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

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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 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 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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1 Introduction

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

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

The introduction of automation-oriented technologies, such as robots, has transformed employment and production methods during the last decades. There is evidence of the effects of robots on wage inequality and within-firm employment (Acemoglu and Restrepo, 2022; Aghion et al., 2020, 2021; Bessen et al., 2020), 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 for robot adopters to hire new workers (Acemoglu et al., 2020; Aghion et al., 2021; Autor, 2015; Graetz and Michaels, 2018), including specialised 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 TWAs 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 TWAs in the United States offer free computer skills training 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 highlight the importance

[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.

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 fulfil 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 organisations (McKinsey Global 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 formalises 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 emphasises that new technologies and TWAs are complementary.

We provide two main testable implications. The first is that the adoption of new technologies increases the probability of using TWAs as a 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]For example, one of the largest TWAs operating in Europe, Randstad, uses as one of its advertising slogans: *'(our) technology is designed to bring you closer to the work you want and employers closer to the talent they seek.' https://www.randstad.com.sg/relevate/*. Thus, they advertise themselves as 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 Survey (2022), based on interviews with CEOs from major U.S. and E.U. 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 TWAs 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 organisation (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 emphasise 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 TWAs, 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 organised 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 TWAs and robots on firm productivity. Section 7 concludes.

2 The model

The model describes how new technologies, which enhance productivity when combined with capable workers, affect the firms' use of TWAs and temporary contracts. We build a matching model in which firms and workers learn over time about match quality *à la* Pries (2004) and Pries and Rogerson (2005). Conditional on their production technology, firms choose between searching for a worker by themselves or outsourcing the search process to a work agency. At any time after matching, firms and workers can choose to upgrade the temporary contract into a permanent one or, conversely, terminate the match.[5]

2.1 The setup

We consider a continuous-time stationary model. Time is discounted at the rate r. Firms produce with constant returns to scale in labour, hence the standard normalisation that a firm has only one job to fill. Once the job is filled, the worker utilises 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 normalised 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 $z = 1$. The factor remains constant throughout the match but it is imperfectly observed by both the firm and the worker. In the absence of additional information, a firm and a worker suppose that they will form a good match with (prior) probability π. A nonoperational worker, or bad match, does not produce anything. Third, the job can turn unproductive for exogenous reasons, at the rate λ.

Agents make the following decisions. Firms with vacant jobs choose a search channel. Once 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 could offer a permanent contract at the hiring stage. See Caggese and Cuñat (2008) for a similar assumption. This is a simplification for other mechanisms explored in the literature, such as investment in firm-specific human capital (Autor, 2003).

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 $[0, 1]$. The function $f(\mu|\pi)$ is differentiable over π. Work agencies propose workers that have the same quality on average as those the firms can find by themselves on the market, $\int_0^1 \mu f(\mu|\pi)d\mu = \pi$ for any π.[7] We also assume that a raise in the prior π increases the probability of a good match in the sense of first-order stochastic dominance, $\int_0^1 \frac{\partial f}{\partial \pi}(\mu|\pi)d\mu \leq 0$ for any μ and π.

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

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

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

When a firm searches on the regular market, it meets a worker at rate q_R, expecting them to be competent with probability π. The firm then receives a share $1-\varphi$ of the surplus $\Omega(\pi) - U - V_R$ if there is a match. A match is formed only if the surplus is positive. When a firm searches with a work agency, it meets a worker at rate q_A, expecting them to be competent with probability μ randomly drawn.[8]

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

[8] Although characterising the labour market equilibrium is not necessary for our analysis, it would not be

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

Contract and experience Firms can employ workers on a temporary or permanent contract. There is no commitment to the type of contract before finding a worker. Firms and workers choose the best contract upon meeting. A temporary contract expires at the rate δ while a permanent contract never expires.[9] Upon expiration, the firm and the worker can stay together if they accept a permanent contract. Otherwise, the firm loses its vacancy and the worker becomes unemployed. A firm can also propose a permanent contract to its temporary 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

difficult to endogenise the worker's value of unemployment and the matching rates q_R and q_A.

[9]This assumption captures an essential feature of temporary contracts while avoiding 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.

dismissing the worker. The cost is not too high to prevent firms from dismissing permanent workers that are unproductive.

Once matched together, a firm and a worker learn by experience the quality of the match. At the Poisson rate β_0, the pair observes a signal $z+\varepsilon$ when the match quality is z. The noise ε is a random draw from a uniform distribution on $[-\frac{1}{2\beta_1}, \frac{1}{2\beta_1}]$, with $0 < \beta_1 \leq 1$. The noises drawn throughout the duration of the match are time-independent. We 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 such new information. The efficiency of learning by experience is captured by β.

For our analysis, we do not need to be explicit about the way wages are formed. We only assume that workers receive a share φ of the surplus upon matching and that the pair achieves efficient contracting that 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 $]0,1]$,

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

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

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

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

and defining by continuity $\Omega_T(0) = \Omega_T(0^+)$. The match produces on expectation $\tau\xi\mu$. At rate $\beta\mu$, the match 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 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 characterise the optimal decision of a firm when meeting a job applicant. The firm decides whether to hire the worker or not, and whether to propose a permanent contract or not. This decision is based on the posterior probability μ that the worker is suitable for the job.

Proposition 1 *Consider a firm, with a vacant job of value $V \geq 0$, that has just met a worker of posterior probability μ.*
The firm and the worker form a match if and only if the odds ratio $\frac{1-\mu}{\mu}$ satisfies

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

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

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

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

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

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

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

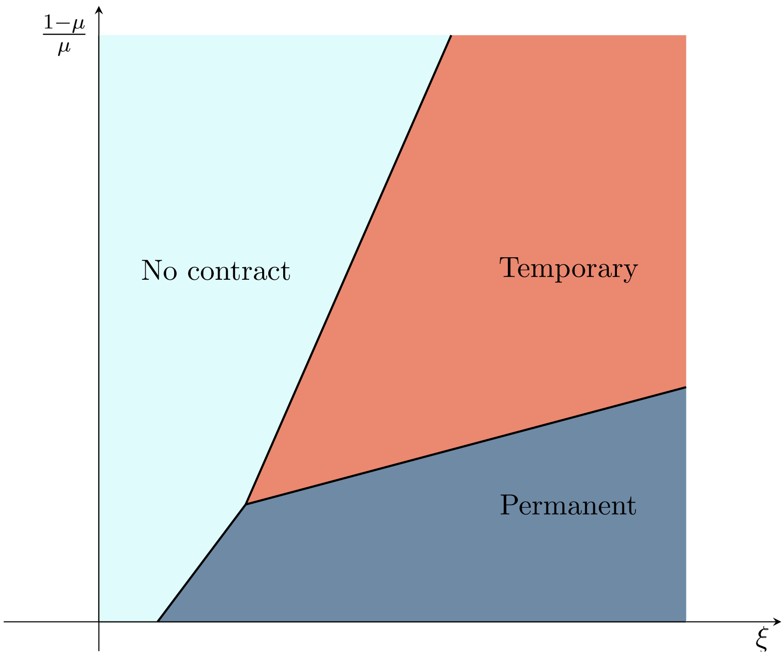

Figure 1: Optimal contract upon meeting

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

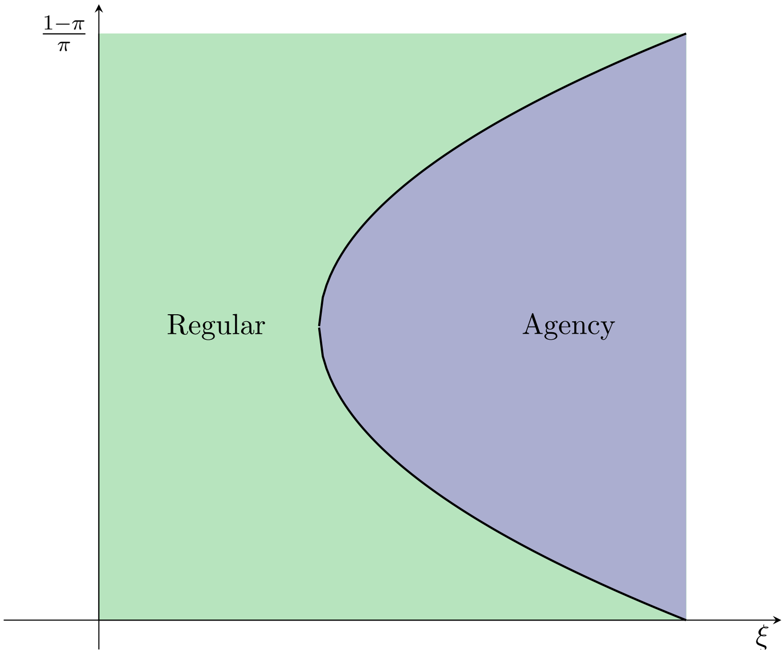

Figure 2: Optimal search channel channel

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.

