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FOR THE REST OF OUR LIVES: FLEXIBILITY AND INNOVATION IN ITALY

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For the rest of our lives: flexibility and innovation in Italy[a]

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Abstract: This paper investigates the relationship between flexibility and innovation. We model a firm's choice concerning: i) the mix of temporary and permanent workers; ii) the optimal level of training intensity by best-responding to the worker's investments in skills. Then, we test our theoretical predictions using micro-data on Italian firms. In line with the expectations, we find that the relationship between flexibility and innovation has the form of an inverted U, suggesting that the innovation-enhancing combination of temporary and permanent workers exists and is unique. In addition, we analyze the mediating role of firm-sponsored training. Our findings suggest that numerical flexibility becomes detrimental to innovation when training intensity is low.

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1. Introduction

The nexus between innovation and labor market dynamics has long attracted the attention of scholars in economics. A large body of literature has investigated the impact of innovation on employment, articulating on the one hand the hypothesis that innovation likely has a destroying impact on employment because of replacement effects, on the other hand a number of compensation effects have been proposed as possible factors that ultimately lead to an overall positive impact of innovation on employment (Pianta, 2005; Piva and Vivarelli, 2018; Dosi et al., 2019).

More recently, the study of the relationship between employment and innovation has been enriched by considerations on the direction of technological change. Accordingly, replacement and compensation effects do not occur in the whole economic system, but rather with respect to specific occupations and skills (Autor et al, 2003; Goos and Mannig, 2007; Acemoglu and Autor, 2011; Goos et al., 2014). While these studies have focused on the impact of innovation on labor market dynamics, a different perspective has gained momentum in the literature, aiming at reversing the terms of the relationship to enquire into the possible impact of labor market dynamics on innovation. Research in this avenue has focused on two main issues. The first concerns the impact of labor mobility and workers' replacement on innovation, stressing the positive effects for hiring firms, and the negative ones for those experiencing separations (Grinza and Quatraro, 2019). The second focuses on the relationship between the employment of temporary workers and firms' innovation outcomes, highlighting the ambiguous effects of numerical flexibility on more or less formalized innovation activities. On the one hand, the literature has stressed that constraints to the termination of job contracts reduces firms' incentives to innovate, above all when innovating would require the hiring of people with appropriate skills (Bassanini and Ernst, 2002; Scarpetta and Tressel, 2004).

Moreover, high turnover rates can ease the flow of new ideas into the firm, while permanent employees might turn out to become less prone to contribute to innovation because of the routinization of their tasks and of lock-in effects (Adams and Brock, 2004; Zhou et al., 2011; Ichniowski et al. 1995). On the other hand, the literature pointing to the negative impact of temporary contracts stresses the importance of training and learning dynamics for firms' innovation outcomes. In this respect, while flexible contracts allow firms to downsize in case of market uncertainty, sales volatility and economic downturns, longer tenures encourage both employers and employees to invest in firm-specific skills, (e.g., Devicienti et al., 2018). Since temporary workers are more likely to leave the firm and employers' incentives to invest in training are decreasing in the probability of separations (Acemoglu and Pischke, 1998), those under flexible contracts are less likely to receive training, as well as to invest in their own human capital (Arulampalam and Booth, 1998; Albert et al., 2005; Fouarge et al., 2012).

In line with these considerations, the empirical evidence on the relationship between temporary contracts and innovation is mixed. Some results support the existences of a negative relation (Franceschini and Mariani, 2015; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; and Michie and Sheenan, 2003), while other studies find a positive correlation (Arvanitis, 2005; Malgarini et al., 2013; Ritter-Hayashi, 2020).

However, there are few efforts in the literature to reconcile these two opposite views. To the best of the authors' knowledge, only Altuzarra and Serrano (2010) articulate a framework in which the relationship between flexibility and innovation is non-monotonic, suggesting that not only too much, but also too little flexibility can be detrimental to innovation. Moreover, existing studies lack proper modelling of these dynamics, while the empirical evidence is based on innovation measures drawn from surveys and self-reported information.

In this respect, our main contribution to this stream of research is manifold. First, we develop a game-theoretic model to formalize the trade-off between flexibility and human capital accumulation. We consider a framework where an employer optimally chooses the mix of temporary and permanent workers to implement a productive project. While the baseline modelling strategy is borrowed from Dughera et al. (2021), we extend the framework developed there to account for firm-sponsored training and human capital portability. Second, we test the relationship between flexibility and innovation using micro-data on Italian firms, finding an inverted-U relationship between the share of temporary workers and the firms' innovative performance. Third, we dig deeper in the relationship between human capital and innovation by providing additional evidence on the impact of firm-sponsored training, showing that the share of temporary workers is positively correlated to innovation only when firms couple numerical flexibility with high training intensity. Fourth, by using information on patent filing and citations, we add to the studies that focus on the relationship between temporary workers and innovative inputs, such as R&D expenditures (see, e.g., Kleinknecht et al., 2014).[1]

The rest of the paper is organized as follows. Section 2 reviews the literature on the relationship between temporary workers and innovation. In section 3, we develop our theoretical model. Section 4 outlines the data used for the estimations, along with some descriptive statistics. Section 5 presents the econometric strategy and the main results. Section 6 comments and concludes.

2. Related literature

The relationship between temporary workers and innovation is not unambiguous. On the one hand, rigidities in downsizing may prevent firms to invest in labor-saving innovations (Bassanini and Ernst, 2002; Scarpetta and Tressel, 2004), while the difficulty to replace old workers with fresher personnel may restrain the flow of new ideas into the firm. In addition,

[1] For another study using patent data, see Zhou et al., (2011).

incumbents may leverage on their insiders' position to bargain higher wages or supply less effort (Malcomson, 1997).

On the other hand, several studies show that the use of permanent contracts can be seen as a signal of trust that foster long-term commitment – see, e.g., Huselid (1995); Buchele and Christiansen (1999); Lorenz (1999); Michie and Sheehan (2001, 2003); Naastepad and Storm (2006) and Svensson (2011). This is consistent with the study of Acharya et al. (2014), who theorize and empirically show that the passage of wrongful discharge laws has a positive effect on labor effort, and by extension, on innovation.

The use of temporary workers discourages the individual accumulation of firm-specific skills, which, in turn, are crucial to successful innovation.[2] Indeed, both knowledge generation and human capital accumulation require long-lasting processes of organizational and on-the-job learning that involve a two-way exchange between firms and their personnel (Schneider et al., 2010). These learning dynamics may unfold across multiple channels, from face-to-face communication (Asheim et al., 2007), to teamwork (Lloréns Montes et al., 2005), absorptive capacity (Cohen and Levinthal, 1990), work experience (Schneider et al., 2010) and so on.

