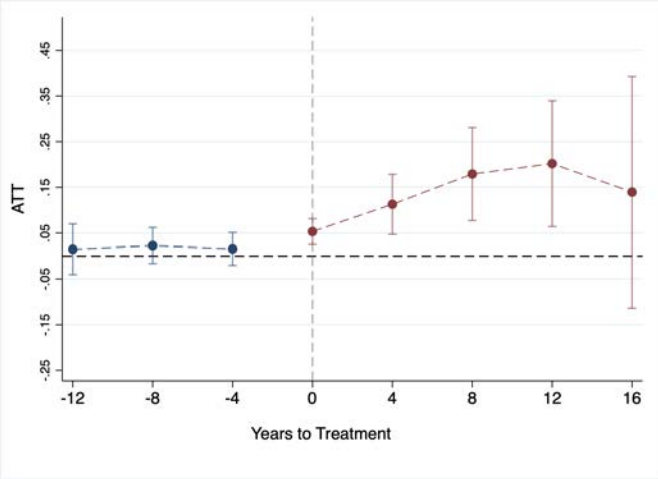

Figure 9: Probability of using TWA after robot adoption. Event Study. The case shown in the figure corresponds to column 3 in Table 1, when never treated controls are used and pre-trends are conditional to previous TWA experience.

suggesting that firms may have adjusted employment by laying off temporary workers. If the agency hiring induced by robot adoption was, as we argue in this paper, driven by the search for skilled (/well-matched) workers, one would expect that the use of TWA after robot adoption would be less affected by the sort of adjustments undertaken during the Great Recession. Table 2 replicates Table 1 without these years. The estimates range from 7.6 to 9 percent increase in the probability of TWA use, and thus largely confirm the idea that the use of TWA that we capture in the DiD estimation is not driven by ups and downs of the economic activity.

Second, we analyse the sensitivity of our results to the way in which we treat observations from firms that report using robots but subsequently report no longer using them. Table C1 in Appendix C shows the results for two alternatives to the one used so far, which is to include observations from firms that use robots up to the point at which they declare they no longer use them. These two alternatives are, firstly, to use all observations from these firms, regardless of whether they report not using robots from some point onwards, and, secondly, to discard all observations (with and without robots) from these firms. The results show that including robot-free years for robot adopters slightly reduces the size of the ATT estimate, ranging from 5.6 to 7.1 percentage points, while excluding robot adopters that at some point stop using robots would increase the estimates to values between 10.0 and 11.6 percentage points. The differences with respect to our benchmark results in Table 1, however, are not sizeable and basically confirm that the positive effect of robots on TWA use is not driven by the particular selection of the sample of robot adopters.

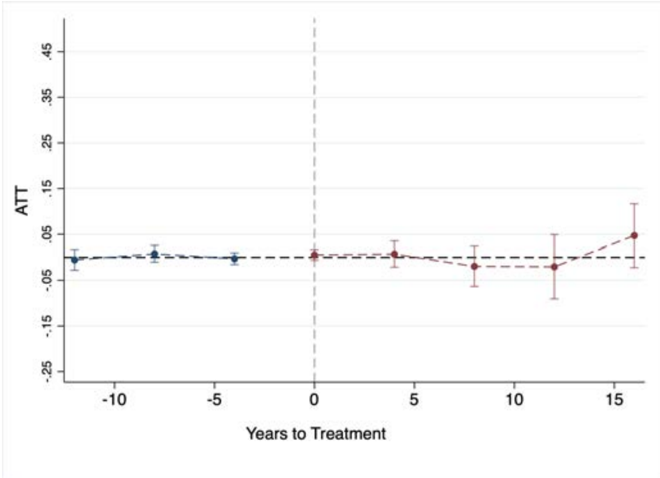

Figure 10: Is it just an intensification of the use of temps? Event Study. The figure shows the case when never treated firms are used as controls and pre-trends are conditional to previous TWA experience. The dependent variable is share of temporary workers of the firm. Results are robust to different lag orders of the dependent variable.

An additional robustness check refers to alternative timing in the construction of the dependent variable. Table C2 and Figure C1 in Appendix C display the obtained results in these cases, together with the rolling average from $t_0 - 3$ to t_0 for comparison reasons. The point estimate of the ATT using the rolling averages tend to diminish as we move the 4-year window of TWA observation towards the future, that is, towards years following the moment when firms are asked about robot adoption (Panel A of the table). This would respond to two possible circumstances: firstly, the fact that the year when firms actually adopt robots could be up to three years before they are asked in the ESEE about robots; secondly, firms might anticipate the installation of robots changing their labour force and channel recruitment in advance. In fact, C1 shows that, as the centre of the rolling average moves forward, the last pre-treatment period shows up as significant, suggesting that the period of the robot adoption indicator is lagged with respect to the moment where changes in terms of TWA use occur.