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.

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

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

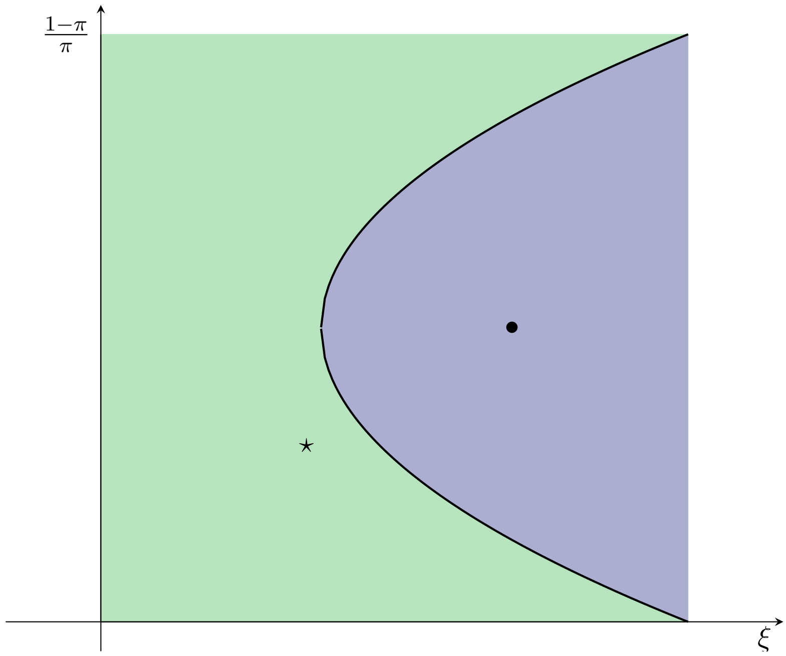

Figure 3: Recruitment channel in two examples

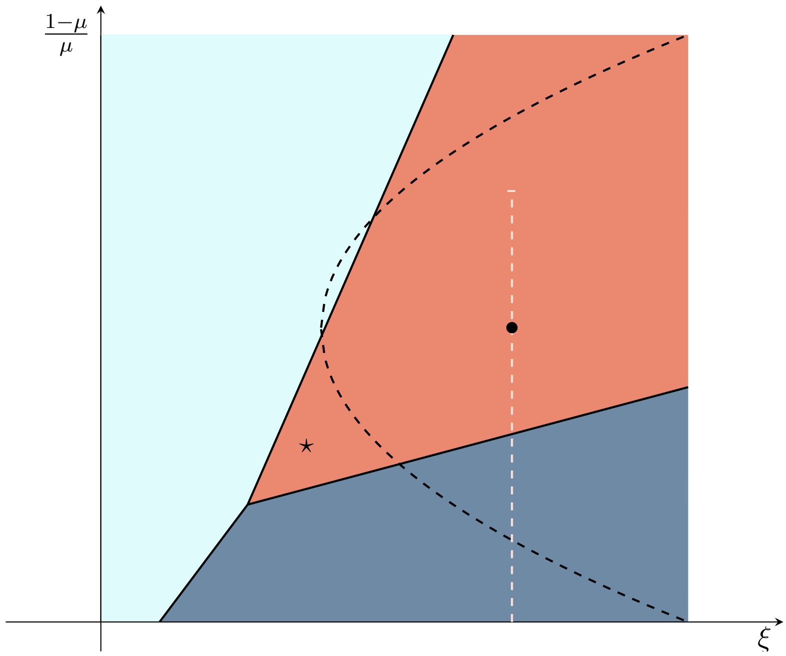

Figure 4: Contracting in two examples

joint choice of a technology and a search channel, $\max\{V_R^\star, V_A^\star - C, V_R^\bullet, V_A^\bullet - C\}$, where $V_R^\star$ and $V_A^\star$ are the values of a vacancy with the first technology, and $V_R^\bullet$ and $V_A^\bullet$ with the second one.

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

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

Implication 2 *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 liberalisation of the 90s in Europe (Countouris et al., 2016). A characteristic of the Spanish law is that once the contract signed between the TWA and the user company expires, the contract has to become permanent if the worker continues to work for the user company (the same as temporary workers hired through the regular market).[12] 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 fill vacancies caused by recent layoffs at the user company.[13] 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. For the user company hiring a temporary worker through a TWA implies paying to the TWA the wage and the fee for the provision of the worker.[14]

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 and medium-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 31%.[15] Within the group of high-skilled workers (including those with

[12] García-Pérez and Muñoz-Bullón (2005) find that the probability of getting a permanent job is higher for workers who use TWAs than for those hired directly through the user company. Moreover, this effect is especially important for high-skilled 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.

[13] 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.

[14] 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 an employment contract with the agency.

[15] 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.

vocational trainning), the percentage of workers with an undergraduate, a MSc or a PhD degree is 64%.

4 Data and descriptive statistics

4.1 Data

The data that we use in this paper is the Encuesta sobre Estrategias Empresariales, ESEE, (Survey of Entrepreneurial Strategies). This is a firm-level annual survey from 1990 covering around 1,800 Spanish manufacturing firms each year. It is sponsored by the Spanish Ministry of Industry and supplied by the SEPI Foundation. The dataset is representative of the Spanish manufacturing sector by industry and firm size. In the initial year of the database 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 in the survey, obtaining a participation rate of about 70% in the initial year. Since then, there have been annual incorporation of new firms to minimise attrition, so that the sample remains representative of the Spanish manufacturing sector. [16]

The dataset reports unique information on robot adoption and use of working agencies for the recruitment process. Our sample spans a period of two decades, from 1997 - first year with information on TWA-use-, to 2016. Our sample is an unbalanced panel of 3,743 firms (30,112 observations). In the survey, besides accounting data, firms provide information on several output and input measures of their production process, including details about the technology used and hire arrangements of their workforce. Most questions are asked every year, but in some cases, such as the robot adoption indicator and some skill-composition indicators, the information is gathered every four years.

In the survey, the firms are asked whether they use robots in their production process. We restrict our sample to firms that do not have adopted robots in the first year of our sample, since we are interested on the effects robot adoption. In the sample, 700 firms report using robots at some point during the sample period, while 3,043 never did. The large majority of the firms in the sample continuously use robots after the first time they report it.[17] We construct

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

[17]Only 5% of firms in the sample are switchers after first reporting its use. In our robustness check section, we

the variable robot adoption as a binary indicator that takes the value one the first time the firm declares the use of robots and the following years and a zero otherwise. The robot adoption has increase steadily over time from 1998 at the beginning of the sample period to 2016?? the end of the sample period. Figure B1 in the Appendix depicts the evolution of firms' adoption of robots in the Spanish manufacturing sector for our sample period.

The companies report yearly whether some of their employees are hired through a TWA. Given that our treatment variable robots is observed every four years, our dependent variable in the first part of the analysis, the likelihood of using TWA, is constructed as the average of the binary indicator of TWA-use over the years between two consecutive response years of the treatment. The dataset also provides information on the number of both temporary and non-temporary workers, so that in our analysis we can identify separately the use of temporary agency work from what would be just a labour hiring strategy based on temporary work. Figure B2 in the Appendix shows the evolution of the share of firms that use TWAs. During the first decade, this share increased by 13 percentage points, representing an increase of around 65% from the initial 20% in 1997. The use of TWAs declined significantly between 2007 and 2009, suggesting that firms adjusted employment through temporary workers during the Great Recession. As a result, in 2009 the proportion of firms using TWAs was similar to that in 1997. During the last eight years of our sample, the growth of the share of firms using TWAs was steady, leading to the recovery of pre-crisis levels by 2016. The upward trend in the last years suggests an even greater increase in the use of TWAs for the most recent out-of-sample years.

On the second part of the analysis, we study the effect of robots adoption and TWA on labor productivity. Similar to Chen and Steinwender (2021), Koch et al. (2021) and Guadalupe et al. (2012), initially, 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.

exclude switchers from the analysis to test the sensitivity of the results.

5 The effect of robot adoption on TWA-use

5.1 Descriptive analysis

In Table 1, we display descriptive statistics of the main variables for the whole sample, for robot adopters before and after adoption, and for firms that never adopt robots during the sample period. On the top part of the table, we show the percentage of firms that use TWA and labor related variables. On the rest of the table, we provide information on a set of variables that we use to evaluate the effects of TWAs and robots on firms' productivity and other variables.

