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Artificial Life and Evolutionary Computation

13th Italian Workshop, WIVACE 2018
Parma, Italy, September 10–12, 2018
Revised Selected Papers

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 Springer

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Evolution of Workers' Behaviour in Dual Labor Markets

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Abstract. The simultaneous increase in the use of temporary contracts and the productivity slowdown recently experienced in some OECD countries, fostered a growing interest in analysing the link between these phenomena.

In this paper we study the effect of the use of temporary contracts on workers' incentives and in particular we focus on effort decisions of temporary workers. We implement an agent-based model where workers interact in the labor market and compete for permanent contracts. Workers choose how much effort to exert in production and, using reinforcement learning, they update their strategies on the basis of past experience.

The main result is that optimal effort strategies depend on the share of available permanent contracts. When the share is low, workers do not bet on their conversion and supply low effort. As the share increases workers exert higher effort but, when it is too high, they have the incentive to shirk since they are confident of being confirmed. Therefore, the relationship between the share of permanent contracts and workers' effort, and consequently labor productivity, has an inverted-U-shape.

Keywords: Agent-based model · Temporary contracts · Effort · Reinforcement learning

1 Introduction

Most of the reforms that have recently been implemented in European labor markets contribute to create what in the literature is called a *dual labor market*, featuring the coexistence of two types of contracts: permanent and temporary contracts; [3]. The motivation of this work builds on the observation of two empirical facts: on one hand, an increase in the use of temporary contracts and, on the other, a slowdown in labor productivity in some OECD countries; see [5].

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In Italy, for example, the sharp increase in the share of temporary contracts is due to a number of reforms that increased the possibility of using this type of agreements; see [5]. Since then, temporary contracts are typically used for many different reasons: screening purposes, temporarily fill-in for staff who are absent or on leave, or to accommodate fluctuations in demand; in many cases employers also save in labor costs and social security benefits.

The aim of this paper is to study the link between the use of temporary employment and labor productivity. The channel we will investigate is that temporary contracts have an effect on workers' incentives, and in particular on their willingness to exert high effort and, consequently, this may have an effect on firms' labor productivity. We implement an agent-based model where workers and firms interact in a dual labor market.¹ In the model, temporary workers compete for a limited number of permanent contracts and they face the following *trade-off*: exerting high effort is costly but it increases the chances of obtaining a permanent contract. In this environment, workers choose how much effort to exert in the production process and update their strategies on the basis of past experience; agents use a form of individual reinforcement learning as a learning algorithm, see [15].

This paper is related to different strands of literature: empirical papers studying the effect of temporary employment on productivity, [4, 11]; studies of workers' behaviour and incentives under different contracts and agent-based models of the labor market; [8]. The work of Guadalupe [9] is the first paper that looks at behavioural responses of temporary contracts showing they cause significantly higher accident rates; our focus is instead on workers' effort. Few empirical papers have documented the effect of temporary employment on workers' effort decisions; this is mainly related to the difficulty of finding good proxies of effort. Among others, three examples using respectively Swiss, Italian and Spanish data are respectively [7], [10] and [6]. In the first paper, effort is proxied by unpaid overtime work and absences; the authors show evidence that temporary workers provide higher effort than permanent employees. The second paper looks at the effect of a change in the employment protection legislation regime on absenteeism, used to proxy effort. The main finding is that the number of days of absence per week increases significantly once employment protection is granted at the end of a three-month probation period, therefore, highly protected contracts may induce lower effort. Finally, [6] analyses the effect of having a large gap in firing costs between permanent and temporary workers on total factor productivity at the firm level. The authors show that firms' temporary-to-permanent conversion rates and consequently temporary workers' effort decrease when the gap increases. Differently from the previous contributions, using an agent-based model we take into account the additional competition channel faced by temporary workers competing for permanent positions in the same firms. Leading labor economists such as [8] suggest the use of these techniques to study the interaction between workers and firms in the labor market, with the aim of replicating

¹ For an introduction to complexity and agent-based models see [12] and [1].

stylized facts and analysing the effects of specific policies (e.g. training policies, unemployment benefits etc...).