Finally, we compare the CS-DiD estimation of the robot causal impact on TWA use with four alternative DiD estimators, namely, standard TWFE-OLS estimation, the DiD design for multiple groups and periods of De Chaisemartin and d'Haultfoeuille (2020), the interaction weighted estimator of Sun and Abraham (2021), and the imputation method of Borusyak et al. (2021).[28] Table 3 and Figure 11 show that the results reported above are strongly robust to the five alternative methods. The point estimate of the ATT range from 7.8 percentage points

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

in TWFE-OLS estimation to 9.1 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, but also show virtually identical effect dynamics.

Summing up our results, we obtain a positive and significant effect of robot adoption on the probability of TWA use that remains strongly robust across different estimation methods, timing of the outcome variable, years included in the estimation and treatment given to firms that discontinue the use of robots. Depending on the specification we consider, the estimate of ATT ranges from 6 probability points to 9 probability points, providing clear evidence in favour of our model's theoretical prediction that the use of robots tends to shift the hiring channel of firms towards professionalised labour intermediaries such as TWA.

5.2 The effect of TWA on firm productivity

To assess the impact on firms' productivity of robots and TWA use, both in isolation and combined, we borrow and extend the DiD framework applied by Koch et al. (2021) to the ESEE data. In (part of) their analysis of robots' productivity, these authors closely follow the empirical methodology proposed by Guadalupe et al. (2012) and combine a firm fixed effects approach with a propensity score reweighting estimator in the spirit of DiNardo et al. (1996). The propensity score aims at correcting the bias induced by non-random firms' selection into robots. As Koch et al. (2021) show, robot adopters and non-adopters in the ESEE data differ before robot adoption in several dimensions that may affect productivity.

Our DiD estimation equation can be written as follows

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

In equation 8, the variable y_{it} represents labour productivity of firm i in period t, and it is constructed as the (log of) firm's value added deflated with ESEE firm-level deflators and divided by (effective) labour-hours. In estimation, we use a standarised measure by industry and firms' size interval (5 evenly distributed intervals); $Robots_{it_a}$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters, and for which we check differences with $t_a = t$ and/or $t_a = t - 4$ given the 4-year basis of the variable; TWA_{it} is an

Table 2:
Robot Adoption ATT on firms' TWA use. Staggered DiD estimation
- Excluding Great Recession years -

control units:	Never treated Uncond. PT (1)	Not-Yet treated Uncond. PT (2)	Never treated Cond. PT (3)	Not-Yet treated Cond. PT (4)
Total ATT	0.097***	0.090***	0.079***	0.076***
	(0.021)	(0.021)	(0.022)	(0.021)
Pre-trends (Chi-sq)	10.982	10.977	2.592	2.710
(p-value)	[0.277]	[0.277]	[0.978]	[0.974]
N Obs.	4,404	4,404	4,404	4,404

Notes: Uncond.PT refers to uconditional parallel trends estimation; Cond.PT: conditional parallel trends estimation (previous experience using TWA). Estimation method: Sant'Anna and Zhao (2020) 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. .

binary indicator variable which takes value one if the firm hires workers through TWA in year t, and 0 otherwise; $Temps_{it}$ stands for the firm's share of temporary workers; η_t includes a full set of time dummies; η_i stands for firm fixed effects; η_{rj} stands for region-sector fixed effects (17 regions and 20 industrial sectors); η_{jt} stands for sector-year effects; and, finally, u_{it} is the error term of the equation.

Equation 8 differs from the estimation framework in Koch et al. (2021), - eq. 3 in p. 2571-, in several dimensions. First, our main objective with equation 8 is to explore the productivity effects of TWA, so that we extend the specification by including the TWA indicator and its interaction with robots, as well as the share of temporary employment. This last variable aims at partialling out the productivity impacts that may stem from the labour-contracting structure of firms. Second, we use all the firm-year observations rather than only the years when firms answer about robots in the ESEE questionnaire. This is because firms can switch agency recruitment on or off each year, a variation that we want to exploit in estimation. Finally, to rule out concerns of residual endogeneity in the TWA indicator, we instrument it through a control function approach as we detail below.

Our terms of interest in equation 8 are mainly two, namely, the TWA indicator, with productivity effect captured by parameter δ, and the interaction term $TWA_{it} \times Robots_{it_a}$, with productivity effect captured by parameter parameter θ. A positive and significant estimate of θ would indicate that the use of a TWA increases robots' productivity; similarly, it would indicate that agency workers combined with robots have a productivity premium.

Table 3:
Robot Adoption ATT on firms' TWA use. Staggered DiD estimation
- Results with five DiD estimators -

	OLS-TWFE (1)	De Ch.-d'H.(2020) (2)	Sun-Ab.(2021) (3)	Borusy. (2021) (4)	Call-Sant.(2021) (5)
Total ATT	0.078***	0.080***	0.079***	0.091***	0.089***
	(0.011)	(0.016)	(0.015)	(0.017)	(0.019)
Pre-trends[a]	0.950	-0.015	-0.023	0.547	2.978
	[0.415]	(0.018)	[0.270]	[0.450]	[0.981]
		-0.097			
		(0.063)			
N.Obs	6447	6447	6447	6447	6447

Notes: All estimations are conditional to pre-treatment firms' previous experience using TWA. [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); The estimates in the table are graphically shown in Figure 11. .