Table 1: Descriptive statistics

	All		**Robots adopters**				**Never robots**	
			Before adoption		**After adoption**			
	(1)		(2)		(3)		(4)	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
TWA(Yes/No)	0.209	0.406	0.339	0.473	0.382	0.486	0.155	0.362
N. Observations	6,836		970		829		5,037	
Labour variables								
Total employment	3.803	1.324	4.557	1.302	4.757	1.370	3.500	1.181
High skills	0.054	0.086	0.055	0.076	0.073	0.095	0.051	0.085
Medium skills	0.072	0.126	0.069	0.110	0.078	0.114	0.071	0.130
Production workers	0.695	0.194	0.696	0.188	0.677	0.187	0.698	0.197
Temporary share	0.159	0.213	0.190	0.218	0.130	0.174	0.157	0.217
Hours worked	11.282	1.310	12.030	1.292	12.223	1.369	10.985	1.167
Productivity variables								
Labour productivity	9.798	0.703	9.933	0.632	10.128	0.717	9.718	0.693
Sales	10.638	0.868	10.884	0.775	11.093	0.824	10.516	0.857
Capital	2.992	1.110	3.369	0.999	3.610	0.932	2.837	1.105
Other variables								
R&D intensity	0.244	0.538	0.342	0.613	0.393	0.628	0.200	0.499
Exports	0.587	0.492	0.731	0.443	0.793	0.404	0.525	0.499
Imports	0.575	0.494	0.733	0.442	0.798	0.401	0.508	0.499
Foreign	0.122	0.327	0.193	0.395	0.218	0.413	0.092	0.290
N. Observations	6,851		973		832		5,046	

Notes: The table reports means and standard deviations of firm-specific variables for all firms, robots adopters before and after adoption and the control group of firms that never adopt robots during the sample period. The sample spans the years 1997-2016 and is restricted to firms that do not use robots in the first year they enter the sample. *Robot adopters* is a dummy variable that takes the value of one if a firm adopts 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. 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. Hours worked is the logarithm of hours effectively worked. *Labour productivity* is the logarithm of value added per hours effectively worked. 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 hours effectively worked. Capital is the logarithm of the deflated capital stock over the number of hours effectively worked. R&D intensity is the logarithm of R&D expenditures over sales. Exports is a dummy variable that takes the value of one if a firm is selling abroad, and zero otherwise. Imports is a dummy variable that takes the value of one if a firm is buying 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.

Firms that never adopt robots exhibit lower capital, R&D intensity, employment, skill share, and participation in international markets (exports and/or import activities) than robot adopters. Comparing robot adopters before and after the adoption, the statistics suggests that the use of TWA increases slightly after adoption (0.391 vs. 0.356) as well as the labor productivity, sales, employment, R&D intensity and internationalization. In the next sections, we describe the identification strategies that we follow in order to determine the causal impact of robots on TWA probability, and the impact of robots, TWA and their combined effect on productivity and how we control for possible confound effects.

Figure 5 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 TWAs is not directly related to the intensification of temporary contracts. The first and second panels 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 suggest 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 TWAs 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 first in terms of the proportion of firms using TWA while 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 (the 4 sectors with the lowest temps' share rank among the top 5 with the highest proportion of temps coming from an 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.

Before explaining our econometric 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 6. In the Figure, we include the firms' shares of high-skilled workers, medium-skilled 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 organisation.[18] The left-side panel shows that, as compared to non-adopters, robot adopters increase the share of high-skilled workers after robot adoption. An increase in the share of medium-skilled workers is also estimated, though the effect is not statistically significant in this case. Robot adopters, though, reduce both the

[18]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 organisation during the year?'.

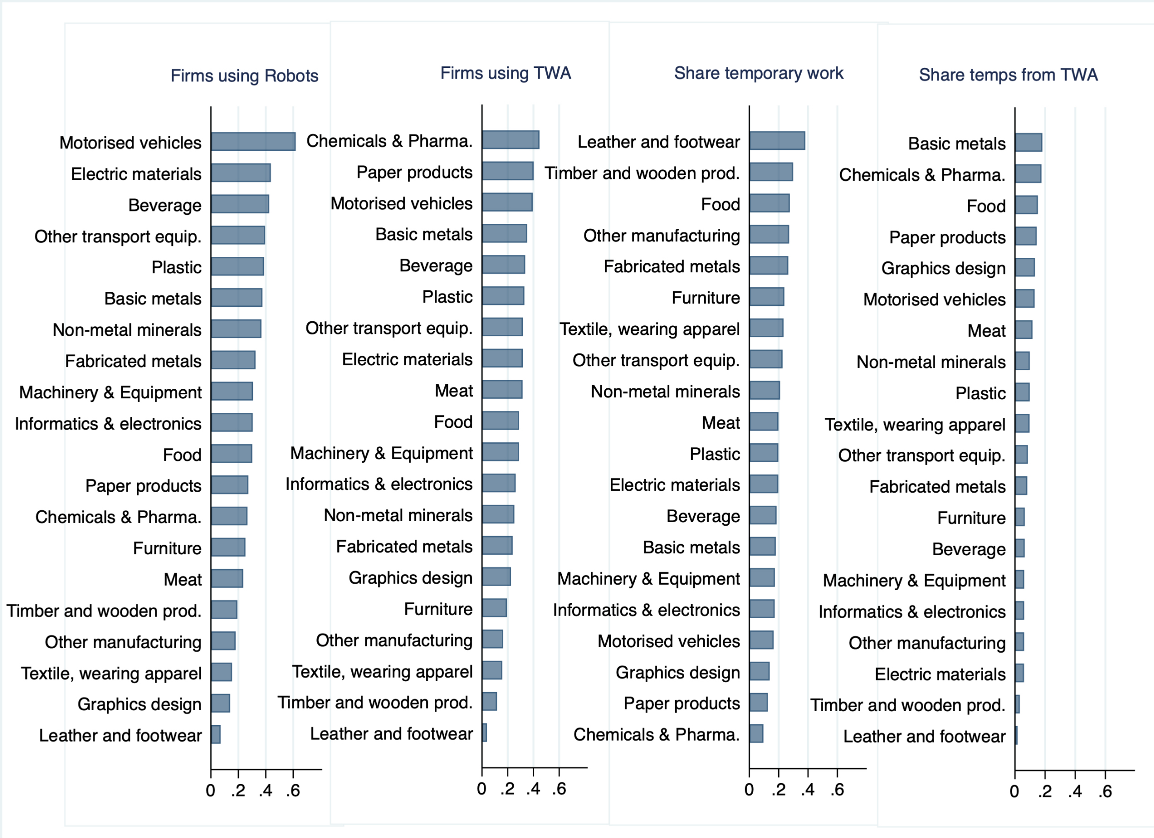

Figure 5: Industrial breakdown of robot adoption, TWA-use, temporary work share and agency-work share.

share of production workers and the share of temporary workers, according to the negative and statistically significant coefficients obtained in these two cases. The negative impact on the temporary share 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 6 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 organisation.

This preliminary analysis highlights that firms restructure 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.

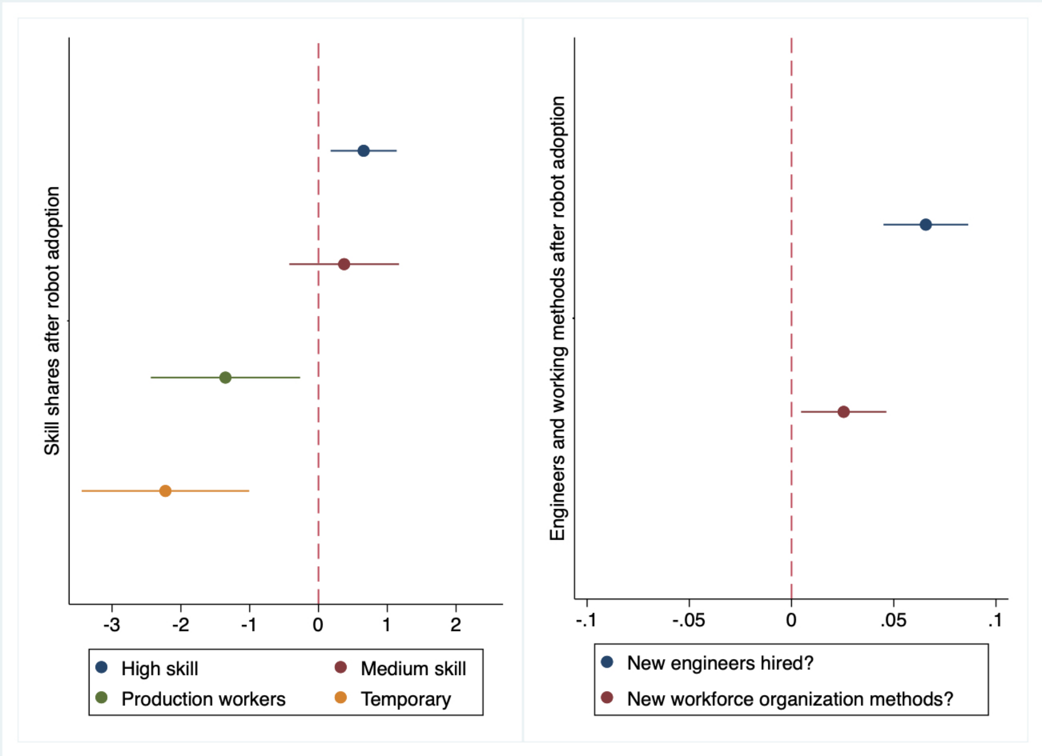

Figure 6: Left panel: Changes in firms' labour skill composition and temporary work share after Robot Adoption; Right panel: Changes in firms' answers to the following questions after Robot Adoption: i) Did the firm hire 'new' engineers during the year?; ii) Has the firm introduced new forms of workforce organisation during the year? (standard DID estimates).