For a recent review on agent-based models applied to labor markets see [14]; early examples are [2] and [16]. The rest of the paper is organized as follows: Sect. 2 describes the characteristics of the model, Sect. 3 presents the computational results and Sect. 4 summarized and concludes the paper.

2 The Model

In the labor market there are N_W workers and N_F firms with $N_W \gg N_F$. Each worker is endowed with one unit of labor which is the only factor of production in the economy; firms supply an homogeneous good. Initially, workers are randomly assigned to firms, all firms employ the same number of workers and all vacancies are filled, therefore, labor force participation is constant. Moreover, u workers are not allocated to any firm and start the period as unemployed. We simply assume that the production function of firm j , Y_j , is defined as the sum of effort provided by the firms' employees:

$$Y_j = \sum_{i=1}^{q_j} e_{ij} \quad (2.1)$$

where q_j is the number of workers employed in firm j and e_{ij} is effort exerted by worker i when matched with firm j .

Two types of contracts characterize the labor market: temporary and permanent contracts; what makes the two contracts different is their duration. Workers with permanent contracts remain matched with the same firm, unless the firm is hit by an exogenous shock that destroys all permanent contracts in the firm. Workers with temporary contracts are employed for a maximum amount of time d ; during this period they remain temporary or can become permanent. After d rounds their contract ends and, if their contract has not been converted into permanent, they separate from the firm and become unemployed.

The problem faced by temporary workers is deciding how much effort they should exert in the production process. The strategy S_i of a temporary worker is defined by a discretized set of effort choices $e_{ijk} \in \{1, 2, \dots, 10\}$ with associated probabilities p_{ijk} such that $\sum_{k=1}^{10} p_{ijk} = 1$ and $p_{ijk} \geq 0$ for all workers. Initially, workers do not know how much effort they should exert in the production process, therefore, all strategies are chosen with equal probability. We simulate the model under two different scenarios. In the first, we assume that workers stick to the strategy S_i also when their temporary contract is upgraded to permanent. In the second, instead, we assume that when workers are converted into permanent they do not sample an effort value from their distribution and, instead, exert a fixed level of effort e^* , exogenously determined. The intuition is that when converted into permanent workers might decide to change their strategy and, for example, lower their effort. Unemployed workers exert 0 effort. All workers are initially employed with temporary contracts. Once workers are allocated to firms, they sample an effort value from their distribution and production occurs.

Each firm can employ only a given fraction P of workers with permanent contracts, for example due to institutional regulations or financial constraints. If in a firm the current fraction of permanent contracts is smaller than P , the conversion process takes place. We assume that firms can observe the level of effort exerted by workers with temporary contracts. Firms therefore rank temporary workers by decreasing level of effort and the top ranked temporary workers become permanent, until the share P is reached, while the others remain temporary; ties are broken randomly.

We assume the utility of a worker with a permanent contract is greater than the utility of a worker employed with a temporary contract. Therefore, workers within each firm compete for permanent contracts. Temporary workers face the following trade-off. Exerting high effort is a costly investment, but it increases the probability that their contract is converted into permanent. Workers suffer a loss of value that is strictly positive and increasing in effort, $c(e_{ijk}) = \alpha e_{ijk}^\beta$ with $\alpha > 0$ and $\beta \geq 1$. All workers simultaneously make their effort decisions, without knowledge on the level of effort exerted by the other workers in the firm. After the conversion process takes place, workers learn their new status, permanent if their contract has been upgraded and temporary if not. The payoff of worker i is defined as:

$$\pi_i(S_i, S_{-i}) = \begin{cases} w - \alpha e_{ijk}^\beta + x_T & \text{if temporary} \\ w - \alpha e_{ijk}^\beta + x_P & \text{if permanent} \end{cases} \quad (2.2)$$

where we assume that all employed workers receive the same exogenous wage w .² $X \in \{x_T, x_P\}$ is a non-monetary benefit that is different according to the type of contract and takes two values: x_P and x_T , respectively for permanent and temporary workers, with $x_P > x_T$.³