The negative relationship between shorter contracts and human capital accumulation hinges accordingly on two (potentially self-reinforcing) pillars. On the one hand, employers offering temporary contracts will be less prone to invest in firm-sponsored training, considering the high probability of future separations (Acemoglu and Pischke, 1998). On the other hand, even when firms are willing to train their temporary workers, the latter may be unwilling to exploit these learning opportunities by anticipating that their human capital investments will be lost when moving across firms. The extent to which they may find it rational

[2] Despite the role of production workers is not directly to invent or innovate, the tacit knowledge they acquire on-the-job represents a key antecedent for the codification of new organizational and technical knowledge (Foss, 1997, 1998). In this perspective, the idea of "complementary capabilities" put forward by Teece et al. (1997) is enlightening: having an innovative idea is just the prerequisite for the successful development of new products or techniques.

to do so, in turn, crucially depends on the degree of human capital portability. As recalled by Kleinknecht et al. (2014: 1210), in fact, “workers will be more interested in acquiring general skills that increase their employability on the external job market, but may be reluctant to acquire firm-specific skills if there is no long-term commitment to their employers”. In this perspective, Kräkel’s critique of traditional human capital theory is captivating (2016: 627): “When a firm decides to invest in human capital, a worker is considered more like a robot to be programmed rather than a human being who is free to learn or not. Often, however, such programming is not possible”.

In this view, the strategic dimension of learning becomes a crucial pillar to incentivize innovative efforts. Manso (2011), for instance, argues that the innovation-motivating contract shows tolerance for early failures and reward for long run success. Grinza and Quatraro (2019: 7), in turn, show that workers’ replacements have a negative effect on the number of patent applications, and that this effect is larger the longer the workers’ tenure in the organization. This is consistent with the idea whereby “when workers leave, they take with them firm-specific knowledge about competencies and routines, as well as about the potential for resource combination for the creation of novelty”.

These contrasting theoretical perspectives are reflected in non-conclusive empirical evidence, supporting both views. Indeed, while a number of studies find a negative relationship between flexibility and innovation (Franceschini and Mariani, 2015; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; and Michie and Sheenan, 2003), others reach opposite conclusions (Arvanitis, 2005; Malgarini et al., 2013; Ritter-Hayashi, 2020). In particular, Malgarini et al. (2013) show that the negative relationship between flexible labor and innovation is confined to the period preceding the financial crisis of 2008, while Arvanitis (2005) show that numerical flexibility has a positive effect on both process and product innovation, despite the latter is not statistically significant. Ritter-Hayashi et al. (2020), in turn, analyze data from developing countries and show that labor flexibility retains firm innovativeness in times of downsizing.

The results from Altuzarra and Serrano (2010) combine these opposite approaches, as they find that firms who do not employ any temporary worker show the lowest propensity to innovate, but also, that the probability of innovation decreases as the rate of fixed-term workers increases beyond the innovation-compatible threshold.

In many studies, the type of technological or innovation regime with which the firm is confronted, emerges as an important factor moderating the impact of temporary jobs.[3] The underlying assumption is that the concentration of innovative activities forces innovators to resort more intensively to internal labor markets to generate new knowledge, because of the poor availability of freely combinable ideas. Consistently with this view, both Kleinknecth et al. (2014) and Wachsen and Blind (2016) show that the use of temporary workers has a negative effect on R&D expenditures only if the dominant innovation regime is "routinized" (Schumpeter mark II). The result, however, is not confirmed by Guarascio et al. (2019), who find that the negative relationship between temporary workers and innovation is robust across innovation regimes. Based on these considerations, in the next sections we develop a theoretical model and an empirical analysis that reconcile positive and negative views on the relationship between temporary jobs and innovation.

[3] According to Schumpeter's seminal distinction, an innovation regime is defined as "entrepreneurial" when new innovators easily incur in novel technological opportunities, face low barriers to entry the market for innovation and can smoothly displace incumbents through a classic process of creative destruction. The alternative process of creative accumulation that conversely characterizes a "routinized" innovation regime takes place in markets dominated by large and powerful firms, high barriers to entry and a significant concertation of R&D efforts. Clearly, the first type of regime is more dynamical and normally gives birth to radical innovations that sets an industry's technological perimeter in its early stage of development. Conversely, the second type of regime tend to characterize older industries where a process of incremental innovations builds up on a well-defined knowledge base (Winter, 1984; Malerba and Orsenigo, 1997; Breschi et al, 2000)

3. The model

3.1. Setup

We develop a two-stage game where a firm optimally chooses the mix of permanent, P, and temporary workers, T, to implement a productive project. In addition, both the firm and its personnel decide how intensively to invest in human capital. As in Kräkel (2016), successful human capital investments require both training offered by the firm and the workers' willingness to learn. Denote as $\tau_i > 0$ the training intensity that the firm chooses for tenure i, and as $\lambda_i > 0$ the workers' human capital investment under contract $i = \{T, P\}$. In line with Dughera et al. (2021), we assume that both contracts pay the same wage $w > 0$, at which labor supply is assumed to be infinite. In addition, w satisfies the participation and incentive compatibility constraint, so that workers find it rational to enter the labor market and exert the required level of effort when employed. While we develop the model by referring to a generic project, we will draw some remarks on the specific case of innovation in the concluding part of the section.

The timing of the game is as follows. In the training period, $t = 1$, the firm and its personnel non-cooperatively choose their human capital investments., i.e., the firm chooses τ_i, followed by the workers' decision on λ_i. In the working period, $t = 2$, employees use their human capital in production. After that, revenues are collected and the game ends.

During the production phase, there is an instantaneous probability $0 < s < 1$ that the project fails due to the arrival of an exogenous shock, in which case, yields zero payoff.[4,5] To model the idea that labor flexibility allows firms to adjust easily to economic conditions, we follow Dughera et al. (2021) and assume that temporary workers can be terminated at no cost

[4] The arrival rate of the exogenous shock may depend on general macroeconomic conditions as well as on specific characteristic of the productive project.
[5] The assumption that the realization of the adverse shock occurs in $t = 2$ implies that the outcome of all training investments is uncertain, otherwise, they could be fine-tuned after observing the state of economic conditions.

upon the arrival of the exogenous shock, while permanent workers must be compensated with a severance payment if dismissed for economic reasons. To keep things simple, we assume that this indemnity is large enough so that firms find it rational not to dismiss their permanent workers. Hence, conditional on the realization of the adverse shock, permanent workers remain with the firm, while all temporary workers enter the unemployment pool and receive their outside option, which we normalize to zero. During the same period, we assume that there is probability $0 < a < 1$ of finding another occupation. In this case, re-employed receive w and work for a different employer until the end of $t = 2$. As usual, we derive the subgame Nash-equilibrium by backward induction.