5.2 Empirical strategy

In order to identify the causal impact of robot adoption on the probability of TWA-use by firms, initially we use the staggered DiD estimation method proposed by Callaway and Sant'Anna (2021), CS-DiD henceforth. In the robustness section, we include additional estimations methods, including a standard two-way fixed effects (TWFE)DiD specification. Recent literature has pointed out the issues of causal interpretation in standard 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, 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 in the case of robot adoption.

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 at the 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 group, by calendar period, by event, and/or total), are all non-negative, and sum to one.[19]

The CS-DiD proposal further allows for covariate-specific pre-trends, that is, for the possibility that pre-trends hold only after conditioning on covariates. For example, in our case, the distribution of observed covariates such as firm's size 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 assumption 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.[20]

Specifically, we estimate the following equation, where we include estimators for the number of years from the first time a firm adopts robots:

$$TWA_{igt} = \alpha_g + \beta_k \times \sum_{k=-12}^{16} Robot_{k(gt)} + \varepsilon_{igt} \tag{8}$$

where TWA_{it} is our measure of TWA use for firm i, $Robot_{k(gt)}$ is the dummy variable that takes the value one when there is robot adoption for the different groups or cohorts g and the variable k indicates the number of years from the introduction of robots. 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

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

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

of firms that report using robots the first year they are observed in the dataset.

5.3 Baseline results

Table 2 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 include in the estimation all observations. In columns 3 and 4, we exclude from the estimation observations coming from switchers, that is from firms that in the survery stop reporting the use of robots in their production process. At the top of the table, we present the ATT estimates, both for unconditional (columns 1 and 3) and conditional pre-trends estimation (columns 2 and 4). For conditioning pre-trends, we include the firm's size (five intervals of total number of employees) and previous experience using TWAs.[21] That is, we assume that only firms with similar size and the same previous experience using TWAs 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 hypothesis of parallel pre-trends (tests provided at the bottom of the table), although the conditional specification increases the value of the estimated coefficient. More specifically, the total aggregated ATT renders an estimated causal impact of robot adoption on the probability of TWA-use that is between 5.8 and 6.2 percentage points for sample 1 and sample 2 respectively under the unconditional specification; with the conditional pre-trends option the estimated effects range from 8.3 percentage point to 8.7 percentage points. As a rough comparison, for sample average probabilities of TWA-use around 20%, the estimated ATT represents increases of more than one-third.

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

Next, we analyse the average effect differentiating by period-specific estimates using the event study specification from column 2. Figure 7 shows this dynamic effect. All estimated coefficients for the pre-treatment period are close to zero and statistically insignificant, which

[21] In all our estimations we use never treated firms as a control group. Using not yet treated observations as controls does not lead to any significant difference in our estimates.

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

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

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

confirms the null differences in pre-trends between robot adopters and non-adopters in terms of TWA-use. We find an increasing and positive effect after robot adoption up to ten years after treatment. This suggests a long-post treatment period on the use of TWA and that once firms start using robots there is a persistence in the use of TWA for the hiring process.

5.4 Robustness checks

Here, we compare the results obtained with our baseline specification to 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

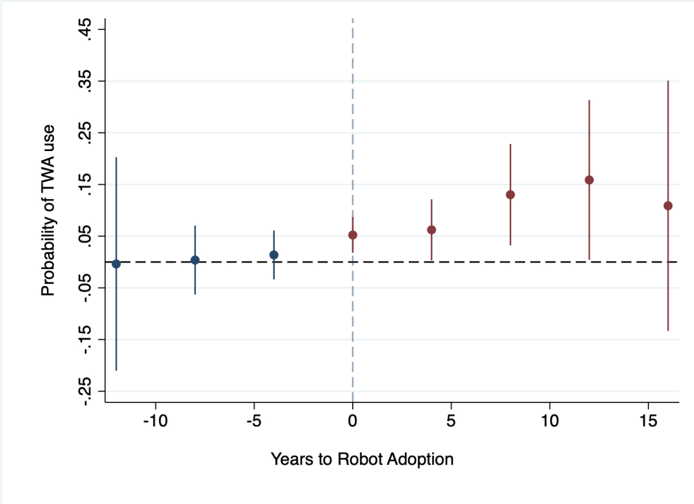

Figure 7: Event Study of the probability of using TWAs after robot adoption. The case shown in the figure corresponds to column 2 in Table 2, when pre-trends are conditional to firm size and previous TWA experience.

Sun and Abraham (2021), and the imputation method of Borusyak et al. (2021).[22] For the sake of comparison, we choose the CS-DiD results reported in column 4 of Table 2, which corresponds to a canonical specification easy to implement in all five cases. We present the results in Table B1 and Figure B3 in the Appendix. The results indicate that our results are strongly robust to the five alternative specification methods. The point estimate of the ATT ranges from 4 percentage points in the TWFE-OLS estimation to 5.2 percentage points in the Borusyak et al. (2021) estimator. The latter estimator and the CS-DiD estimator are not only the most similar in terms of the estimated ATT value, but also show virtually identical dynamic effects.

Next, we consider additional robustness checks that we present in Table B2 in the Appendix. First, in column (1), we include a placebo test where we randomized the timing of the robot adoption. The estimated ATT is negative and not significant at standard statistical levels. Second, it is possible that the adoption of robots coincides with the introduction of other technologies, such as machinery and computers. To control for this potential omitted variables and similar to Acemoglu et al. (2023), we include as controls the expenditures in machinery and computers. We present this estimation in column (2). The estimated coefficient is very similar to the previously estimated, which suggests that the effects we are capturing come from the introduction of robots and not from adopting other technologies. Another potential concern is that the control group of non-robot adopters might be negatively affected by the adoption of

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

robots, which in turn might have an impact on their hiring decisions. We follow Acemoglu et al. (2023) who account for the potential violation of the stable unit treatment value assumption (SUTVA) excluding observations in the control group that could be affected by the treatment. We consider that the potential negative spillover is likely to be sector and geographical specific and therefore exclude from our analysis all observations in the control group that are in the same industry and region than the firms that adopt robots. We present this estimation in column (3). The results are consistent with the previous evidence.

Is there an intensification in the use of temporary workers? It is possible that that the higher likelihood of using TWA may be due to a more intensive use of temporary contracts following the adoption of robots. For example, firms adopting robots might want to increase their temporary workforce in order to raise flexibility and adjust their production more accurately to their demand volatility. Another possibility is that firms adopting robots are following a cost-reducing strategy and increase their proportion of temporary workers through agencies because they might be easier to fire.

In order to assess this possible channel, we estimate the effect of robots on the share of temporary contracts (defined as the ratio of temporary workers over total number of workers) at the firm level using our baseline methodology. The estimated ATT is equal to 0.0009, with std error equal to 0.0076 (p-value is 0.897), and the pre-trends test has a p-value equal to 0.475. These results indicate that there is no effect of robots on the share of temporary contracts at the firm level. In Figure 8, we disentangle the ATT in different pre and post-adoption periods. Both before and after the adoption of robots the estimated coefficients are negligible and not statistically significantly different from zero. This suggests that the optimal share of temporary workers in the production process does not change after the adoption of robots.