In the initial stage workers choose the level of effort to exert from the set of feasible strategies with equal probability. Workers keep track of payoffs obtained with the different strategies and, as time passes, they realized that some strategies work better than others. Workers learn how much effort they should exert in the production process only when they are temporary and they are in a firm that can convert some temporary workers into permanent, to reach the share P , so after the job destruction of permanent contracts occurs. We model this as a process of individual reinforcement learning; average payoffs drive the learning process. Worker i will choose effort e_{ijk} with probability:

$$p(e_{ijk}) = \frac{\exp^{\lambda \cdot \text{payoffAve}(i, e_{ijk})}}{\sum_{k=1}^{10} \exp^{\lambda \cdot \text{payoffAve}(i, e_{ijk})}} \quad (2.3)$$

² In the formula $\pi_i(S_i, S_{-i})$ is the payoff of worker i using strategy S_i , when all other temporary workers are exerting strategy S_{-i} .

³ Written in this way, the payoff is simple to interpret, but w , x_T and x_P are constant parameters therefore we could simplify the expression using just two different constants, one for each type of contract.

where $\lambda > 0$ determines the speed of the learning process and $\text{payoffAve}(i, e_{ijk})$ are average payoffs of worker i , when he played strategy e_{ijk} . In this learning process strategies that lead to relatively higher payoffs will be played with higher probability in the next rounds.⁴

Every d rounds temporary contracts end and workers separate from firms. Workers that were previously unemployed become temporary and the temporary workers that became unemployed are either randomly matched to a new firm (or the same one by chance) or remain unemployed.

Moreover, in a randomly determined order, in each round one firm is hit by a job destruction shock and permanent workers separate from firms. Temporary and permanent workers that separated from firms are randomly reallocated to firms in the next round; in each round, the number of employed workers remains constant, as firms fill all their vacancies, but workers reallocate across the three states: temporary, permanent or unemployed. We call period a sequence of rounds, such that each firm has updated once the share of its permanent workers. A new period begins, with an updated allocation of workers, contracts and strategies. After enough stages, workers learn the optimal level of effort they should exert to maximize their expected payoffs.

3 Computational Results

In this section, we discuss the results of the model for a representative set of parameters. In Table 1 the description of the parameters used in the simulation is presented. We consider an economy with $N_W = 300$ workers; 10 workers are allocated to each firm, hence, there are $N_F = 30$ firms in the labor market. We assume that in a given simulation all firms can employ the same number of workers with permanent contracts. Therefore, we average across firms simply to net out sampling variation. We assume all workers earn an exogenous wage and normalize it to $w = 1$; the non-monetary benefit temporary workers get if they are (not) converted into permanent is set to 0 (-1). We observe interactions among workers in the labor market for 500 periods. In the model the workers move across different states and they can be permanent or temporary at different times. Nevertheless, we will focus on the second group and in particular on strategies learnt by temporary workers when they are in firms that can upgrade some contracts into permanent. We start by looking at average payoffs earned by temporary workers during the reinforcement learning process and show that the algorithm converges to a steady state which is an approximation of an equilibrium. Then, we describe the strategies evolved by temporary workers at the end of the simulation.

3.1 Payoffs

As the learning process takes place temporary workers update their strategies and increase the probability of playing effort choices that lead to higher payoffs.

⁴ Equation (2.3) is known as Gibbs-Boltzmann probability measure, used for example in [13].

Table 1. Description and value of the parameters used for the simulations.