3.2. Workers' human capital investments

In the training period, workers decide how intensively to invest in their own skills. As in Kräkel (2016) and Dughera et al. (2021), we assume that acquiring human capital in $t = 1$ decreases the cost of providing effort in $t = 2$. In addition, we assume that the benefits of effort reduction are transferable across firms, depending on the degree $0 < p < 1$ of portability (or generality) of the acquired skills. When $p = 1$ ($p = 0$), human capital is purely general (firm-specific) and the workers' investments in skills are fully recovered (lost) when moving across firms. That human capital is neither completely general nor completely specific, however, is now empirically established—see, e.g., Neal (1995), Poletaev and Robinson (2008), Angelides (2008), and Suleman and Lagoa (2013). Hence, when temporary workers change occupation due to the arrival of the adverse shock, a share of their human capital investment will be lost, and this, by backward induction, will provide smaller incentives to learn. The workers' problem is given by:

$$\max_{\lambda} u_P(\lambda) = w - (1 - \delta\lambda)e - \frac{1}{2\tau_T}\lambda^2 \tag{1}$$

$$\max_{\lambda} u_T(\lambda) = (1-s)[w-(1-\delta\lambda)e] + sa[w-(1-p\delta\lambda)e] - \frac{1}{2\tau_P}\lambda^2 \tag{2}$$

The quadratic term on the r.h.s. of equations (1) and (2) measures the (convex) cost of learning under tenure i, which is assumed to be decreasing in the levels of training intensity τ_i chosen by the firm.[6] The parameter $\delta > 0$, in turn, captures the marginal decrease of effort following an increase in λ, and can be seen as a measure of investment efficiency. To avoid abuse of notation, but w.l.o.g., we normalize $e = \delta = 1$.[7] Solving the maximization problem in equations (1) and (2), we obtain the workers' human capital investments as functions of the level of training intensity chosen by the firm, as resumed by the following Lemma:

Lemma 1—*For any given $\tau_i > 0, i = \{T, P\}$, the workers' human capital investment is given by:*

$$\lambda_P(\tau_P) = \tau_P \tag{3}$$

$$\lambda_T(\tau_T) = [1 - s(1 - ap)]\tau_T \tag{4}$$

In addition, for any $\tau_P \geq \tau_T$, permanent workers invest more than temporary workers. In this case, the investment differential is increasing in s and decreasing in p.

Proof: see the Appendix ■

The result in Lemma 1 is intuitive: since temporary workers anticipate that a share of the acquired skills will be lost conditional on the realization of the adverse shock, they adjust their human capital investments to the probability of separations (increasing in s) and to the portability of the acquired skills (increasing in p). Straightforwardly, the higher is the frequency

[6] The convexity of the cost function, together with the assumption that e decreases linearly with λ, models the idea that the that there are decreasing returns to learning and thus, that an interior solution of the maximization problem in equations (1) and (2) exists and is unique. As is well known, any maximization problem of the form $\max_{x>0} u(x) = f(x) - g(x)$ has a unique solution iff $f(x)$ is quasi-concave and $g(x)$ is quasi-convex, at least one strictly so. The choice of convex costs and linear benefits is made for algebraic tractability.

[7] This entails that λ must take values that are interior to $(0,1)$.

of adverse shocks and the degree of human capital specificity, the lower their human capital investments. Although this difference could potentially be realigned by the firm's decision on τ_i, the workers' willingness to learn and training intensity are complements in this model, which implies that the more workers are willing to invest int their own skills, the more the firm will find it rational to give them the opportunity to do so. Together with the assumption that temporary contracts can be broken at no cost upon the realization of s, the trade-off between temporary and permanent workers is straightforward in this model: while temporary contracts allow greater flexibility in downsizing and thus, greater adaptivity, open-ended tenures generate greater human capital incentives, with positive repercussions on profitability. In this framework, the parameter s turns out be key to the functioning of the model, since it channels both the benefits and costs of numerical flexibility. The implications of this tradeoff are analyzed in the following section, where we study the firm's optimal behavior.

3.3. Firm behavior

In the training period, the firm chooses the optimal mix of permanent and temporary workers, as well as a level of training intensity τ_i for tenure i. To do so, it maximizes an only-labor-inputs production function, $f(\lambda_T, T, \lambda_P, P)$, that depend positively on the number of employed workers as well as on their human capital investments. Since temporary and permanent workers can potentially be used as substitute in production, we assume that f takes the specific additive form $f = q(\lambda_T)g(T) + q(\lambda_P)g(P)$, where $q(\lambda_i)$ is a function defining a relationship between productivity and human capital, and $g(i)$ maps inputs into output. To keep things simple, we use linear specifications of both $g(i)$ and $q(\lambda_i)$[8], so that $g(i) = i, i \in \{T, P\}$, and:

[8] The global concavity of the firm's optimization is ensured by the features of the cost functions, discussed below.

$$q(\lambda_i) = \beta + \alpha\lambda_i \equiv q_i \tag{5}$$

In equation (5), $\beta > 0$ is a constant, while $\alpha > 0$ measures the project's idiosyncratic sensitivity to human capital. Together with the arrival rate of the exogenous shock, α is a key driver of the firm's decision on T and P, and thus, an important parameter of the model. Given Lemma 1 and the discussion that follows, it is straightforward to observe that, given equation (5), permanent workers are more productive, given their greater human capital investments. Putting things together, the firm's problem is given by:

$$\max_{P\ T,\tau_i} \pi_i(P,T,\tau_i) = [(1-s)(q_T - w) - c(\tau_T)]T + [(1-s)q_P - w - c(\tau_P)]P - C(T,P) \tag{6}$$

where $c(\tau_i)$ and $C(T,P)$ are convex functions that measure training expenditures per employee and coordination costs, respectively.[9] In what follows, but w.l.o.g., we will consider the following functional specifications:

$$\begin{cases} c(\tau_i) = \tau_i^2/2 \\ C(T,P) = (T^2 + P^2)/2 \end{cases} \quad i \in \{P,T\} \tag{7}$$