The matching and propensity-score weighting technique implies calculating the predicted probability of robot adoption, or propensity score, in terms of observable characteristics and use the propensity scores as weights in the DiD regression. The identifying assumption is that, by matching on the observable characteristics that are relevant for robot adoption, the productivity of adopters and non-adopters would not differ systematically in the absence of robot adoption. To calculate the propensity score, we conduct industry-specific probit regressions for robot adoption on one-year lagged sales, sales growth, labour productivity, labour productivity growth, capital-,skill- and R&D intensity, indicators for exporter, importer and foreign ownership, and year dummies. The propensity scores estimate, $\hat{p_i}$, is used to reweigh each treated firm, and $1 - \hat{p_i}$ is used to reweigh each non-treated firm. The analysis is conducted for the firms with common support and for which the balancing property on covariates is satisfied within each industry. Standard errors are adjusted for clustering at the firm level.

Table 4 displays the main results. 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. Column 1 shows that it is the switch to robot use declared by firms four-years ago that impacts positively and significantly current year productivity, while the estimated effect of the current year indicator is very small and insignificant. From column 2 onwards we use the four-year lag robot indicator variable and leave out the current year indicator. The estimated effect indicates that adopting robots increase firms' productivity four years later by 0.153 SD, which amounts to an increase of 10.71% (for the average

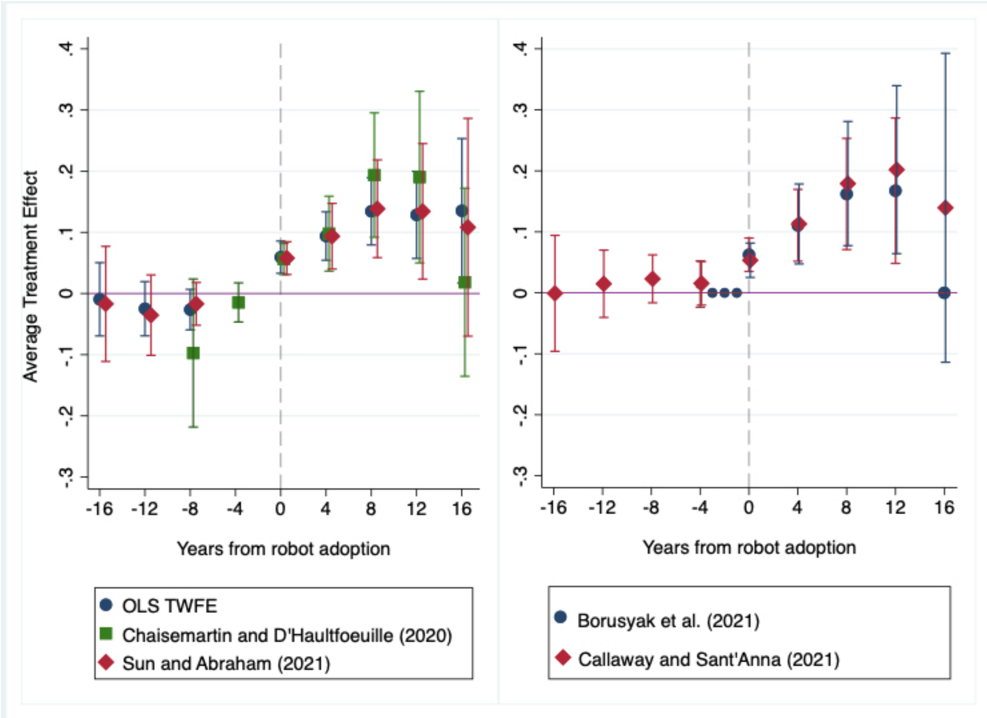

Figure 11: Probability of using TWA after robot adoption using five diff-in-diff estimators. The plot displays the point ATT estimates and 95% CI corresponding to results provided in Table 3.

SD of 0.7 in the estimation sample).

Column 3 includes the TWA indicator variable and the share of temps in the labour workforce of firms. A higher share of temporary work reduces firms' productivity by around 0.6 SD. This result would come to confirm the hypothesis frequently posed by research in the labour economics literature pointing to a lower productivity of temporary as compared to permanent workers. However, and constituting one of the novelties of our work, the use of TWA has a differential positive impact on productivity estimated at 0.117 SD, which is around 8.2% higher productivity of TWA users with respect to TWA non-users for a same share of temps.

Next in column 4 we further extend the estimation equation by including the interaction term of robots and TWA use. The estimated impact is also positive and significant in this case, amounting to 0.121 SD, that is, a gain of 8.5% higher productivity. This latter result confirms our working hypothesis that firms introducing robots will be able to achieve greater productivity gains if they can employ workers well suited to the needs of the new technology, a possibility facilitated by the use of recruitment agencies. It also suggests that agency workers who are in demand to be combined with new automation technologies are more productive than temporary workers hired for other reasons.