Parameter	Description	Value
N_W	Number of workers	300
N_F	Number of firms	30
q_j	Number of workers per firm	10
u	Number of unemployed (among N_W)	10
d	Temporary contract maximum duration	10
γ	Job destruction of permanent contracts	$1/N_F$
λ	Learning parameter	10
P	Share of permanent contracts	$\{0.1, 0.2, \dots, 1\}$
t	Periods	500
w	Wage	1
α	Cost of 1 unit of effort	$U \sim [0.05, 0.15]$
β	Convex cost parameter	1
x_T	Non-monetary benefit if temporary	-1
x_P	Non-monetary benefit if permanent	0

We conduct a complete run of the model ($t = 500$ periods) for each of the possible values of the share of permanent contracts. Figure 1 depicts the time series of average payoffs earned by temporary workers, when they are in firms that can convert workers into permanent, as the learning process takes place.

In each data-point all firms updated once their share of permanent contracts to reach the desired share P , therefore, each point is the average payoff of $N_W = 300$ workers. Each time series corresponds to a simulation for a different share of permanent contracts and moving from bottom to top $P = \{0.1, 0.2, \dots, 1\}$. As expected, the higher is the share of available permanent contracts P the larger are average payoffs earned by workers. Nevertheless, in the different simulations workers have different learning patterns. For low values of P , say up to $P = 0.6$, payoffs initially decrease and then increase before converging; for higher values of P instead payoffs follow an opposite pattern, first increasing than decreasing and for $P = 1$ payoffs increase over time. Moreover, the speed of convergence differs across simulations. For low values of the share of permanent contracts, say up to $P = 0.7$, the learning process is fast and approximately 10 to 15 updates are sufficient to reach convergence. Instead, for higher values of P the learning process is faster in the initial stages but converges slowly in a high number of iterations.

3.2 Strategies

Figure 2 depicts strategies learnt by workers at the end of a simulation; each barplot corresponds to a different value of the share of permanent contracts

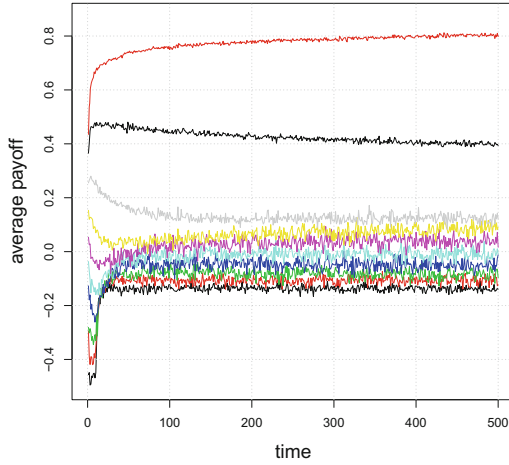


Fig. 1. Time series of average payoffs for different values of the share of permanent contracts, from bottom to top $P = \{0.1, 0.2, \dots, 1\}$.

$P = \{0.1, 0.2, \dots, 1\}$. At the end of the learning process workers evolve strategies that are very similar, but not identical both because of sampling variation and because workers have different effort costs, sampled from a uniform distribution. Therefore, we compute and plot workers' strategies averaging across all workers in the model, at the end of a simulation. The support of effort values is represented on the x -axis and the probability of choosing each strategy on the y -axis. Some patterns clearly emerge. As shown by the plots, workers' optimal strategy changes as a function of the share of available permanent contracts and, in general, workers learn to play mixed strategies. For example, when $P = 0.1$ workers obtain higher payoffs exerting minimum effort and therefore play effort equal to 1 with higher probability. In this case, only one worker out of ten is promoted to a permanent position, therefore, workers realize that it is not worth it to bear high effort costs. Nevertheless, when workers exert maximum effort chances are high that they are chosen for promotion, therefore, on average the strategy $e_{ijk} = 10$ is chosen with 11 percent of probability.

Moving from the case $P = 0.1$ to $P = 0.2$ the probability of playing $e_{ijk} = 1$ decreases from 0.51 to 0.45 and the probability of playing $e_{ijk} = 10$ increases from 0.11 to 0.2. As the share of available permanent contracts increases workers realize that their chances of being promoted increase, therefore, they optimally decrease the probability of exerting minimum effort and increase the probability of exerting maximum effort. This is true up to the case $P = 0.5$ but, as the share of available permanent contracts further increases, something changes. Workers decrease their effort and, as P increases, the distribution shifts to the left; when $P = 1$ workers choose to exert the minimum effort level with probability 0.64.