A few details about equation (6) are worth noticing. First, given the assumption that the project yields zero payoff upon the arrival of the exogenous shock, the workers' output is realized with probability $1-s$. Second, since temporary workers can be dismissed at no cost upon the realization of s, their wage payment is also weighted for the same probability, $1-s$. This is not the case for permanent workers, who are retained regardless of whether the project

[9] Since the specifications chosen in equations (1) and (2) are such that the workers' human capital increases linearly with training intensity, the assumption that $c'(\tau_i) > 0$ ensures that there are decreasing returns to training, and thus, that an optimal level of τ_i exists and is unique. Similarly, since we choose to work with a linear specification of both $g(i)$ and $q(\lambda_i)$, that together define the firm's production function, the assumption of convex coordination costs ensures that a solution the optimization problem in (6) exists and it unique. That coordination costs increase at an increasing rate, however, is not unlikely. The same results would have followed had we assumed concave benefits and linear costs.

is successful or not. Finally, since human capital investments are made in $t = 1$ while the shock potentially occurs in $t = 2$, training expenditures are sunk at the time of the realization of s, and thus, $c(\tau_i)$ is paid whatever the state of economic conditions. The following Proposition analyzes the firm's optimal strategy:

Lemma 2—*For any given* $\lambda_i > 0, i = \{T, P\}$*, the firm's human capital investments are given by:*

$$\tau_P^* = (1 - s)\alpha \tag{8}$$

$$\tau_T^* = [1 - s(1 - ap)](1 - s)\alpha \tag{9}$$

from which it is straightforward to see that $\tau_P^* > \tau_T^*$ *is always satisfied, but for the limit case* $a = p = 1$*. In addition, both* τ_P^* *and* τ_T^* *are increasing in* α *and decreasing in s.*

Proof: see the Appendix ■

The marginal benefits of an additional unit of training depend jointly on two elements: on the *direct* increase in expected output, measured $(1 - s)\alpha$, and on the *indirect* increase following the worker's reaction. Since learning is less demanding when the firm provides more training, workers under tenure $i = \{T, P\}$ will best-respond to an increase in τ_i but increasing λ_i.While the direct efficiency gain is equal for both type of contracts and crucially depends on the project's specific sensitivity to human capital, measured by α, the second efficiency gain is mediated by the workers' decision on λ, described in equations (3) and (4). Hence, the result in Lemma 2 confirms what already anticipated in the discussion following Lemma 1: since the workers' willingness to learn and training intensity are complements in this model, the firm finds it rational to invest more in its permanent workers, as the latter are more prone to invest in their own skills. The comparative statics in the conclusions of Lemma 2, in turn, are intuitive. First, since the returns to training depends on the project's specific sensitivity to human capital, an both τ_P^* and τ_T^* are increasing in α, although the effect on τ_P^* is more significant - $\partial\tau_P^*/\partial\alpha >$

$\partial\tau_T^*/\partial\alpha$. Second, since all human capital expenditures are lost upon the arrival of the exogenous shock, the firm's training investments are decreasing in s. Curiously, there exists a "pathological" situation where the frequency of exogenous shocks is so high ($s > 1/2$) that a further increase in s leads the firm to reduce τ_T^* more than τ_P^* – formally, $|\partial\tau_P^*/\partial s|_{s\in(1/2,1)} > |\partial\tau_T^*/\partial s|_{s\in(1/2,1)}$.[10] With these facts in mind, we are now in the position to study the firm's decision on the optimal mix of temporary and permanent workers, which is resumed in the following Proposition:

Proposition 1—*For any given $\tau_i^* > 0$ and $\lambda_i > 0, i = \{T, P\}$, the optimal workforce composition is given by:*

$$P^* = (\tau_P^*)^2/2 + (1-s)\beta - w \tag{10}$$

$$T^* = (\tau_T^*)^2/2 + (1-s)(\beta - w) \tag{11}$$

In addition, while both P^* and T^* are increasing in α and decreasing in s, an increase in α leads the firm to unambiguously increment the ratio between permanent and temporary workers, while an increase in s has an ambiguous effect on the optimal workforce's composition.

Proof: see the Appendix ■

Proposition 1 shows that the combination of temporary and permanent exists and is unique. In addition, it also suggests that the more important is the workers' human capital, the higher is the ratio between permanent and temporary workers. The result, as anticipated, is determined by the fact that those under permanent contracts have greater incentives to learn and, given this, that the firm finds it rational to best-respond to this higher willingness to learn

[10] Beware, however, that this is a relative change: in absolute terms, is always satisfied.

by increasing their training investments. The relationship between uncertainty and the optimal combination of P^* and T^*, in turn, is less clear-cut. On the one hand, since temporary workers can be dismissed at no cost upon the realization of s, the more uncertain is the environment, the greater the use of flexible contracts. This can be seen from the fact that the third argument in equation (10), $-w$, is clearly larger than the third argument in equation (11), $-(1-s)w$. On the other hand, an increase in s leads the firm to reduce its training investments for both temporary and permanent workers, and it additionally induces the latter to invest less in their own skills. Altogether, this leads to a reduction of the equilibrium values of both P^* and T^*, although which of the two effects is the most sizeable depends on parameters' values.

3.4. Discussion: the case of innovation

The model we have just presented refers a generic project. Since innovation is particularly interesting for us, we will now draw some remarks on this particular case. As both Lemmas 1 and 2 and Proposition 1 have made clear, the key parameters of the model are two, s and α. While the arrival rate of the exogenous shock may depend on general macroeconomic conditions that have nothing to do with the productive activity itself, it may also depend on its volatility and instability. Given the profound uncertainty that normally characterizes the creation of novelty, one may expect s to be higher in the case of innovation. Numerical flexibility can be particularly important in this case, as it provides firms with the adaptivity that is required to cope with the process of exploration and discovery. As to the role of human capital, one may expect the implementation of innovative activities to depend more on the workers' skills and less on the "memory of the organization", as Nelson and Winter (1982) call it. Implementing novel services, products and techniques, in fact, can require a whole array of adaptive abilities that are probably less important in more standardized procedures. Hence, given that our results suggest that firms will rely more on permanent workers when the projects' sensitivity to the workers' skills is high, we may expect that the ratio between permanent and temporary contracts will be higher in innovative firms. The next step is to assess empirically the effect of temporary workers on the firms' innovating behavior.