We present additional evidence in Table B3 in the Appendix, where we estimate how robots influence effective hours worked of different types of workers. In particular, we show that the total hours worked in the company (column 1), the hours worked by temporary workers hired by TWAs (column 2), and the ratio between the hours worked by temporary workers hired by TWAs and total number of hours (column 3). In all cases there is an increase after robot adoption. However, the proportion of hours of temporary workers (column 4) remains constant after robot adoption. This suggests that firms are not intensifying the use of temporary workers after the adoption of robots and that the underlying reasons for using TWAs are likely to be

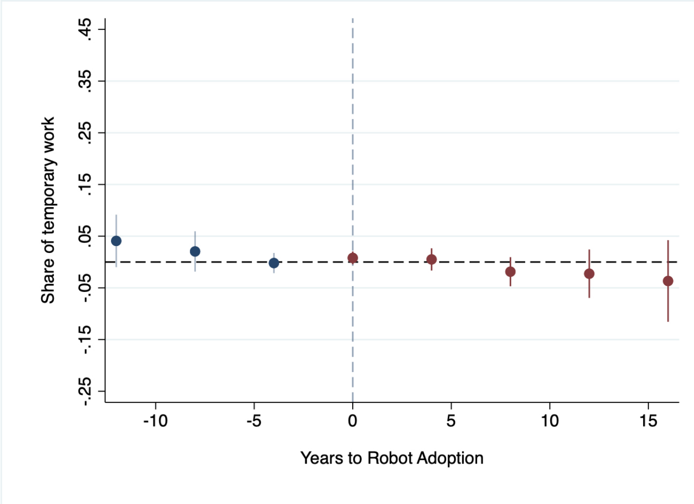

Figure 8: Is it just an intensification on the use of temps? Event Study.

different from an increase in the share of temporary workers.

TWA-use after robot adoption and demand adjustments One possible explanation for the increase in the use of agency after the adoption of robots is that hiring through agencies allow companies to adjust their labor force to the potential variability of the demand. We evaluate the importance of this mechanism, by exploring, first the years of the Great Recession and, second, industries that experienced high economic performance.

The Spanish Sovereign Debt Crisis (from 2008 to 2014) was a period that particularly affected the Spanish economy (Almunia et al., 2021). As shown in Figure B2, in 2008 the use of TWAs fell sharply, suggesting that firms may have adjusted employment by laying off temporary workers. If the agency hiring induced by robot adoption is mostly to adjust the production to the demand changes, then we would expect that our results would be very sensitive to the recession years. In contrast, if an important reason for the use of TWAs is driven by the search for well-matched workers, the use of TWAs after robot adoption would be less affected by the adjustments taken during the Great Recession.

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

Next, we further explore this potential mechanism by studying the effects of robots adoption

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

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

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

on TWA-use excluding observations that experience large economic growth. In order to do that, we drop from our analysis observations that in a given industry and year their sales are above the 90% percentile in the sales distribution. The results presented in Table B4 in the Appendix are consistent with the previous estimations.

To summarize, so far, we have obtained a positive and significant effect of robot adoption on the probability of TWA-use providing evidence in favour of our model's theoretical prediction that the use of robots tends to shift the hiring channel of firms towards TWAs, which are professionalised labour intermediaries. It does not seem that the reasons for this change are the intensification of the use of temporary workers or the need to adjust the labor force to the demand cycle.

6 The complementarity between robots and TWAs on firm productivity

In this section, we test the second prediction of our model namely that there is complementarity between robot adoption and TWAs leading to an increase on firm productivity. For this purpose, we estimate the following DiD equation at the firm level:

$$\begin{aligned} y_{it} &= \alpha + \gamma\ Robots_{it_a} + \delta\ TWA_{it} + \theta\ TWA_{it} \times Robots_{it_a} + \\ &\quad + \lambda\ Temps_{it} + \eta_t + \eta_i + \eta_{jt} + \eta_{rt} + u_{it} \end{aligned} \tag{9}$$

In equation 9, 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 firm-level deflators available in our dataset and divided by (effective) labour-hours.[23] $Robots_{it_a}$ is the post-treatment variable for robot adopters. Following (Koch et al., 2021), we explore different time-specifications of this variable. Specifically, we consider the effect of robot adoption on labor productivity from the year of adoption (t_a= t_0) and also the effect of lagged robots (the previous response year or t_a=t_{-4}); TWA_{it} is the indicator of TWA-use in period t; $Temps_{it}$ stands for the firm's share of temporary workers and aims at partiality out the productivity impacts that may stem from the labour-contracting structure of firms; η_t includes a full set of time dummies; η_i stands for firm fixed effects; η_{jt} stands for sector-year effects; η_{rj} stands for region-year effects (17 regions and 20 industrial sectors); and, finally, u_{it} is the error term of the equation.[24]

Our main term of interest in equation 9 is the interaction term $TWA_{it} \times Robots_{it_a}$, with productivity effect captured by parameter θ. A positive and significant estimate of θ would indicate, as our model predicts, that there is a positive complementarity between robots and TWAs. Or in other words, that the use of a TWA increases robots' productivity; similarly, it would indicate that agency workers combined with robots have a productivity premium.

To estimate the causal effect of complementarity in this framework using a staggered DiD strategy is challenging because we have two treatments, robots and TWA, and we are interested in their combined effect. Moreover, as we have shown in the previous section, robots induce the use of TWA, therefore the timing between treatments might be lagged dependent. For these reasons, first we use a static DiD strategy, which allow us to compare our estimates with previous results in the literature on the effects of robots on productivity (Koch et al., 2021) and

[23]Given that the variable robots is available every four years, the other variables are calculated as the average over the years between two consecutive response years for the variable robots. Thus, period t in equation 9 refers to these years.

[24]The firm-level productivity variable, as well as the TWA-use and temporary share measures are deviated from the industry mean within 5-size firms' size intervals.

second we use a flexible staggered DiD strategy following the Wooldridge (2021) methodology discussed in Section 5.4.

A common concern with static DiD methodology is that there can be differences between treated and untreated firms before the treatment. In particular, robot adopters and non-adopters might differ before robot adoption in several dimensions correlated with productivity (Graetz and Michaels, 2018). Thus, a estimation concern refers to the possible bias induced by non-random self-selection into the adoption of robots. With a panel of firm level data, a way in the literature to address this potential bias is to apply a fixed effects DiD methodology with pre-estimation balancing of the sample data and reweighting. More specifically, we apply two alternative balancing methods before estimating the DiD equation. First, as in Koch et al. (2021), we follow the empirical methodology proposed by Guadalupe et al. (2012) and combine a TWFE approach with a propensity score reweighting estimator in the spirit of DiNardo et al. (1996). As a second alternative, we use the entropy balance reweighting algorithm of Hainmueller (2012), implemented following Hainmueller and Xu (2013). The main advantage of the entropy balance is that the control group data can be reweighted to exactly match several distribution moments of the covariates in the treatment group. This ensures that the treatment and control groups are similar not only in terms of average characteristics, but also at higher moments of the distribution. This further reduces concerns that changes following robot adoption may be due to pre-existing differential trends between robot adopters and non-adopters.

In both p-score matching and entropy balancing, the identifying assumption is that, by balancing the pre-treated and control samples on the observable characteristics that are relevant determinants of robot adoption and productivity, the productivity of adopters and non-adopters would not differ systematically in the absence of robot adoption. In the case of the propensity-score balancing, we first conduct industry-specific probit regressions for robot adoption on real sales, sales growth, labour productivity, labour productivity growth, capital-, skill- and R&D intensity, indicators for exporter, importer and foreign ownership, and year dummies. Importantly for our analysis, the variable TWA-use is also balanced in this phase. This implies for the reweighted sample, control and treated firms also have similar trends in terms of TWA use before the treatment. All the variables refer to the year before robot adoption. The final DiD analysis is conducted for the firms with common support and for which the balancing property on the average values of covariates is satisfied within each industry. In the case of entropy balancing, we balance the treated and control samples in terms of both the mean and the variance of the set of covariates just mentioned, including the share of firms within each industry. The final DiD analysis is conducted for the firms with common support. In both cases, a weight is assigned to each firm based on the chosen balancing method.[25]

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. In columns (1) to (4), we present results using the p-score matching methodology and in columns (5) to (7), we show the entropy balancing method. In column (1) we include the effect of robots on firm productivity from the moment of the first adoption and also the lagged value of robots. Column 1 shows that it is the lagged switch to robot use that impacts positively and significantly the productivity measure, while the estimated effect of the current year indicator is very small and insignificant. This result suggests that it takes some years for the robot adoption to impact productivity. From column 2 onwards we use the lagged robot indicator variable and leave out the current robot year indicator.

The estimates in column 2, using the propensity-score balancing, indicate that adopting robots increases firms' productivity by around 16 percent. The entropy balance method in column (5) yields somewhat smaller estimated effects of around 10.4 percent. These estimated effects compare quite closely to the productivity effects estimated by (Koch et al., 2021).[26]

Columns 3 and 6 include the TWA-use variable and the share of temporary workers. The estimated coefficient for the share of temporary workers in column (3) where we use the p-score method is very small and not statistically significantly different from zero. In column (6), with the entropy method, we find a negative and significant effect. This negative productivity effect is in line with the idea that temporary workers might be less productive than permanent workers (Lisi and Malo, 2017). Conditional on the share of temporary work, the use of TWAs has a differential positive impact on productivity, with estimated values that range in this case from around 18 percent in column 3 to near 9 percent in column 6.