Why is there a tipping point after which temporary workers decrease their effort? The intuition is the following. Within each firm, temporary workers

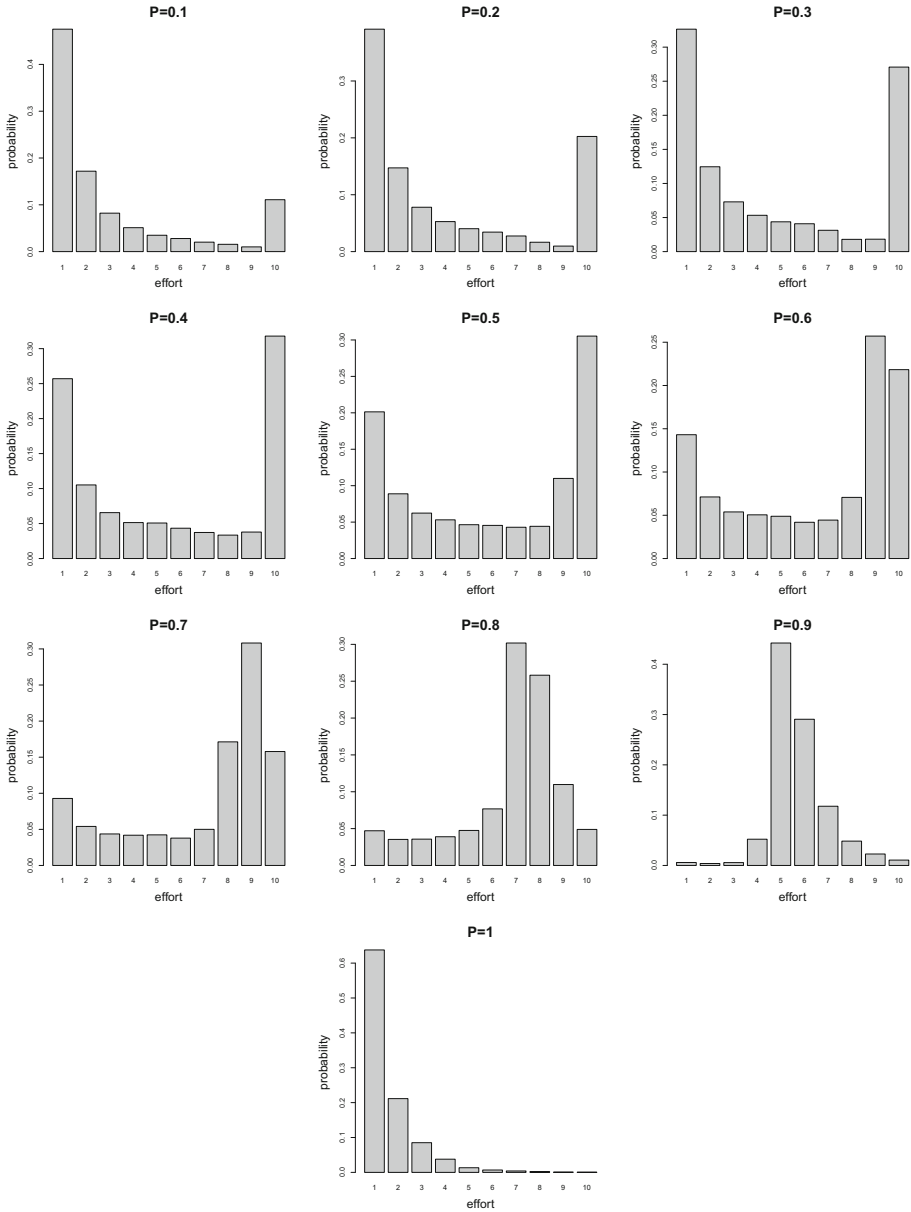


Fig. 2. Workers’ average strategy at the end of a simulation for all possible values of the share of permanent contracts in $P \in \{0.1, 0.2, \dots, 1\}$, on the x -axis effort values are in $e_{ijk} \in \{1, 2, \dots, 10\}$.