4. Data, variables and methodology

4.1. Data

The main purpose of this paper is to investigate the relationship between numerical flexibility and firms' innovation outcomes, as well as the interplay between the use of flexible labor and training. Our hypotheses are tested using three different data sources. First, information on firm-level variables is retrieved from the first three waves of the Employer and Employee Survey (Rilevazione Longitudinale su Imprese e Lavoro, RIL, 2005, 2007 and 2010) conducted by the National Institute for Public Policy Analysis (INAPP). Each of these waves provides a rich set of information about employment composition (e.g., type of contracts), personnel organization (activities), industrial relations and other workplace characteristics and covers over 25000 firms operating in the non-agricultural private sector in Italy. Second, by using the firms' tax number, the RIL dataset is merged with the AIDA database by Bureau van Dijk in order to get information on R&D expenditures. Third, we take the OECD REGPAT dataset to add information on the firms' patent-filing activities. The latter is merged with RIL-AIL following the matching procedure developed by Lotti and Marin (2013).

More in detail, the aforementioned dataset is built as follows. OECD REGPAT on firm's patent-filing activities over the period 2006-2008 is merged with wave 2005 of RIL-AIDA; OECD REGPAT 2008-2010 is merged with wave 2007 of RIL-AIDA and finally, the 2011-2013 OECD REGPAT dataset is merged with wave 2010 of RIL-AIDA. In this way, we end up with a dataset containing information on patents-filing activity in a 7-year window (from 2006 to

2013) and lagged firm-level variables (2005, 2007 and 2010). We finally end up with a sample of around 70000 firms over the total period of analysis. [11]

4.2. Variables description

To account for the firms' innovative performance, we use measures drawing on patent statistics, that provide a reasonable approximation of firm-level innovation dynamics[12]. Since firms' innovation outcomes can be very different from one another as far as their quality is concerned, we follow the extant empirical literature and develop a variable reflecting the patents' technological importance as well as the economic value of inventions (Hall et al., 2005). We refer to the OECD patent quality indicators (Squicciarini et al., 2013) and the forward citations a patent has received in a 7-year window (Colombelli et al, 2020). This is the yearly stock of citations to all of the patents of the firm, deflated with the permanent inventory method (PIM) that assumes a yearly depreciation rate of 15% (Hall, 1999) and divided by the count of patent applications of the firm in each year. This measure allows us to consider not only the *size*, but also the *quality* of the firm's knowledge stock (Sandner and Block, 2011) and will be used as a dependent variable (*CIT*) ion all our models, as described in the section that follows.

We then construct two firm-level indicators capturing first, numerical flexibility and second, the intensity of training. The former is the share of temporary workers (*SHARET*) hired by a firm, calculated as the ratio between the number of employees with temporary contracts and the total number of employees hired by each firm, while the latter is calculated as the ratio between the number of workers who receive training and the total number of employees hired by each firm, therefore accounting for the intensity of training at the firm-level (*TRAININT*).

[11] In each wave there are, respectively, 21,728 firms (2005), 24230 firms (2007) and 24,453 firms (2010). Individual firms are excluded from the sample.
[12] The limits of patent data as proxies of innovation output are well known in the literature – see Griliches (1990) for a detailed discussion. Yet, they represent an option that is in most cases more reliable than R&D statistics or self-reported survey-based information.

Consistently with our focus on the relationship between flexibility and innovation *output*, we also proxy the notion of innovation regimes by constructing two indicators. First, we build an Herfindahl-Hirschman index that measures the concentration of patents applications in a given industry (*CONC*). This is a key difference with, for example, Kleinknecht et al. (2014), who conversely use data on R&D expenditures. In our sample, industries are thus characterized by a value belonging to a continuous scale between 0 (perfect dispersion) and 1 (perfect concentration). Values closer to zero indicate that the industry tends towards an "entrepreneurial" or "garage business" innovation regime (Schumpeter mark I); values closer to 1 indicates a "routinized" innovation regime (Schumpeter mark II).

Second, we rank firms each year in each sector according to their innovation performance. Then we calculate the Spearman rank correlation index between the hierarchy of innovators in the sample (*INST*). This provides us with a proxy of the instability of the relative positioning of innovators in the sector. According to the extant literature (Breschi et al, 2000), a turbulent environment is associated with the Schumpeter Mark I regime (*STABILITY* close to 0), while a stable environment is associated with a Schumpeter Mark II regime (*STABILITY* close to 1). Both *CONC* and *STABILITY* are calculated by using data on R&D expenditures from OECD-REGPAT

Finally, to proxy the inputs of the knowledge production function, we include, as further control, the logarithm of R&D intensity (*RDINT*), calculated as the ratio between the firms' R&D expenditures and their total employment (Giliches, 1984). Information on R&D expenditures is taken from the AIDA balance-sheet. However, since it is well known that only a limited number of firms undertake formal R&D activities, these values are adjusted to account for selection problems. We thus predict R&D intensity with a selection equation that follows the Wooldridge approach in a panel setting Wooldridge's (1995). This method has been used in several studies and it allows potential R&D intensity to be predicted for non-reporting firms (see, for instance, Colombelli et al. 2020)

4.3. Methodology

The relationship between temporary workers and the quality of the firm's knowledge stock is estimated with a Poisson model based on the method of Hall et al. (1984). This is a standard procedure when the dependent variable is a count data that takes non-negative, integer values (Cameron and Trivedi, 1998). As in Colombelli et al. (2020) we use as dependent variable the patents' forward citations to control for the *quality* and economic value of inventions (Sandner and Block, 2011). Our model is reported below:

$$CIT_{it,t+6} = \alpha + \delta_1 SHARET_{i,t-1} + \delta_2 \left(SHARET_{i,t-1}\right)^2 + \varphi \ln\ RDINT_{i,t-1} + \beta X_{i,t-1} + \rho_{sr} + \gamma_t + \varepsilon_{i,t} \quad (12)$$

The dependent variable, $CIT_{it,t+6}$ captures the quality of the knowledge stock of firm i at time t, and the subscript $t+6$ indicates that we consider the patents' forward citations over a 7-year time window span (2006-2013), as explained in section 4.2. Our parameters of interest are δ_1 and δ_2, capturing the possibly non-linear effect of labor flexibility, proxied by the lagged share of flexible workers, $SHARET_{i,t-1}$, on firms' innovation performances. $X_{i,t-1}$, in turn, is a vector of lagged time-varying characteristics including: 1-digit sector, firm-size (in log), a dummy indicating if the firm is involved in a merger or acquisition process in the year prior the survey, and the share of executives over the total firm's workforce. Finally, we also include region-sector fixed effects, ρ_{sr}, and time fixed effects γ_t, while $\varepsilon_{i,t}$ is the error term.