[25]The commonly used matching or propensity score adjustments are usually cumbersome to apply and often result in inadequate covariate balance. In Hainmueller and Xu (2013)'s words, (p.2), 'Researchers often go back and forth between propensity score estimation, matching, balance checking to "manually" search for a suitable weighting that balances the covariate distributions.' The entropy balancing method takes a different approach. Instead of evaluating covariate balance after preprocessing, users start specifying their desired balance level through a set of moment conditions. The method finds the weights that satisfy such conditions and minimise the loss of information to retain efficiency for the subsequent analysis (Hainmueller, 2012).

[26]Their estimates lie between 16.1 percent and 10.5 percent, depending on the specification being used - their Table 2 in p. 2573.

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

	p-score matching				entropy balancing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Robots_{t_0}$	-0.001						
	(0.022)						
$Robots_{t_{-4}}$	0.162***	0.162***	0.155***	0.141***	0.104***	0.100***	0.077***
	(0.028)	(0.019)	(0.019)	(0.020)	(0.013)	(0.013)	(0.015)
TWA			0.178***	0.137***		0.088***	0.053***
			(0.014)	(0.016)		(0.009)	(0.011)
$Robots_{t_{-4}} \times TWA$				0.190***			0.137***
				(0.040)			(0.031)
$Temps$			0.003	-0.009		-0.202***	-0.197***
			(0.029)	(0.032)		(0.020)	(0.021)
Observations	2,584	2,584	2,584	2,584	2,368	2,368	2,368
R-squared	0.833	0.833	0.835	0.836	0.828	0.829	0.830
p-score weights	Yes	Yes	Yes	Yes	No	No	No
Entropy weights	No	No	No	No	Yes	Yes	Yes
Industry-year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: outcome variable is 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; the outcome variable is averaged over the years between two consecutive ESEE response years, including the last one. $Robots_{t_0}$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters that report for the first time using robots in the current ESEE response year; $Robots_{t_{(-4)}}$ is similarly defined for firms reporting robot use for the first time in the previous ESEE response year - that is, 4 years before; TWA is the average of the binary indicator of TWA-use in period t comprised between two ESEE response years; $Temps$ stands for the firm's share of temporary workers during that period. Bootstrapped standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01.

Next in columns 4 and 7 we further estimate the complementarity between robots and TWA-use by including the interaction term. The estimated coefficient in both columns is positive and significantly different from zero, suggesting gains in productivity that range from 19 percent in column 4 to near 14 percent in column 7. This latter result confirms our theoretical prediction 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.

Next, we present several robustness checks. First, we use an alternative measure of productivity in Table B5 in the Appendix. We repeat the analysis using real sales per worker instead of value added as measure of firm productivity. The main findings of the above analysis remain here, with negative estimated effects of the temporary share now being large, negative and statistically significant with both balancing methods used. Second, we use a staggered methodology. So far we are estimating a standard DiD estimation of the complementarity between robots and TWA. We use the staggered methodology of Wooldridge (2021). In Figure B4 in the Appendix.

7 Summary and concluding remarks

In this paper, we study, theoretically and empirically, the effects of robot adoption on the use of TWAs and the combined effect of robots and TWAs on firm productivity. This is important for understanding the relationship between robots and labour arrangements within firms. We develop a theoretical framework where the adoption of new technologies increases firm productivity, but it also increases the need for 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 a 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 search strategies increasing their likelihood to use TWAs. The model also predicts that firms that adopt new technologies can increase their productivity with the use of TWAs due to the better and faster quality match between workers and technologies.

We test the model implications with panel data of Spanish firms from 1997 to 2016 with information on robot adoption and use of TWAs. We estimate causal effects of robot adoption on TWAs using staggered difference-in-difference (DiD) estimations. We find that firms that introduce robots increase the probability of using TWAs by more than 10 percent and up to 16 percent, depending on the specification. We further find that firms that combine robots with TWA-use achieve considerable additional productivity gains beyond the productivity effects of robot adoption. This suggests that TWAs increase the matching quality between new technologies and labour.

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A Mathematical appendix

A.1 The Bellman equations

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

$$r\Omega_P(0) = \lambda\left[\max\left\{\Omega_P(0), U - F\right\} - \Omega_P(0)\right], \tag{10}$$

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

$$r\Omega_P(\mu) = \xi\mu + \beta\mu\left[\Omega_P(1) - \Omega_P(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right)\left[\max\left\{\Omega_P(0), U - F\right\} - \Omega_P(\mu)\right]. \tag{11}$$

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

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

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

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

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

$$\begin{aligned} r\Omega_T(\mu) = {} & \tau\xi\mu + \beta\mu\left[\max\left\{\Omega_T(1), \Omega_P(1)\right\} - \Omega_T(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right]\left[\max\left\{\Omega_T(0), U - F\right\} - \Omega_T(\mu)\right] \\ & + \delta\left[\max\left\{\Omega_P(\mu), U\right\} - \Omega_T(\mu)\right]. \end{aligned} \tag{14}$$

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

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

$$(r+\lambda)\left[U - \Omega_T(1)\right] = rU - \tau\xi + \lambda\left(U - \omega_0\right) - \delta\left[\max\left\{\Omega_P(1), U\right\} - \Omega_T(1)\right], \tag{16}$$

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

$$\begin{cases} (1-\tau)\xi - \lambda(\omega_0 - U + F) \leq 0 \\ rU - \tau\xi + \lambda(U - \omega_0) \leq 0 \end{cases} \tag{17}$$

Combining the two inequalities, we find

$$-\tau\lambda(\omega_0 - U + F) + (1-\tau)\left(rU + \lambda\left(U - \omega_0\right)\right) \leq 0, \tag{18}$$

which contradicts Assumption 2.

We therefore obtain equation (4) as a simplification of (14).

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 $]0,1[$,

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

$$r\Omega_T^P(\mu) = \tau\xi\mu + \beta\mu\left[\omega_1 - \Omega_T^P(\mu)\right] + \left(\beta\left(1-\mu\right) + \lambda\right)\left[\omega_0 - \Omega_T^P(\mu)\right] + \delta\left[\Omega_P(\mu) - \Omega_T^P(\mu)\right], \tag{20}$$

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:

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

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

$$\Omega_T^P(\mu) = (1-\mu)\Omega_T^P(0^+) + \mu\Omega_T^P(1^-), \tag{23}$$

where

$$\Omega_P(0^+) = \frac{\beta+\lambda}{r+\beta+\lambda}(U-F) \qquad \text{and} \qquad \Omega_P(1) = \omega_1, \tag{24}$$

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

$$\Omega_T^P(0^+) = \omega_0 - \frac{\delta}{r+\beta+\lambda+\delta}(U - \Omega_P(0^+)) \qquad \text{and} \qquad \Omega_T^P(1^-) = \frac{\tau\xi + (\beta+\delta)\omega_1 + \lambda\omega_0}{r+\beta+\lambda+\delta}. \tag{26}$$

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

$$H(\xi, V) = \max\left(\frac{\omega_1 - U - V}{U+V-\Omega_P(0^+)}, \frac{\Omega_T^U(1^-) - U - V}{U+V-\omega_0}, \frac{\Omega_T^P(1^-) - U - V}{U+V-\Omega_T^P(0^+)}\right). \tag{27}$$

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

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

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

$$(r+\beta+\lambda+\delta)\left(\Omega_P(\mu) - \Omega_T^P(\mu)\right) = (1-\tau)\xi\mu + (\beta(1-\mu)+\lambda)\left[U - F - \omega_0\right], \tag{28}$$

we find the condition in Proposition 1.

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

A.3 Proposition 2

A.3.1 Existence

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

$$r\tilde{V}_A = q_A(1-\varphi)\int_0^1 \left(\Omega(\mu) - U - \tilde{V}_A\right) f(\mu|\pi)d\mu. \tag{29}$$

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,

$$\tilde{V}_A - V_R \geq \frac{q_R(1-\varphi)}{r + q_R(1-\varphi)}\left(\int_0^1 \Omega(\mu)f(\mu|\pi)d\mu - \Omega(\pi)\right). \tag{30}$$

Equations (21), (22) and (23) imply that $\Omega(\mu)$ can be decomposed as

$$\Omega(\mu) = \begin{cases} \Omega_T^U(\mu) \text{ if } \mu < \mu_1 \\ \Omega_T^P(\mu) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \Omega_P(\mu) \text{ if } \mu_2 \leq \mu \end{cases}, \tag{31}$$

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

$$\frac{\partial\Omega}{\partial\mu}(\mu) = \begin{cases} \Omega_T^U(1^-) - \Omega_T^U(0^+) \text{ if } \mu < \mu_1 \\ \Omega_T^P(1^-) - \Omega_T^P(0^+) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \Omega_P(1) - \Omega_P(0^+) \text{ if } \mu_2 \leq \mu \end{cases}. \tag{32}$$

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 (30), we find that $\tilde{V}_A - V_R \geq 0$.