Table 4: Productivity of Robots and TWA use

	(1)	(2)	(3)	(4)	(5)
Robots_t	-0.025				
	(0.031)				
Robots_{t-4}	0.156***	0.153***	0.148***	0.119***	0.125***
	(0.046)	(0.024)	(0.025)	(0.026)	(0.025)
TWA use			0.117***	0.094***	0.054
			(0.023)	(0.026)	(0.043)
Robots×TWA				0.121***	0.138***
				(0.046)	(0.050)
Share temporary			-0.059***	-0.058***	-0.058***
			(0.011)	(0.011)	(0.011)
Control function					0.064*
					(0.036)
1st stage F of IVs=0					69.17
IVs(1) in main eq.					0.970
p-value					[0.324]
IVs(2) in main eq.					0.380
p-value					[0.537]
Observations	9,816	9,816	9,798	9,798	9,405
R-squared	0.601	0.601	0.603	0.603	0.602
Propensity scores	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Industry-year effects	Yes	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes	Yes
IVs for TWA use	No	No	No	No	Yes

Notes: productivity measured as... Standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01. .

In column 5 we further examine some possible endogeneity in the TWA indicator variable that might remain even after matching the sample as explained above and accounting for the full set of fixed effects. The problem could arise, for instance, if firms self-select as TWA users on the basis of time-varying firm-level factors potentially affecting productivity that are different from those determining robot adoption; in such a case, they would probably remain unaccounted for in the reweighted DiD methodology explained above. For example, it could be the case that firms introducing managerial and organisational changes with potential productivity effects decide to recruit workers through agencies to save labour search time in favour of other firm's activities or, more in general, as part of the reorganisation of the firm's practices. To explore this possibility we implement a 2-stage control function approach as follows. In a first stage we run a probit estimation of the TWA indicator on the full set of variables of the main equation plus two instrumental variables (IVs) that we expect to predict significantly the use of TWA while not impacting directly firms' productivity.[29] In a second stage, the generalised residual

[29] In the probit estimation firm fixed effects are included in the form of 3-year firm-specific pre-sample mean of

Table 5: Productivity of Robots and TWA use (only 4-year basis data)

	(1)	(2)	(3)	(4)	(5)	(6)†
Robots_t	-0.035					
	(0.032)					
Robots_{t-4}	0.139***	0.137***	0.132***	0.131***	0.073**	0.116***
	(0.046)	(0.046)	(0.033)	(0.033)	(0.037)	(0.044)
TWA use			0.073***	0.065***	0.046***	0.202***
			(0.018)	(0.018)	(0.015)	(0.028)
Robots×TWA					0.137**	0.177*
					(0.069)	(0.093)
Share Temporary				-0.175***	-0.171***	-0.270***
				(0.027)	(0.028)	(0.046)
Constant	0.195***	0.184***	0.174***	0.164***	0.169***	0.236***
	(0.052)	(0.052)	(0.003)	(0.003)	(0.004)	(0.007)
Observations	2,570	2,570	2,570	2,566	2,566	2,926
Adj R-squared	0.641	0.641	0.642	0.645	0.645	0.612
Propensity scores	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: outcome (dependent) variable constructed as rolling average of firm's productivity from t=-2 to t=+1. † In column (6) the outcome measure is current year firm's productivity (as in Koch et al). Standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01. .

coming from the probit estimation, meant to absorb the endogeneity if it exists, is plugged into the main equation. If that generalised residual is not significant in the second stage it would be indicating absence of endogeneity bias. In case exogeneity is rejected, maintaining it in the equation corrects the bias - see, e.g., Wooldridge (2015).

The two IVs are a dummy variable indicating whether or not the firm has its own internet domain, and a dummy variable indicating if the firm contracts safety and cleaning services externally. Both are meant to help firms contacting with external labour intermediaries. The exclusion restriction for the first of these IVs is based on the fact that having and maintaining an internet domain - something relatively common, easy and cheap-, does not constitute necessarily any sort of productive factor. As for the safety and cleaning services, we can assess as well that they neither are likely to constitute inputs nor shifters of the production process of firms.

In column 5 we provide evidence that these instruments help predict firms' TWA use while they do not have any direct impact on firms' productivity in our data. In the probit stage, although not reported in the table, the estimated coefficients of the two IVs are positive and significant, with estimated coefficients of 0.240 and 0.258 for web-domain and safety-cleaning outsourcing, with p-values of 0.000 in both cases. The F-test of joint significance of the two

the TWA indicator.