compete among each other to get permanent contracts and, when only few workers can be converted into permanent, competition induces workers to increase their effort, as the number of available promotions increases. However, when the

share of permanent contracts increases above $P = 0.5$, the pressure to compete for permanent contracts decreases as workers realize that, even exerting low effort, their contract will anyway be upgraded into permanent with high probability. In other words, temporary workers have an incentive to shirk as there is no need for them to work hard and compete for permanent contracts.

3.3 Effort and Productivity

The share of available permanent contracts induces different incentives on workers' willingness to exert low/high effort and as a consequence shapes workers' strategies. We take an aggregate approach and look at the effect of the trade-off faced by temporary workers on average effort and consequently on firm productivity. Figure 3 shows the expected value of effort exerted by all temporary workers in the model at the end of a simulation.

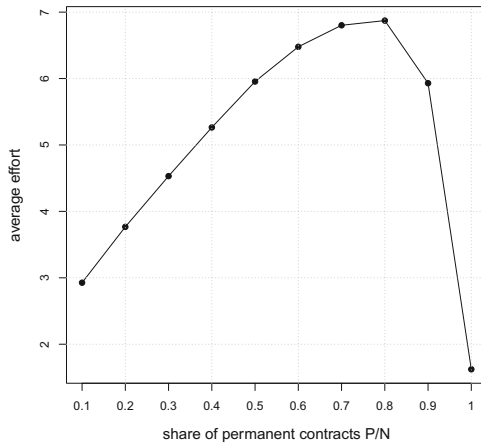


Fig. 3. Workers' average effort for each value of the share of permanent contracts $P \in \{0.1, 0.2, \dots, 1\}$.

The graph summarizes results for 10 different runs of the model, one for each of the possible values of the share of permanent contracts $P = \{0.1, 0.2, \dots, 1\}$. Each data-point is the expected value of effort from a different simulation and it is computed using the average strategies plotted in the previous figure. The main message is that the relationship between the share of permanent contracts and average effort has an inverted-U-shape. As the number of available contract upgrades increases, workers learn to exert higher effort, as this increases their chances to get a permanent contract, but, if the share of permanent contracts is too high average effort decreases. Temporary workers do not feel the pressure to compete for promotions as, with high probability, they will anyway get a permanent contract and therefore they decrease their effort. If temporary workers

do not change their effort strategies when they become permanent, from firms' point of view it is optimal to convert 80% of temporary workers into permanent as at this point effort is maximized. In this case average effort is 6.87 out of 10, instead, the lowest levels of effort correspond to the cases in which all workers are temporary and all workers are permanent, average effort is respectively 2.93 and 1.62. Recall that in this labor market production of firms is defined as the sum of effort exerted by employed workers. Figure 4 *left* and *right* shows the relationship between the share of available permanent contracts and labor productivity at the firm level, computed as the sum of effort over the number of workers, within each firm. The only difference in the two plots is the assumption on workers' behaviour when their contract is converted into permanent. In the simulations corresponding to the *left* plot we assume permanent workers stick to the strategy they learnt when they were temporary and competing for promotion, and simply sample an effort value from their distribution also when they are permanent. On the *right* instead we assume that when workers are converted into permanent they switch to a fixed level of effort that is set to the minimum level $e^* = 1$. Each data-point represents labor productivity of one of the 30 firms in the labor market; the red line joins the average labor productivity for all values of the parameter P . The results of the first assumption on permanent workers' behaviour (Fig. 3, *left*) show that there is a considerable amount of noise and different firms have different productivity values, even when they have the same share of permanent workers. Nevertheless, when considering average values the relationship between the share of available permanent contracts and labor productivity shows the same pattern as Fig. 3 on workers' effort. In fact, in the model productivity is a consequence of effort decisions. Therefore if firms could observe workers' effort decisions and the conversion process was not costly, firms would optimally set the share of permanent contracts to 80%, inducing high effort, to maximize labor productivity. Empirical evidence instead shows that yearly transition probabilities from fixed-term to permanent contracts are relatively small, they never exceed 50% and are as low as 12–13% in Portugal and Spain. In light of the model, this low temporary-to-permanent conversion probability may be one of the factors causing low productivity values recently observed in some OECD countries, as firms are not providing temporary workers the “right” incentives to exert high effort.

