

For the rest of our lives:

Flexibility and innovation in Italy

We study the effect of temporary workers on innovation both theoretically and empirically. First, we develop a model where a representative firm chooses between different types of projects (routine vs innovative) and different types of labor contracts (temporary vs permanent). In doing so, it considers the effect of these different strategies on the workers' incentives to invest in firm-specific skills. Our key finding is that firms offering temporary contracts are less likely to invest in innovative projects, and that this effect is stronger in industries characterized by a "garage-business" innovation regime. Second, we test our hypotheses using firm-level data on employment composition and patent filing. Consistently with our theoretical predictions, we find that temporary workers are detrimental to innovation, and that this effect is mitigated by the concentration of patent-filing at the industry-level.

Keywords: temporary jobs; innovation; citations; Schumpeterian regimes; game theory

JEL classification: J50, M50, O15, O31.

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).

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, Manning and Salomons, 2014).

While these studies have focused on the impact of innovation on labour 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 labour market dynamics on innovation. This literature moves from the established tenet concerning the importance of human capital for firms' innovation and productivity (Bartelsman et al., 2014). Different channels are at stake in this respect.

On the one hand, better trained or better educated people are more productive in knowledge-intensive if not explicitly innovative tasks, thereby playing a direct role in the firms' innovation performance. On the other hand, according to the resource-based theory of the firm¹, even when these individuals are not directly involved in R&D or knowledge production,

¹ In this framework, successful organizations are considered as "resource-pickers" that compete to seize the assets with the highest productivity (e.g., Barney, 1991).

they likely generate new tacit expertise, that, in turn, stands as a key antecedent for the codification of new organizational and technical knowledge (Foss, 1997, 1998; Penrose, 1959). Moreover, the dynamic-capabilities approach posits that organizations are loci of competences accumulation that create value through the continuous building of superior capabilities and organizational rules (Teece et al., 1997).² To survive and increase their fitness with the environment, firms must find ways to secure the skills that nurture adaptation and change. These dynamics lead to the accumulation of skills, knowledge and competences that are largely embodied in the workers' human capital, and are likely to contribute to firms' innovation outcomes (Consoli et al., 2021).

In view of these considerations, the basic question arises as to what extent firms' innovation is hampered by the loss of firm-specific human capital. Research in this avenue has focused on two main issues. The first one concerns the impact of labour 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 one focuses on the relationship between the employment of temporary workers and firms' innovation outcomes, highlighting the adverse effects of labour market deregulation and flexibility on more or less formalized innovation activities (Guarascio et al., 2019; Wachsen and Blind, 2016; Franceschini and Mariani, 2015; Kleinknecht et al., 2014; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; Michie and Sheenan, 2003).

This paper contributes to the last stream of literature. Specifically, we address both theoretically and empirically a key research question related to how temporary workers affect the firm's innovation performance. From a theoretical standpoint, we develop a simple model that analyzes how workers' incentives to invest in firm-specific skills are affected by the type of project (routine vs innovative) and labor contract (temporary vs permanent) chosen by the

² For a comparison of these approaches, see Makadok (2001).

firm, and how these, in turn, influence the innovation performance of the latter. Our key theoretical finding is that firms offering temporary contracts are less likely to invest in innovative projects. In addition, we highlight a mechanism whereby this effect is stronger in younger industries characterized by a “garage-business” or “entrepreneurial” innovation regime. This is at odds with a number of previous results that emphasize that flexibility should have no impact on the firms’ innovation performance in sectors that tend towards this type of innovation regime (Kleinknecht et al., 2014; Wachsen and Blind, 2016)³.

Our theoretical predictions are then tested using an original dataset containing firm-level information on numerical flexibility, patent filing activities, R&D expenditures, and a number of relevant controls. In line with previous findings (Guarascio et al., 2019; Wachsen and Blind, 2016; Franceschini and Mariani, 2015; Kleinknecht et al., 2014; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; Michie and Sheenan, 2003) we find that temporary workers are detrimental to innovation. In addition, we make three complementary contributions.

First, by using information on patent filing and citations, we depart from the studies that focus on the relationship between temporary workers and innovation inputs, such as R&D expenditures (see, e.g., Kleinknecht et al., 2014). Indeed, these measures may be partially misleading when it comes to the assessment of firm-level innovation performances (Griliches, 1990). Second, by using OECD patent quality indicators (Squicciarini et al., 2013) and the number of forward citations in a 7-year window (Colombelli et al. 2020) we do not only consider the size of the knowledge stock of the firm, but also, its economic value (Trajtenberg, 1990; Hall et al., 2005; Sandner and Block, 2011). Third, by following previous contributions in the literature (Kleinknecht et al., 2014; Wachsen and Blind, 2016; Guarascio et al., 2019), we account for the concentration of patent-filing at the industry level by means of a standard Herfindahl-Hirschman index that proxies the nature of the innovation regime (“routinized”

³ For further discussions, see section 2.2

when concentration is high; “entrepreneurial” when concentration is low). In line with our theoretical predictions – but in contrast with previous findings (Kleinknecht et al., 2014; Wachsen and Blind, 2016) – we find that the negative effect of temporary workers on innovation is mitigated in industries where the issuing of new patents is more concentrated.