In some specifications, we additionally include both our "Schumpeterian" variables, *CONC* and *STABILITY*, as well as the interaction between the concentration of patenting activity, *CONC*, and our focal regressor, *SHARET*. The resulting term, *SHARETCONC*, aims to capture whether the relationship between temporary workers and innovation is mediated by the industry-specific (un)availability of freely disposable knowledge, proxied by the concentration of patenting activities.

4.3. Descriptive statistics

Table 1 and 2 provide some descriptive statistics of our main variables of interest, while Table 3 shows the Spearman rank correlations of all regressors included in the analysis. More specifically, the top panel of Table 1 reports information on the absolute number, as well as on the relative shares, of firms that have at least one citation over the period 2006-2013 (*CIT*), that employ positive shares of temporary workers (*SHARET*), and that make some investment in training (*TRAININT*). First of all, it comes as no surprise that only 3% of the firms in our dataset have at least one citation. This is in line with previous evidence describing Italy as a low-to-moderate innovative performer over the period analyzed (European Commission, 2021). As to flexibility, a large share of the firms (around 4 out of 10) makes use of temporary contracts. Finally, it is worth noticing that only a small group of firms in the sample invest in training, less than 30%, meaning that 7 out of 10 firms do not invest in training at all.

Table 1: Descriptive statistics: Citations, temporary workers and training

	$CIT = 0$	$CIT > 0$	$SHARET = 0$	$SHARET > 0$	$TRAININT = 0$	$TRAININT > 0$
Freq.	70210	201	41215	29196	19390	51021
%	99.7	0.3	58.53	41.47	27.5	72,5

	$SHARET$			$TRAININT$		
	Whole sample	$CIT = 0$	$CIT > 0$	Whole sample	$CIT = 0$	$CIT > 0$
Mean	11.9	11.9	6.5	15.5	15.4	26.3
St Dev	22.1	22.2	7.7	30.7	30.7	29.4
Min	0	0	0	0	0	0
Max	100	100	55.3	100	100	100

Source: own computations on RIL-AIDA-REGPAT data.

In the bottom panel of Table 1, in turn, we show mean, standard deviation, max and min of our main regressors, *SHARET* and *TRAININT*, both for the whole sample and across the two sub-groups of innovative ($CIT > 0$, i.e., those with at least one citation) and non-innovative firms ($CIT = 0$, i.e., those with zero citations). From these figures, some important remarks are in order: innovative firms tend to be larger, employ lower share of temporary workers and rely much more on firm-sponsored training. Indeed, while the average share of temporary workers is around 11.8% in the whole sample, and that of those who receive firm-sponsored training around 15.4%, the picture significantly changes when we focus on the sub-group of innovators**.** From the third and sixth columns of the bottom panel of Table 1, in fact, we see that innovators rely much less on temporary workers (the average share is 6.5%) and invest more in training (the average share is 26.3%).

Table 2: Firm size distribution

	Whole sample			$CIT > 0$			$CIT = 0$		
$SIZE$	Freq.	%	Cum.	Freq.	%	Cum.	Freq.	%	Cum.
< 50	62446	88.7	88.7	35	18	18	62410	89	89
$\in (50{,}250)$	5851	8.3	97	71	35.3	53.2	5780	8.2	97
> 250	2114	3	100	94	46.8	100	2020	3	100

Source: own computations on RIL-AIDA-REGPAT data. $SIZE$ =number of employees. The average size in the whole sample is 46.4.

Finally, Table 2 looks at the distribution of firm size (which is the denominator of both *SHARET* and *TRAININT*) both for the whole sample and for the subsamples of innovative and non-innovative firms. Unsurprisingly, our dataset features a large share of small-to-medium firms (88.7% have less than 50 employees), consistently with previous evidence on the system of Italian enterprises (Sestito and Torrini, 2020). However, as expected, innovative firms tend to be much larger, having on average 636 employees. When we further decompose the sub-group for size classes, we see that 18% of innovators have less than 50 employees, and almost a half, 46.8%, more than 250 employees.

Table 3: Spearman's rank correlation coefficients

	CIT	*SHARET*	*TRAININT*	ln *RDINT*	*CONC*	*STABILITY*	ln *SIZE*
CIT	1.0000						
SHARET	0.0058	1.0000					
TRAININT	0.0274	0.0012	1.0000				
log(*RDINT*)	0.2141*	0.0535*	0.0921*	1.0000			
CONC	-0.0632	-0.0163*	-0.0010	0.0703*	1.0000		
STABILITY	0.0813	0.0802*	-0.0319*	0.0540	-0.4145*	1.0000	
log(*SIZE*)	0.2246*	0.0774*	0.2042*	0.4596*	0.0556*	0.0112	1.0000

Source: own computations on RIL-AIDA-REGPAT data. The asterisks identify all correlation coefficients significant at the 5% level or lower.

5. Estimation results

5.1. Main results

Table 4 reports our main results. We estimate four different specifications of the baseline model presented in equation (12) – see columns 1-4 of Table 4. The vector of controls described in section 4 is included in all models. As anticipated, Model 2 replicates the same estimates presented in column 1, but it also includes the Herfindahl-Hirschman index, *CONC*, measuring the degree of concentration of patents acquisition. The model in column 3, in turn, adds *STABILITY*, i.e. the Spearman rank correlation index of innovators, that measure the sector-specific stability in the hierarchy of innovative firms. Finally, the model presented in column 4 adds both our measure of patenting concentration, *CONC*, as well as an interaction term that captures the interplay between the latter and the share of temporary workers, *SHARETCONC*.

Table 4: Poisson estimations.

	(1)	(2)	(3)	(4)
	CIT	CIT	CIT	CIT
$SHARET$	0.1216^{***}	0.1106^{***}	0.1107^{***}	0.0311^{***}
	(0.0042)	(0.0042)	(0.0039)	(0.0014)
$(SHARET)^2$	-0.0054^{***}	-0.0046^{***}	-0.0042^{***}	
	(0.0002)	(0.0002)	(0.0002)	
$\log(RDINT)$	0.4924^{***}	0.4195^{***}	0.4450^{***}	0.4340^{***}
	(0.0065)	(0.0071)	(0.0071)	(0.0071)
$\log(SIZE)$	0.9700^{***}	1.1483^{***}	1.1104^{***}	1.1654^{***}
	(0.0078)	(0.0086)	(0.0083)	(0.0085)
$CONC$		-3.5887^{***}		-1.8449^{***}
		(0.0980)		(0.1160)
$STABILITY$			1.1417^{***}	
			(0.0313)	
$SHARETCONC$				-0.3738^{***}
				(0.0148)
N	26351	15981	16967	15981
AIC	74079.4512	65558.0540	67495.0275	65825.9526
BIC	75429.0294	66740.6440	68679.0984	67008.5426