Figure 4 *right* summarizes the outcome of the model when we assume that workers that become permanent switch to the minimum level of effort $e^* = 1$. Under this assumption, the model suggests that firms should convert 40% of temporary workers into permanent to maximize labor productivity. At this point average labor productivity is 3.6. Note that the scale on the y -axis on the two plots is different and, as expected, higher levels of labor productivity can be reached in the scenario plotted on the *left*. The black lines are average labor productivity plus/minus one standard deviation. Note that, as expected, when the share of permanent contracts increases above 50%, the standard deviation monotonically decreases as more workers are exerting the minimum effort level.

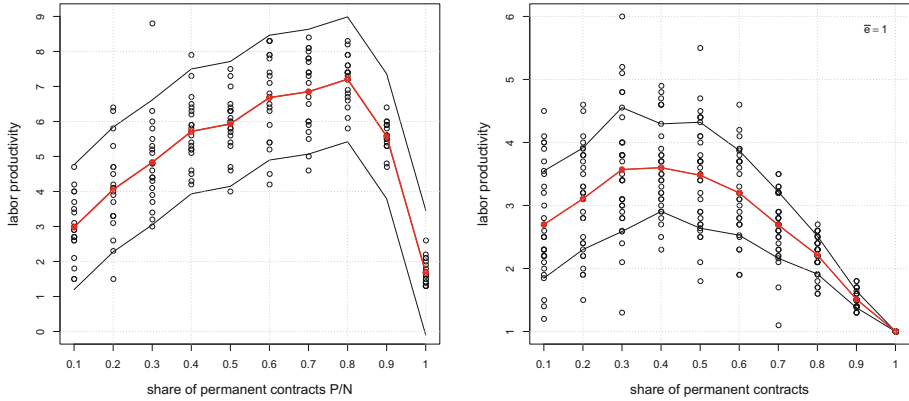


Fig. 4. Share of permanent contracts and labor productivity under two different assumptions on permanent workers' behaviour. The black lines in the *right* plot are average labor productivity plus/minus one standard deviation.

4 Concluding Remarks

This paper is a contribution to the recent and growing literature trying to assess the effect of temporary employment on labor market outcomes. We focus on behavioural aspects of this phenomenon and, in particular, the goal of this paper is to assess whether, and under which conditions, temporary employment induces an increase in workers' willingness to exert high effort. We implement an agent-based model where workers and firms interact in a dual labor market, with temporary and permanent contracts. The main result is that temporary workers' optimal effort depends on the share of available permanent contracts; the relationship between the share of permanent contracts and effort, has an inverted-U-shape. Our results should be taken as suggestive rather than conclusive: the model is very simple and therefore could be improved in several ways. For example, in this simulation firms cannot choose or adjust the share of permanent contracts, as it is an exogenous parameter, but it could instead be a firms' choice variable to maximize profits, taking into account workers' effort responses. Moreover, effort is assumed to be observable but a more realistic scenario would be to observe a noisy measure of it. For OECD countries the transition probability that a temporary contract is converted into permanent is relatively small, never larger than 50% and as low as 12%–13% in Portugal and France. Therefore, the model suggests that converting too few contracts into permanent may be providing workers incentives to exert low effort and, consequently, this may be one of causes of low productivity values, recently experienced in some European countries.

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