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

$$rV_A = q_A(1-\varphi)\int_{\pi_A}^{1} \left(\Omega(\mu) - U - V_A\right) f(\mu|\pi) d\mu. \tag{33}$$

Second,

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

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

$$V_A - \tilde{V}_A = \frac{q_A(1-\varphi)}{r + q_A(1-\varphi)} \int_0^{\pi_A} \frac{\partial\Omega(\mu)}{\partial\mu}(\mu)(1 - G(\mu|\pi))d\mu. \tag{35}$$

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).

$$\frac{\partial V_R}{\partial\xi} = \frac{q_R(1-\varphi)}{r + q_R(1-\varphi)} \frac{\partial\Omega}{\partial\xi}(\pi) \text{ if } \pi > \pi_R \text{, and 0 otherwise,} \tag{36}$$

$$\frac{\partial V_A}{\partial\xi} = \frac{q_A(1-\varphi)}{r + q_A(1-\varphi)G(\pi_A|\pi)} \int_{\pi_A}^1 \frac{\partial\Omega}{\partial\xi}(\mu) f(\mu|\pi) d\mu. \tag{37}$$

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:

$$\frac{\partial V_R}{\partial\xi} = \frac{\partial\Omega}{\partial\xi}(\pi), \tag{38}$$

$$\frac{\partial V_A}{\partial\xi} = \int_{\pi_A}^1 \frac{\partial\Omega}{\partial\xi}(\mu) \frac{f(\mu|\pi)}{G(\pi_A|\pi)} d\mu. \tag{39}$$

We now show that $\frac{\partial\Omega}{\partial\xi}(\mu)$ is convex in μ. The parameters μ_1 and μ_2 in equation (31) depend on ξ, but we can use the envelope theorem to find that

$$\frac{\partial \Omega}{\partial \xi}(\mu) = \begin{cases} \mu \frac{\partial \Omega_T^U}{\partial \xi}(1^-) \text{ if } \mu < \mu_1 \\ \mu \frac{\partial \Omega_T^P}{\partial \xi}(1^-) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \mu \frac{\partial \Omega_P}{\partial \xi}(1) \text{ if } \mu_2 \leq \mu \end{cases} \quad \text{hence } \frac{\partial^2 \Omega}{\partial \mu \partial \xi}(\mu) = \begin{cases} \frac{\partial \Omega_T^U}{\partial \xi}(1^-) \text{ if } \mu < \mu_1 \\ \frac{\partial \Omega_T^P}{\partial \xi}(1^-) \text{ if } \mu_1 \leq \mu < \mu_2 \\ \frac{\partial \Omega_P}{\partial \xi}(1) \text{ if } \mu_2 \leq \mu. \end{cases} \tag{40}$$

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 (39):

$$\frac{\partial V_A}{\partial \xi} \geq \frac{\partial \Omega}{\partial \xi}\left(\int_{\pi_A}^1 \mu \frac{f(\mu|\pi)}{G(\pi_A|\pi)} d\mu\right). \tag{41}$$

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

$$\frac{\partial V_A}{\partial \xi} > \frac{\partial \Omega}{\partial \xi}(\pi) = \frac{\partial V_R}{\partial \xi}. \tag{42}$$

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.

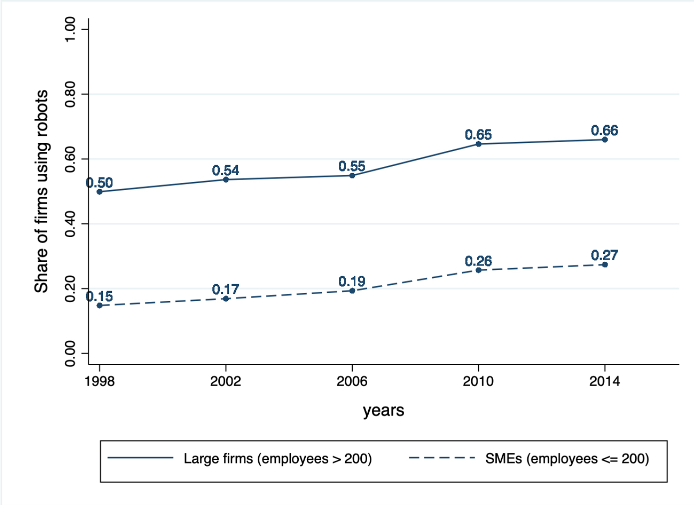

Figure B1: Share of Firms using Robots

B Appendix: Additional descriptive statistics and figures

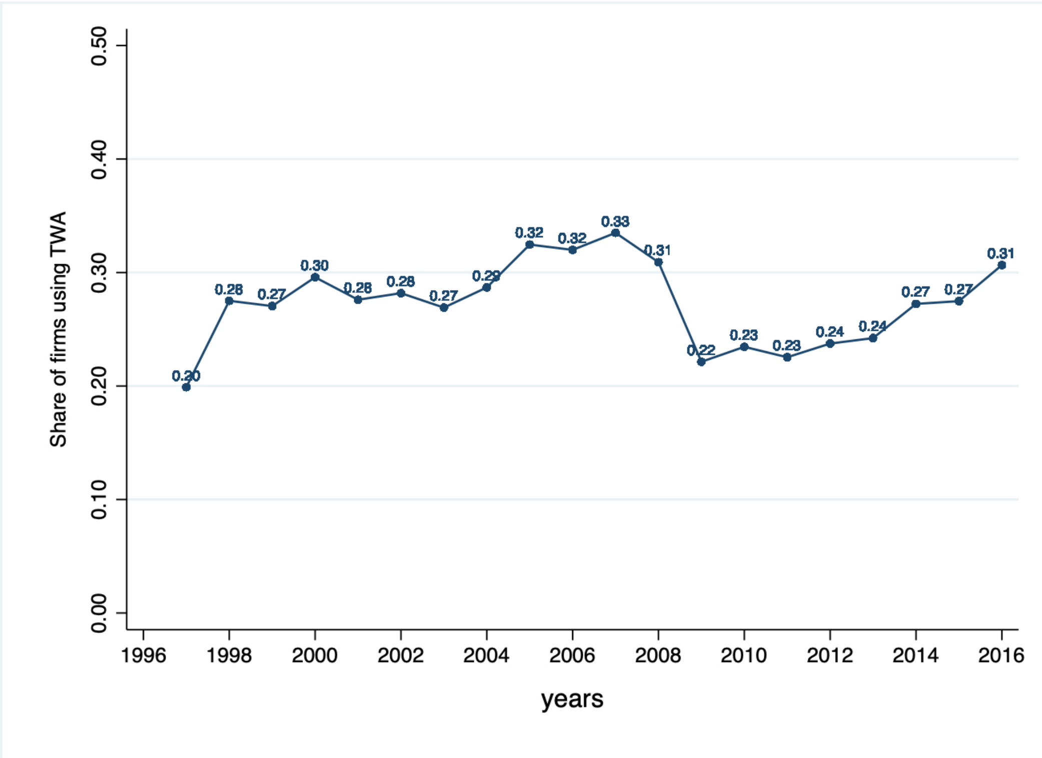

Figure B2: Share of Firms using TWA

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

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

Notes: All estimations are conditional to pre-treatment firms' previous experience using TWAs. [a] Pre-trends tests p-values in squared brackets; in the case of column (2), standard errors of the pre-period differences are provided in parenthesis. * p-value<0.10 ** p-value<0.05 *** p-value<0.01. Column labels: (1) TWFE OLS estimation; (2) De Chaisemartin and d'Haultfoeuille (2020); (3) Sun and Abraham (2021); (4) Borusyak et al. (2021); (5) Callaway and Sant'Anna (2021), column 1 of Table 2; The estimates in the table are graphically shown in Figure B3.