Source: own computations on RIL-AIDA-REGPAT data. All models include regional-sectoral and time dummies. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our results unambiguously suggest that the relationship between temporary workers and innovation follows an inverted U-shaped pattern, consistently with the idea that some degree of flexibility is a prerequisite for successful innovation, but also, that the share of temporary workers in innovative firms must be lower than a critical threshold, beyond which the human capital losses are too harmful to new knowledge production.[13] In addition, all our controls have intuitive and reasonable signs: in particular, we see that larger firms and higher R&D effort

[13] All our results are robust to reasonable sample restrictions, like for instance by excluding firms with less than 9 employees. Results are available from the authors upon request.

improve the quality of the firm's knowledge stock. As to our "Schumpeterian" variables, it interesting to note that the Herfindahl-Hirschman index included in Model 2, *CONC*, is negatively correlated with the quality of the firms' knowledge stock, thus suggesting that patenting concentration has a negative effect on innovation, ceteris paribus. By contrast, we also see that the Spearman correlation index in Model 3, *STABILITY*, is positively correlated with the firms' innovative performance, thus suggesting that increasing degrees of competition among innovators lead to lower knowledge production. Taken together, these two insights lead to mixed predictions as to which type of innovation regime is more conducive to innovation, at least in our sample. While the negative coefficient of our concentration index seems to indicate that firms will innovate less in industries that tend towards a "routinized" innovation regime, the positive correlation between patent filing and stability in the hierarchy of innovators suggests otherwise.

More to the point of the present paper, it is important to stress that the specification presented in Model 4 of Table 4 presents results that are consistent with the literature (Kleinknecht et al., 2014; Wachsen and Blind, 2016), namely, that temporary workers are particularly detrimental to new knowledge generation when innovative activities are concentrated at the industry-level. Indeed, although the non-mediated relationship between temporary workers and innovation seems to be positive (i.e., the coefficient in the first row of table 5 is always positive), it becomes negative when we consider the effect of patenting concentration, that, as anticipated, proxies the degree of freely disposable knowledge. This can be seen from the fact that the coefficient of our interaction term, *SHARETCONC*, is negative and statistically significant. The intuition is straightforward: when external knowledge is poorly available, firms have no other option but to rely on internal labor markets to encourage the accumulation of firm-specific skills.

5.2. Are temporary contracts all alike? Some additional evidence on firm-sponsored training

The main results presented in the previous section suggest that the relationship between numerical flexibility and the quality of the firm's patent stock is non-monotonic, in line with previous results by Altuzarra and Serrano (2010). As anticipated, this is consistent with the idea that a positive share of temporary workers allows innovators to downsize in case of innovative failures, thus mitigating the risk associated to exploration and discovery. At the same time, it also suggests that the benefits of flexibility are not unbounded, and must be weighted for the losses of human capital put forward by our theoretical model. To dig deeper in this channel, we take advantage of the fact that RIL provides detailed information on firm-sponsored training and that such information can be interacted with that concerning the use of temporary contracts, thus allowing us to appreciate the interaction between training intensity and the use of flexible contracts. More precisely, we re-estimate equation (12) by adding two focal variables. The fist, *TRAININT,* measures the portion of workers over the firms' total workforce who receive firm-sponsored training, which we take as a proxy for the level of training-intensity chosen by the firm. The second, *TRAININT-SHARET,* is an interaction term between training intensity and our focal regressor, *SHARET*. More specifically, the first model in column 1 of Table 5 replicates the baseline specification reported in column 1 of Table 4 by adding our measure of training intensity, *TRAININT.* The signs of the estimated coefficients are reassuring: even after controlling for training intensity, we see that the relationship between temporary workers and innovation has still the form of an inverted U. The first row of Table 5, in turn, reveals another important result: the intensity of training is positively correlated with our innovation measure, thus supporting the view that the workers' human capital is an essential element for successful innovation (Leiponen, 2005; OECD, 2011; Consoli et al, 2021).

Table 5: Poisson estimations (training)

	(1)	(2)	(3)	(4)
	CIT	CIT	CIT	CIT
TRAINSHARE	0.0155^{***}	0.0069^{***}	0.0088^{***}	0.0077^{***}
	(0.0002)	(0.0003)	(0.0004)	(0.0003)
SHARET	0.0861^{***}	-0.0696^{***}	-0.0865^{***}	-0.0715^{***}
	(0.0044)	(0.0026)	(0.0031)	(0.0029)
TRAININT SHARET		0.0013^{***}	0.0015^{***}	0.0014^{***}
		(0.0000)	(0.0000)	(0.0000)
$(SHARET)^2$	-0.0044^{***}			
	(0.0002)			
$\log(RDINT)$	0.4838^{***}	0.4949^{***}	0.3802^{***}	0.4337^{***}
	(0.0066)	(0.0065)	(0.0071)	(0.0069)
$\log(SIZE)$	0.9853^{***}	1.0067^{***}	1.2703^{***}	1.1614^{***}
	(0.0082)	(0.0083)	(0.0098)	(0.0090)
CONC			-4.6003^{***}	
			(0.0987)	
STABILITY				0.9990^{***}
				(0.0320)
N	26351	26351	15981	16967
AIC	69623.2546	68931.2181	58294.6586	61568.1285
BIC	70981.0120	70321.6926	59484.9277	62759.9384

Source: own computations on RIL-AIDA-REGPAT data. All models include regional-sectoral and time dummies. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, by looking at the second and third row of Table 5, another insightful conclusion can be derived: when we interact our information on training intensity with that regarding the use of temporary workers, we see the pure relationship between flexibility and innovation turns out to be negative, while the mediated correlation between innovation, on the one hand, and the interaction between flexibility and training, on the other, is positive. This can be immediately seen from the fact that the coefficient of our focal regressor, *SHARET*, becomes negative when the interaction between the latter and training intensity is included in the regression, while the interacted term between the two variables, *TRAININT-SHARET*, is positive and statistically significant.