The rest of the paper is organized as follows. Section 2 reviews the literature on the relationship between temporary labor 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. Background

2.1. Related literature

From a theoretical viewpoint, the relationship between temporary workers and innovation can be ambiguous. 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 (see, e.g., Nickell and Layard, 1999). In addition, incumbents may leverage on their insiders’ position to bargain higher wages or supply less effort (Malcomson, 1997).

On the other hand, as recalled by Kleinknecht et al. (2014) and argued by Belot et al. (2002) “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” (Kleinknecht et al., 2014: p. 1210). As innovation is to a large extent firm-specific, this seems to suggest that temporary workers will be more productive in routine than in innovative activities. In addition, several studies show that “high road” human resources management (HRM) practices have a positive effect on

innovation, as the use of permanent contracts can be seen as a signal of trust that foster long-term commitment and human capital accumulation—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 then empirically show that the passage of wrongful discharge laws has a positive effect on labor effort, and thus, by extension, on innovation.

A key point in the above discussion is that both innovation and human capital accumulation require long-lasting processes of organizational learning that involve a two-way exchange between the organization and its 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 on-the-job training. A key but often forgotten requirement of these transmission channels, however, is that workers must be willing to learn. As rightfully recalled by Kräkel (2016), in fact, “traditional human capital theory assumes that a worker has no choice whether to acquire knowledge or not. 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” Kräkel (2016: p. 627).

In this view, the strategic dimension of learning is a crucial pillar underpinning employees’ incentives to spur innovation. Manso (2011) argues that the innovation-motivating contract shows tolerance for early failures and reward for long run success, while Acharaya et al. (2014) find that wrongful discharge laws spur innovation by securing better employment protection. Grinza and Quatraro (2019), in turn, show that workers’ replacements have a negative effect on the number of patent applications, and that this effect is larger the longer is 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” (Grinza and Quatraro 2019: p. 7).

Despite this unsolved theoretical puzzle, the available evidence is almost unanimous in claiming that flexible work has a negative effect on innovation—see, e.g., Franceschini and Mariani (2015), Dekker et al. (2011), Lucidi and Kleinknecht (2009) and Michie and Sheenan (2003). Both Kleinknecht et al. (2014) and Wachsen and Blind (2016) takes it one step further and 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), as firms in this regime put relative emphasis on their historically accumulated knowledge rather than on that which is generally available in the workers’ human capital.⁴ 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. Malgarini et al. (2013), in turn, use Italian data and show that the negative relationship between flexible labor and innovation is confined to the period preceding the financial crisis of 2008, after which innovating firms seem more likely to hire on a temporary basis.

Opposite conclusions are reached by Arvanitis (2005), who 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) stand somewhat in between these opposite poles, 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. This seems to

⁴ The Schumpeterian concept of “innovation regime” is reviewed in Malerba and Orsenigo (1995)

suggest that a certain degree of numerical flexibility is a prerequisite for innovation, but also, that the relationship between temporary workers and innovation is non-monotonic.

2.2. On innovation regimes

Kleinknecht et al. (2014) postulate that firms operating in a “routinized” regime must rely greatly on the tacit knowledge accumulated in the past and thus, encourage their employees to invest in firm-specific human capital by hiring on a permanent basis.⁵ In this view, the negative effect of temporary workers on the firms’ innovation performance should be weakened in industries that tend towards an “entrepreneurial” innovation regime. Both their and Wachsen’s and Blind’s (2016) findings confirm this intuition. That permanent contracts provide workers with greater incentives to invest in firm-specific human capital is uncontroversial. However, an alternative mechanism may also be in place.

As industries approach maturity and the main foundations of their knowledge base have already been laid, in fact, innovation becomes less erratic, since organizations tend to follow partially codified paths when pursuing an innovative project. As a result, innovation across firms starts to display significant homogeneity, and innovative skills becomes somewhat portable outside the firm. Hence, in “routinized” innovation regime, temporary workers employed in innovative projects will be able to recover a part of their human capital investment when moving across firms and this, in turn, generates greater incentives to invest in the acquisition of innovative skills. Conversely, in a more “entrepreneurial” or “garage-business” regime that normally characterizes younger industries, the major breakthroughs in innovation patterns are yet to be introduced and innovative efforts are purely firm-specific. When there is no convergence towards a technological paradigm, in fact, firms pursue their innovative

⁵ Differently from Kleinknecht et al. (2014) who use data on R&D expenditures, we use the concentration index of patent applications to proxy the idea of innovation regimes. In doing so, we follow the common classification strategy where higher (resp., lower) concentration rates indicate a routinized (resp., entrepreneurial or garage business) innovation regime.

projects following routes that are idiosyncratic and heterogeneous. The upshot is that innovative skills are not portable outside the firm and hence, that temporary workers will lose their human capital investment when changing occupation. The model in the next section rationalizes these mechanisms.