IVs in the first stage (as reported in the table) is 69.17, thus appreciably above the Staiger and Stock's rule of thumb critical value of 10 for one endogenous variable. The generalised residual -or control function- is statistically significant in the equation, though just at the 10 percent level, thus suggesting that some endogeneity can still remain in the TWA indicator variable. After including the control function neither the first nor the second of the IVs mentioned above show significant explanatory power over firms' productivity (labeled IV-1 and and IV-2 at the bottom of the table), leading us to not rejection of the overidentifying conditions with sufficiently high p-values (0.324 and 0.537, respectively).[30] The IV procedure renders a coefficient of the TWA indicator that is now non significant in isolation while it remains positive, sizeable and significant when interacted with robots. According to this last result, agency workers who are more productive than regular temps are those who are combined with more advanced technologies.

6 Summary and concluding remarks

In this paper, we study, theoretically and empirically, the effects of robots adoption on the use of TWAs and the combine effect of robots and TWAs on firm productivity. This is important for understanding the relationship between robots and labour arrangements within firms. We develop a theoretical framework where the adoption of new technologies increases firm productivity, but it also increases the need of a higher quality matching between jobs and workers. In the model, TWAs are market intermediaries that provide a signal to the companies about the appropriateness of the workers to the new technologies. Moreover, TWAs can provide workers in faster way than if the company goes directly to the job market. As a consequence, after the adoption of robots firms have incentives to change their searching strategies of workers 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 a panel data of Spanish firms from 1997 to 2016 with information on robot adoption and use of TWAs. We estimate causal effects of robot adoption

[30] Testing for overidentifying restrictions in the control function approach consists on checking the non-significance of the IVs in the main equation once the control function has been also included. The logic behind this procedure is that the instruments have not direct impact on the dependent variable other than through their impact on the endogenous regressor. All instruments except one must be included, and the result should hold irrespective of the IV being excluded - see Rivers and Vuong (1988).

on TWAs using staggered difference-in-difference (DiD) estimations. We find that firms that introduce robots increase the probability of use TWAs by seven percentage points. Using DiD matching techniques and an instrumental variable strategy, we find that firms that combine robots with TWAs raise their productivity by around 8.5% additionally to the increase of productivity of the adoption of robots. This suggests that TWAs increase the matching quality between new technologies and labour.

References

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childress, E., Dinlersoz, E., Foster, L., and Goldschlag, N. (2020). *Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey.* University of Chicago Press.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, 90(5):1973–2016.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2020). What are the labor and product market effects of automation? New evidence from France. *CEPR Discussion Paper No. DP14443*.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2021). The direct and indirect effects of automation on employment: A survey of the recent literature.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79.

Autor, D. (2001). Why do temporary help firms provide free general skills training? *The Quarterly Journal of Economics*, 116(4):1409–1448.

Autor, D. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21(1):1–42.

Autor, D. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3):3–30.

Bertrand, M., Hsieh, C., and Tsivanidis, N. (2021). Contract labor and firm growth in India. *National Bureau of Economic Research*, No. w29151.

Bessen, J., Goos, M., Salomons, A., and van den Berge, W. (2020). Firm-level automation: Evidence from the Netherlands. *AEA Papers and Proceedings*, 110:389–93.

Bilal, A. and Lhuillier, H. (2021). Outsourcing, inequality and aggregate output. *National Bureau of Economic Research*, w29348.

Bonfiglioli, A., Crinò, R., Fadinger, H., and Gancia, G. (2020). Robot imports and firm-level outcomes. *CEPR Discussion Paper No. DP14593.*

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Brown, M., Setren, E., and Topa, G. (2016). Do informal referrals lead to better matches? Evidence from a firm's employee referral system. *Journal of Labor Economics*, 34(1):161–209.

Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., and Subramaniam, A. (2018). Skill shift: Automation and the future of the workforce. *McKinsey Global Institute*, 1:3–84.

Caggese, A. and Cuñat, V. (2008). Financing constraints and fixed-term employment contracts. *The Economic Journal*, 118(533):2013–2046.

Cahuc, P., Charlot, O., and Malherbet, F. (2016). Explaining the spread of temporary jobs and its impact on labor turnover. *International Economic Review*, 57(2):533–572.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Carrasco, R., Gálvez Iniesta, I., and Jerez, B. (2022). Do temporary help agencies help? Temporary employment transitions for low-skilled workers. Technical report, Working paper, Universidad Carlos III. Available at SSRN: https://ssrn.com/abstract=4257448 or http://dx.doi.org/10.2139/ssrn.4257448.

Carrillo-Tudela, C., Kaas, L., and Lochner, B. (2022). Matching through search channels.

Countouris, N., Deakin, S., Freedland, M., Koukiadaki, A., and Prassl, J. (2016). Report on temporary employment agencies and temporary agency work. *International Labour Office. Geneva.*

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153.

de Blas, A. M., Martín-Román, Á. L., and Caballero, J. C. R. (2013). El papel de las ETTs en la reducción del riesgo moral asociado al seguro por accidentes de trabajo: El caso de España. *Estudios de economía aplicada*, 31(2):497–522.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–1044.

Doraszelski, U. and Jaumandreu, J. (2013). R&D and productivity: Estimating endogenous productivity. *Review of Economic Studies*, 80(4):1338–1383.