The take-home message is straightforward: when firms use temporary contracts as pure flexibility buffers and do not invest in training, numerical flexibility becomes detrimental to innovation. However, this negative effect disappears when the decision to hire on a temporary basis conceals some form of long-term commitment, as signalled by the choice to complement numerical flexibility with firm-sponsored training. Tentatively, this allows us to draw a distinction between firms using temporary contracts as a screening device to identify able workers – and that normally constitute a "stepping stone" towards regular contracts – and those that use the latter as a pure flexibility buffer to cut on expected labor costs – where these contracts conversely represent a "dead end" for the workers' careers. While labor economists have been long struggling to distinguish between these inherently different types of temporary contracts – for a recent review of the literature, see Filomena and Picchio (2021), for a study of the Italian case, see Berton et al. (2011) – our results suggest that the employment of temporary workers is detrimental to innovation only when it is used as a pure flexibility buffer and thus, patently discourages the accumulation of firm-specific skills.

6. Conclusions

In this paper, we have studied the relationship between numerical flexibility and innovation both theoretically and empirically. First, by reviewing different streams of economic and managerial research (Huselid, 1995; Buchele and Christiansen 1999; Lorenz, 1999; Michie and Sheehan, 2001, 2003; Belot et al., 2002; Naastepad and Storm, 2006; Svensson, 2011; Acharya et al., 2014; Kleinknecht et al., 2014: 1210), we have recalled that longer labor contracts are conducive to larger human capital investments. Second, we have recalled that the workers' human capital stands as a key antecedent for the development of new organizational and technical knowledge, thus constituting a key element of successful innovation. In doing that, we have also highlighted that the accumulation of firm-specific skills hinges on two pillars: on the workers' incentives to invest in their own human capital as well as on the employers' willingness to pay for firm-sponsored training. Third, following previous contribution in the literature (Kleinknecht et al., 2014; Wachsen and Blind, 2016), we have recalled that the typo of innovation regimes – "routinized" vs "entrepreneurial" (Malerba and Orsenigo, 1996; Breschi et al., 2000) – is not neutral when it comes to assessing the relationship between temporary workers and innovation. The idea is that the amount of freely available knowledge depends on the type of innovation regimes and thus, that the poor accumulation of firm-specific skills is more detrimental in situations where firms cannot rely on external substitutes.

To put together these different insights, we have developed a game-theoretic model where the relationship between temporary workers and innovation is driven by the trade-off between flexibility and human and capital accumulation. Our theoretical predictions are then tested using firm-level data on employment composition and patents acquisition in Italy. Using forward citations to measure the economic value of the firms' knowledge stocks, we find that the relationship between quality of innovation and flexibility has the form of an inverted U, suggesting that a positive share of temporary workers is key to successful innovation, but also, that this share must be lower than a critical threshold beyond which the losses of human capital resulting from temporary employment become too severe to implement an innovative strategy. In addition, we have shown that such relationship is crucially driven by the firms' training decision, as the positive link between flexibility and innovation is only confirmed for firms extending their training programs to those under temporary contracts. This evidence provides further support to the long-debated idea that temporary contracts are not all alike, as firms may use the latter as a screening device to select more talented workers or, conversely, as pure flexibility buffers to economize on expected labor costs. If this diction is relevant to discuss the policy implications of labor market deregulation in terms of employment stability and worker well-being, it is equally important to understand its economic consequences on investments and innovation, precisely as shown by the present paper.

The results of this paper open up interesting avenues for further research. First, some more efforts are needed to ascertain the differential impact of the various typologies of fixed-terms contracts on innovation, by explicitly accounting for separations and transformations in permanent contracts. Second, future research should aim at developing an empirical framework able to assess the causal relationships between the dependent variable and the focal regressor. This is indeed a major limitation of this paper. Third, in view of the relationship between the use of fixed-term contracts and innovation, it would be interesting to investigate how the excessive reliance on fixed-term jobs might hinder the capacity of firms to respond to external shocks and economic crises.

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Appendix: Proofs

1. Proof of Lemma 1

Maximizing equations (1) and (2) and solving the f.o.c. for λ gives the best-response functions in equations (3) and (4). Comparing these, we see that $\lambda_P(\tau_P) - \lambda_T(\tau_T) \geq 0$ iff $\tau_P/\tau_T \geq 1 - s(1-ap)$, which is always satisfied iff $\tau_P \geq \tau_T$. Finally, differentiating $\lambda_P(\tau_P) - \lambda_T(\tau_T)$ w.r.t. to s and p gives, respectively, $\partial[\lambda_P(\tau_P) - \lambda_T(\tau_T)]/\partial s = (1-ap)\tau_T > 0$ and $\partial[\lambda_P(\tau_P) - \lambda_T(\tau_T)]/\partial p = sa\tau_T < 0$ ■

2. Proof of Lemma 2

Maximizing equations (6) w.r.t. τ_T and τ_P gives equations (8) and (9). That $\tau_P^* \geq \tau_T^*$ follows from the fact that s, p and a are all < 1. Differentiating τ_P^* and τ_T^* w.r.t. to α and s, in turn, gives $\partial\tau_P^*/\partial\alpha = 1 - s > 0$, $\partial\tau_T^*/\partial\alpha = [1 - s(1-ap)](1-s) > 0$, $\partial\tau_P^*/\partial s = -\alpha < 0$ and $\partial\tau_T^*/\partial s = -[1 + (1-2s)(1-ap)]\alpha < 0 \; \forall \; a, s, p \in (0,1)$, which proves the last part of Lemma 2 ■

3. Proof of Proposition 1

Inserting the optimal training intensities derived in Lemma 2 in the workers' human capital investments derived in Lemma 1 we obtain the equilibrium levels of λ_i^*. Inserting these in equations (6) and maximizing w.r.t. P and T, gives equations (10) and (11). Differentiating P^* and T^* w.r.t. to α, in turn, gives $\partial i^*/\partial\alpha = \tau_i^* \, \partial\tau_i^*/\partial\alpha \, , i = \{P; T\}$, which are both > 0 according to Lemma 2. In addition, and always according to Lemma 2, we have that $\tau_P^* > \tau_T^*$ and $\partial\tau_P^*/\partial\alpha > \partial\tau_T^*/\partial\alpha > 0$, which is sufficient to prove that $\partial P^*/\partial\alpha > \partial T^*/\partial\alpha$. Finally, differentiating P^* and T^* w.r.t. to s gives $\partial P^*/\partial s = \tau_P^* \, \partial\tau_P^*/\partial s - \beta$ and $\partial T^*/\partial s = \tau_T^* \, \partial\tau_T^*/\partial s - (\beta - w)$, which are both < 0 according to Lemma 2. In addition, and always according to Lemma 2, $\partial\tau_P^*/\partial\alpha \gtreqless \partial\tau_T^*/\partial\alpha$, which is sufficient to prove that $\partial P^*/\partial s \gtreqless \partial\tau_T^*/\partial s$ ■