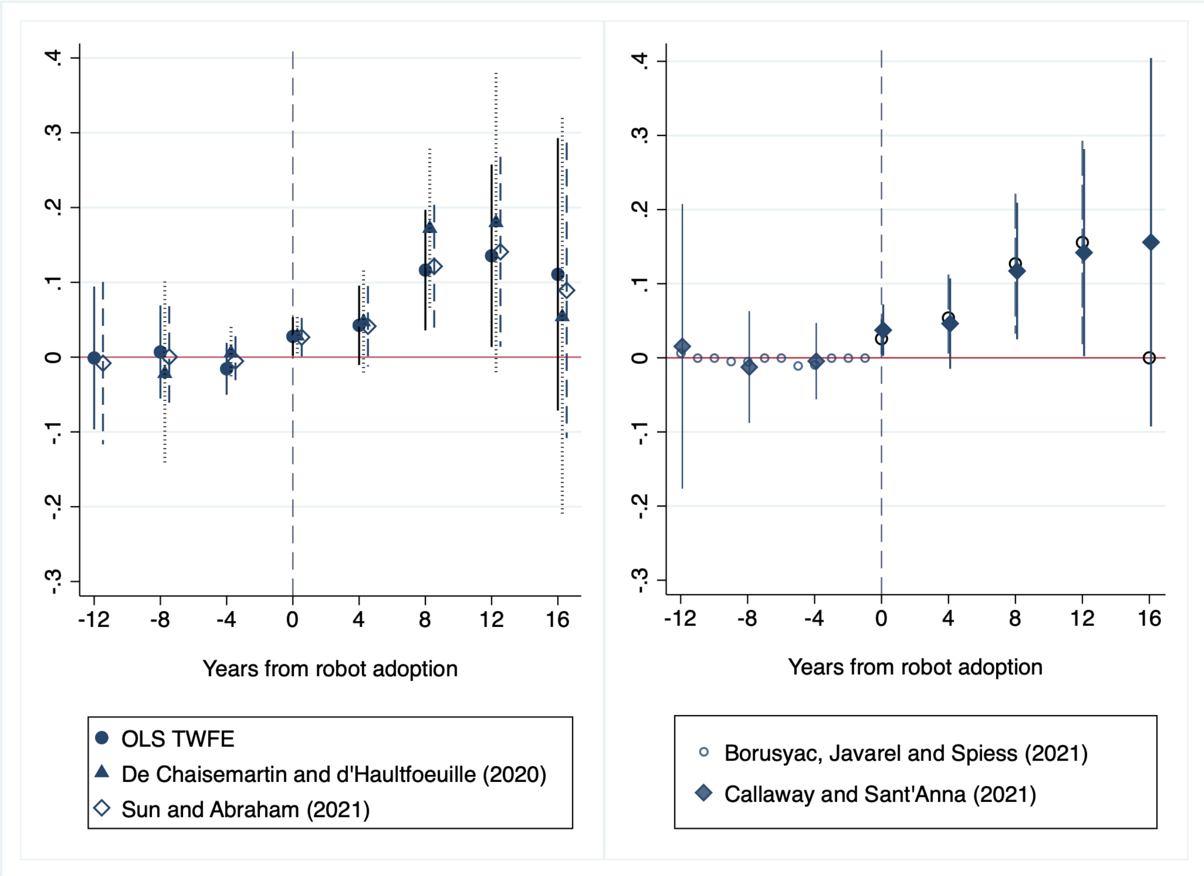

Figure B3: Probability of using TWAs after robot adoption using five DiD estimators. The plot displays the point ATT estimates and the 95% confidence interval corresponding to results provided in Table B1.

Table B2:
Robustness checks. Staggered DiD estimation

	Placebo	Controlling for machin & comp	SUTVA
	(1)	(2)	(3)
Total ATT	-0.059	0.050*	0.066***
	(0.066)	(0.026)	(0.022)
Pre-trends (Chi-sq)	186.6	3.329	0.748
(p-value)	[0.000]	[0.766]	[0.993]
N Obs.	2,512	4,142	2,515

Notes: In column (1), we construct a placebo test, where we assign randomly the timing of the robot adoption. In column (2), we include as additional controls the expenditures (in logs) of the investments in machinery and computer and software. In column (3), we exclude observations in the control group that are in the same industry and region than the firms that adopt robots. * p-value<0.10 ** p-value<0.05 *** p-value<0.01.

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

	Total hours (1)	Temps TWA (2)	Temps TWA over total (3)	Temps over total (4)
Total ATT	61816.24***	5005.109***	0.011***	2700.63
	(24042.2)	(1642.78)	(0.003)	(14667.83)
Pre-trends[a]	8.313	8.399	8.019	8.842
	[0.216]	[0.210]	[0.236]	[0.182]
N.Obs	6,418	3,126	6,173	6,227

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

Table B4:
Robot Adoption ATT on firms' TWA-use. Staggered DiD estimation
- Excluding observations in periods of high economic performance -

	Uncond. PT (1)	Cond. PT (2)	Uncond. PT (3)	Cond. PT (4)
Total ATT	0.053**	0.061**	0.0472*	0.0691**
	(0.021)	(0.023)	(0.025)	(0.025)
Pre-trends (Chi-sq)	0.898	1.805	0.8981	1.805
(p-value)	[0.989]	[0.936]	[0.989]	[0.936]
N Obs.	5,991	5,991	5,664	5,664
Sample	All firms	All firms	Without switchers	Without switchers

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

Table B5: Sales per hour of labour, Robots and TWA-use (DiD estimation with re-weighting).

	p-score matching			entropy balancing		
	(1)	(2)	(3)	(4)	(5)	(6)
$Robots_{t-4}$	0.181***	0.168***	0.161***	0.117***	0.111***	0.094***
	(0.017)	(0.018)	(0.020)	(0.013)	(0.012)	(0.015)
TWA		0.190***	0.169***		0.116***	0.089***
		(0.010)	(0.012)		(0.009)	(0.010)
$Robots_{t-4} \times TWA$			0.099***			0.106***
			(0.036)			(0.034)
Share temporary		-0.305***	-0.311***		-0.385***	-0.381***
		(0.021)	(0.021)		(0.022)	(0.022)
Observations	2,585	2,585	2,585	2,369	2,369	2,369
R-squared	0.955	0.957	0.957	0.936	0.938	0.938
p-score weights	Yes	Yes	Yes	No	No	No
Entropy weights	No	No	No	Yes	Yes	Yes
Industry-year effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional-year effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: outcome variable is (log of) real sales per (effective) hour worked of firm i in period t; the outcome variable is averaged over the years between two consecutive ESEE response years, including the last one. $Robots_{t(-4)}$ is a dummy variable that takes the value of one in all post-robot adoption periods for robot adopters that report for the first time using robots in the previous ESEE response year - that is, 4 years before; TWA is the average of the binary indicator of TWA-use in period t comprised between two ESEE response years; $Temps$ stands for the firm's share of temporary workers during that period. Bootstrapped standard errors clustered by firm in parenthesis.* p-value<0.10 ** p-value<0.05 *** p-value<0.01.

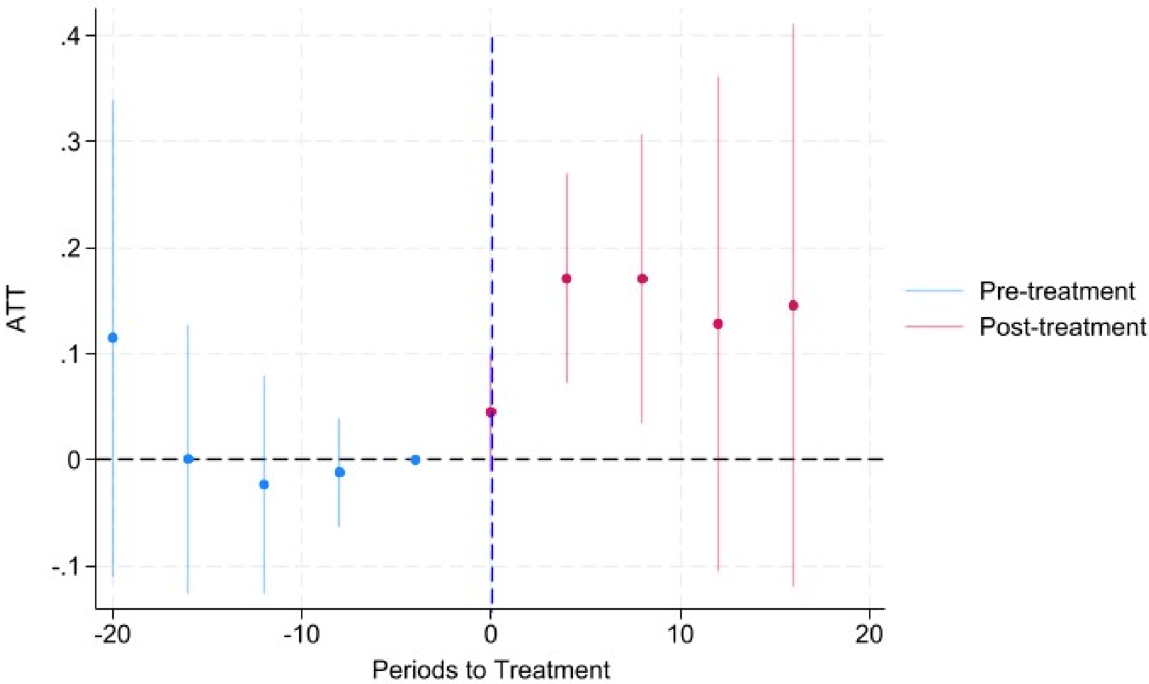

Figure B4: Complementarity effect between TWA and robots on firm productivity. Staggered estimation using Wooldridge (2021) The plot displays the point ATT estimates and the 95% confidence interval.