Doraszelski, U. and Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, 126(3):1027–1084.

Drenik, A., Jäger, S., Plotkin, P., and Schoefer, B. (2023). Paying outsourced labor: Direct evidence from linked temp agency-worker-client data. *Review of Economics and Statistics*, 105(1):206–216.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2):514–546.

Estadística de Empresas de Trabajo Temporal (2021). Ministerio de trabajo. `https://www.mites.gob.es/es/estadisticas/contenidos/anuario.htm`. Last Accessed 22 January 2023.

Faccini, R. (2014). Reassessing labour market reforms: Temporary contracts as a screening device. *The Economic Journal*, 124(575):167–200.

Faia, E., G., O., and ella S., S. (2022). Robot adoption, worker-firm sorting and wage inequality: Evidence from administrative panel data. *CEPR Discussion Paper*, (17451).

Galenianos, M. (2013). Learning about match quality and the use of referrals. *Review of Economic Dynamics*, 16(4):668–690.

García-Pérez, J. I. and Muñoz-Bullón, F. (2005). Temporary help agencies and occupational mobility. *Oxford Bulletin of Economics and Statistics*, 67(2):163–180.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Guadalupe, M., Kuzmina, O., and Thomas, C. (2012). Innovation and foreign ownership. *American Economic Review*, 102(7):3594–3627.

Hirsch, B. and Mueller, S. (2012). The productivity effect of temporary agency work: Evidence from German panel data. *The Economic Journal*, 122(562):F216–F235.

Holzer, H. J. (1987). Hiring procedures in the firm: Their economic determinants and outcomes. NBER Working Papers 2185, National Bureau of Economic Research, Inc.

Humlum, A. (2021). Robot adoption and labor market dynamics. *Working Paper*.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638):2553–2584.

Kuzmina, O. (2022). Employment flexibility and capital structure: Evidence from a natural experiment. *Management Science*.

Lips, B. (1998). Temps and the labor market: Why unions fear staffing companies. *Regulation*, 21:31.

Litwin, A. S. and Tanious, S. M. (2021). Information technology, business strategy and the reassignment of work from in-house employees to agency temps. *British Journal of Industrial Relations*, 59(3):816–847.

Montgomery, J. D. (1991). Social networks and labor-market outcomes: Toward an economic analysis. *The American Economic Review*, 81(5):1408–1418.

Neugart, M. and Storrie, D. (2006). The emergence of temporary work agencies. *Oxford Economic Papers*, 58(1):137–156.

Pissarides, C. A. (1979). Job matchings with state employment agencies and random search. *Economic Journal*, 89(356):818–833.

Pries, M. and Rogerson, R. (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy*, 113(4):811–839.

Pries, M. J. (2004). Persistence of employment fluctuations: A model of recurring job loss. *Review of Economic Studies*, 71(1):193–215.

Rios-Avila, F., Callaway, B., and Sant'Anna, P. H. (2022). csdid: Difference-in-differences with multiple time periods in Stata. Technical report, Working paper, Boston University.

Rivers, D. and Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39(3):347–366.

Sant'Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1):101–122.

Stiebale, J., Suedekum, J., and Woessner, N. (2020). Robots and the rise of European superstar firms. *Heinrich Heine University Düsseldorf, Düsseldorf Institute for Competition Economics (DICE). Working paper*, (347).

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Survey, M. G. (2022). Your questions about automation, answered. Technical report, McKinsey Institute.

Topa, G. (2011). Chapter 22 - labor markets and referrals. volume 1 of *Handbook of Social Economics*, pages 1193–1221. North-Holland.

Wasmer, E. (2001). Competition for jobs in a growing economy and the emergence of dualism. *The Economic Journal*, 109(457):349–371.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.

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

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

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 $\Omega_T(1) \geq \max\{\Omega_P(1), U\}$. 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 $]0,1[$,

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

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

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 $G(\xi, V)$ 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 $\tilde{V}_A$.

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

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:

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

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

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

Second,

$$V_A - \tilde{V}_A = -\frac{q_A(1-\varphi)}{r + q_A(1-\varphi)}\int_{0}^{\pi_A} (\Omega(\mu) - U - V_A)\, f(\mu|\pi)d\mu. \tag{33}$$

Let $G(\mu|\pi)$ be the complementary cumulative distribution function of the posterior, $G(\mu|\pi) = \int_\mu^1 f(x|\pi)dx$. 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

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

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 descriptives

Table B1: Descriptive statistics

	Full sample		Large		Small	
Variables	Mean	SD	Mean	SD	Mean	SD
Main variables						
Robot adopters	0.301	0.459	0.551	0.497	0.210	0.407
TWA(Yes/No)	0.272	0.445	0.523	0.499	0.186	0.389
N. Observations	31,663		8,476		23,187	
Productivity variables						
Labour productivity	10.551	0.702	10.900	0.623	10.395	0.683
Sales	11.715	0.849	12.205	0.733	11.504	0.806
Capital	3.332	1.106	3.855	0.876	3.166	1.120
Hours worked	11.647	1.452	13.607	0.753	10.977	0.935
Labour variables						
Total employment	4.173	1.467	6.146	0.761	3.493	0.944
High skills	0.060	0.085	0.087	0.096	0.051	0.079
Medium skills	0.086	0.141	0.085	0.116	0.086	0.149
Production workers	0.691	0.191	0.646	0.203	0.705	0.185
Temporary share	0.134	0.187	0.125	0.149	0.138	0.199
Other controls						
R&D intensity	0.292	0.575	0.539	0.664	0.207	0.514
Exports	0.656	0.474	0.931	0.251	0.562	0.496
Imports	0.644	0.478	0.934	0.247	0.544	0.498
Foreign	0.160	0.367	0.401	0.490	0.077	0.267
N. Observations	21,065		3,583		17,482	

Notes: The table reports means and standard deviations of firm-specific variables for the full sample, the sample of large firms and the sample of small firms. 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 adopt a robot, and zero otherwise. TWA is a dummy variable that takes the value of one if a firm hires temporary agency workers, and zero otherwise. Labour productivity is the logarithm of value added per worker. Value added is calculated as the sum of sales, stock changes and other operating income, minus purchases and external services. Sales is the logarithm of sales per worker. Capital is the logarithm of the deflated capital stock over the number of hours effectively worked. Hours worked is the logarithm of hours effecttively worked. Total employment is the logarithm of total personnel employed at the company on December 31st. High skills is the percentage that engineers and graduates represent on the total personnel of the company on December 31st. Medium skills is the percentage that graduates after a 3-year degree course represent on the total personnel of the company on December 31st. Production workers is the percentage that processing workers represent on the company's total personnel on December 31st. Temporary share is the percentage of temporary staff employed at the company on December 31st. 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 abroad, and zero otherwise. Foreign is a dummy variable that takes the value of one if more than 50% of the firm capital is foreign.

Table B2: Descriptive statistics by TWA users and robot adopters

	Temporary work agencies				Robots					
	TWA users		TWA non-users		Control group		Before		After	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Main variables										
Robot adopters	0.452	0.497	0.245	0.430	-	-	-	-	-	-
TWA(Yes/No)	-	-	-	-	0.172	0.377	0.356	0.478	0.391	0.488
N. Observations	8,676		22,987		16,280		3,212		12,171	
Productivity variables										
Labour productivity	10.867	0.592	10.433	0.703	10.379	0.686	10.611	0.640	10.779	0.678
Sales	12.160	0.687	11.548	0.843	11.471	0.845	11.829	0.777	12.037	0.764
Capital	3.574	0.961	2.975	1.109	2.901	1.087	3.464	0.980	3.637	0.960
Hours worked	12.611	1.229	11.287	1.362	11.018	1.174	12.107	1.310	12.465	1.448
Labour variables										
Total employment	5.138	1.234	3.812	1.382	3.534	1.188	4.630	1.321	5.000	1.459
High skills	0.086	0.094	0.051	0.079	0.052	0.086	0.056	0.075	0.071	0.082
Medium skills	0.101	0.134	0.081	0.143	0.081	0.145	0.071	0.112	0.091	0.132
Production workers	0.647	0.192	0.707	0.188	0.697	0.199	0.696	0.188	0.680	0.179
Temporary share	0.114	0.142	0.142	0.201	0.138	0.202	0.163	0.197	0.113	0.151
Other controls										
R&D intensity	0.459	0.648	0.229	0.531	0.201	0.506	0.332	0.627	0.412	0.626
Exports	0.869	0.336	0.577	0.494	0.532	0.498	0.747	0.434	0.819	0.384
Imports	0.872	0.333	0.558	0.496	0.519	0.499	0.742	0.437	0.811	0.391
Foreign	0.317	0.465	0.102	0.302	0.085	0.279	0.203	0.402	0.266	0.441
N. Observations	4,620		16,445		14,305		2,382		3,630	

Notes: The table reports means and standard deviations of firm-specific variables for the TWA users, the TWA non-users, the control group of non-robot adopters and the treated group of robot adopters before and after adopting the robot. 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 adopt a robot, and zero otherwise. TWA is a dummy variable that takes the value of one if a firm hires temporary agency workers, and zero otherwise. Labour productivity is the logarithm of value added per worker. Value added is calculated as the sum of sales, stock changes and other operating income, minus purchases and external services. Sales is the logarithm of sales per worker. R&D intensity is the logarithm of R&D expenditures over sales. Total employment is the logarithm of total personnel employed at the company on December 31st. High skills is the percentage that engineers and graduates represent on the total personnel of the company on December 31st. Medium skills is the percentage that graduates after a 3-year degree course represent on the total personnel of the company on December 31st. Production workers is the percentage that processing workers represent on the company's total personnel on December 31st. Temporary share is the percentage of temporary staff employed at the company on December 31st. 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 abroad, and zero otherwise. Capital is the logarithm of the deflated capital stock over the number of hours effectively worked. Foreign is a dummy variable that takes the value of one if more than 50% of the firm capital is foreign.

C Appendix: additional robustness and sensitivity tests

Table C1:
Robot Adoption ATT on firms' TWA use. Staggered DiD estimation
- Robustness to including/excluding adopters that stop using robots-

	All panel years for robot adopters		Excluding robot adopters that stop using robots	
	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.071***	0.056***	0.116***	0.100***
	(0.022)	(0.022)	(0.028)	(0.027)
Pre-trends (Chi-sq)	10.977	2.710	10.977	2.710
(p-value)	[0.277]	[0.970]	[0.277]	[0.974]
N Obs.	4,522	4,522	4,144	4,144

Notes: Uncond.PT refers to uconditional parallel trends estimation; Cond.PT: conditional parallel trends estimation (previous experience using TWA). Estimation method: Sant'Anna and Zhao (2020) 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 C2:
Robot Adoption treatment effects on firms' TWA use.
Staggered DiD estimation
- Exploring different timing of the outcome variable -

TWA rolling average:	[-3, 0]	[-2, +1]	[-1, +2]	[0, +4]
	(1)	(2)	(3)	(4)
Total ATT	0.089***	0.063***	0.043***	0.009
	(0.019)	(0.017)	(0.016)	(0.015)
Pre-trends (Chi-sq)	2.978	11.888	15.246	32.621
(p-value)	[0.981]	[0.292]	[0.123]	[0.000]
N Obs.	6,447	6,447	6,447	6,447

Notes: Uncond.PT refers to unconditional parallel trends estimation; Cond.PT: conditional parallel trends estimation (previous experience using TWA). Estimation method: Sant'Anna and Zhao (2020) 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. .

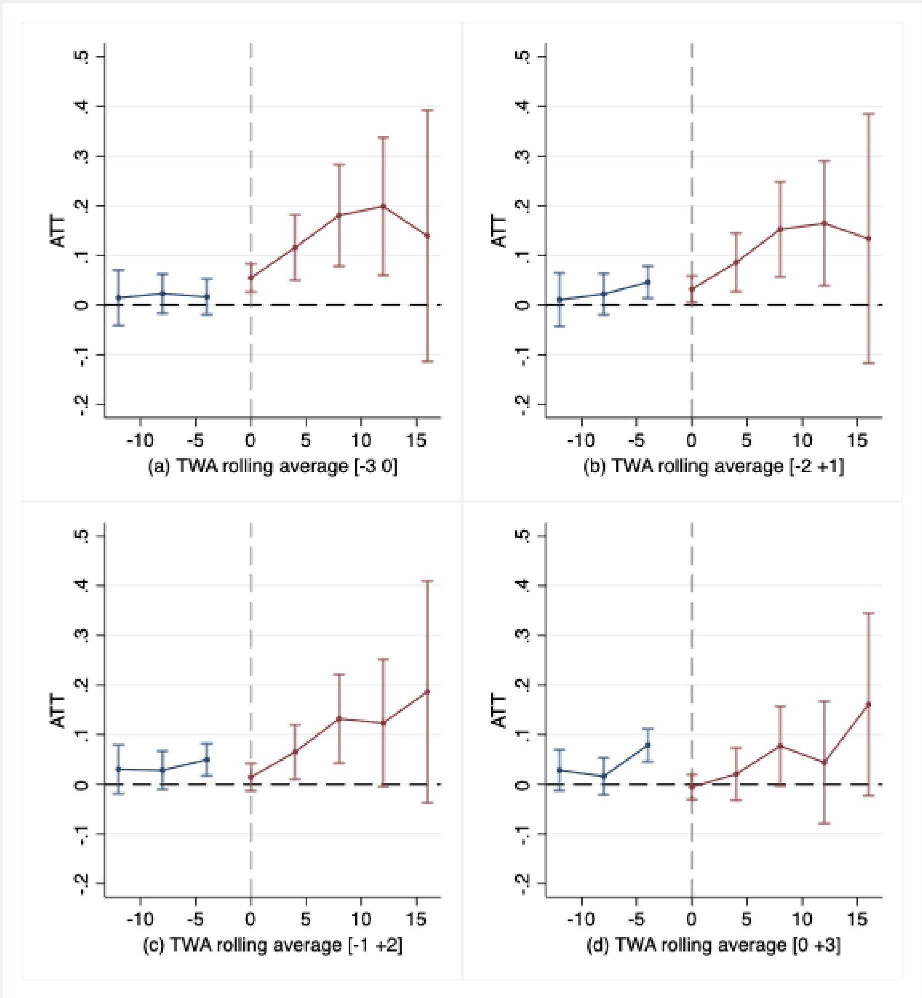

Figure C1: Robots effect on TWA use. Event Study. The 4 plots in the figure show the event studies corresponding to columns 1 to 4 of Table C2, that is, to alternative centering of the 4-year rolling average of the outcome variable (TWA use).