In view of the discussion conducted so far, we can summarize as follows the main working hypotheses that will drive the development of the model and the empirical analysis:

- (i) The workers' human capital stands as a key antecedent for the development of new organizational and technical knowledge.
- (ii) Open-ended contracts are conducive to greater human capital investments, as the benefits of skill accumulation will endure in the long run.
- (iii) Firm-specific skills developed in innovative projects are not portable outside the firm. Hence, temporary workers will accumulate more human capital when employed in routinized activities.
- (iv) As industries approach maturity, innovation patterns become less erratic. Hence, innovative skills should be more portable in a "routinized" than in a "entrepreneurial" innovation regime.

3. The model

In this section we develop a two-stage game where a firm (F , "she") hires an employee (E , "he")) to work on a chosen project. In the first stage, F chooses between two activities that differ in their degree of innovation. We denote the "routine" project by R and the "innovative" project by I . Following Acharya et al. (2014), we assume that key distinction between the two is that project- I is riskier but potentially more profitable than project- R —see section 3.2. Besides choosing the project, F chooses whether to offer E a temporary (T) or a permanent (P) contract.

In the second stage of the game, E makes a learning choice and decides whether to invest in human capital. As in Kräkel (2016), we assume that human capital investments reduce the cost of effort. In addition, we let the benefits of effort-reduction to vary according to the type of project and labor contract chosen by F and to the dominant innovation regime, where we follow the standard classification in the Schumpeterian literature and distinguish between “entrepreneurial” and “routinized” regimes that characterize, respectively, young and mature industries.

A key driver of E 's learning decision is the degree of human capital portability. When human capital is purely firm-specific, temporary workers have lesser incentives to learn, as the future gains from their human-capital investment are nil.⁶

As usual, we solve the game by backward induction. Hence, we first analyze E 's decision to invest in human capital and then, given this, F 's hiring and investment strategy.

3.1. E 's learning decision

E lives for two periods, t_1 and t_2 . At the beginning of t_1 , F hires E to work on a chosen project under a given labor contract. All projects last for one period, at the end of which, wages are paid, and profits are collected. For the sake of simplicity, we assume that E has no incentive to leave F when he is offered a permanent contract and, in addition, that he will work on the same type of project that F has chosen in t_1 also in t_2 .⁷ Conversely, when he is offered a temporary contract, we assume that he will either remain unemployed or find another job (either temporary or permanent) in t_2 .

At the beginning of t_1 , E makes a learning decision and chooses whether to costly invest in human capital. As in Kräkel (2016), we assume that learning reduces the cost of effort when

⁶ That human capital is neither completely general nor completely firm-specific is now empirically established—see, e.g., Neal (1995), Poletaev and Robinson (2008), Zangelidis (2008), and Suleman and Lagoa (2013).

⁷ As it will appear below, when F finds it optimal to choose a given project in t_1 , there is no reason why it should switch to the other project in t_2 but for exogenous changes in the model's parameters.

E works for F . In addition—and always in line with Kräkel (2016)—we assume that E may be able to recover some of her human capital investment also when he works for a different employer, depending on the degree of portability (or generality) of the acquired skills.

Our working hypothesis is that the skills acquired in innovative projects (hereafter, innovative skills) are less portable than those acquired in routine projects (hereafter, routine skills). The idea is that while innovation is firm-specific, routine activities tend to be similar across firms, at least in the same sector, and, in addition, that some routine skills may be useful in innovative projects as well. Hence, when F chooses the innovative project and offers a temporary contract, E will lose some of her human capital investment in t_2 .

Moreover, we assume that the portability of innovative skills depends on the dominant innovation regime. In particular, we assume that innovative skills are (at least partly portable) under a routinized innovation regime, while they are purely specific in entrepreneurial regimes—see section 2.2. for a discussion. To summarize, we make a threefold assumption:

Assumptions:

- 1) *Learning reduces the cost of effort when E works for F .*
- 2) *Routine skills are always portable outside the firm.*
- 3) *Innovative skills are portable outside the firm only when the innovation regime is “routinized”.*

Formally, we assume that when E is offered a temporary contract, he chooses $\lambda \in (0,1)$ —where $\lambda = 1$ indicates that he learns and $\lambda = 0$ indicates that he does not learn—to maximize:

$$U_T^I(\lambda) = w_T - e(1 - \lambda) + r \left\{ uw_0 + (1 - u) \left[\frac{w_P + w_T}{2} - e(1 - \delta\lambda p) \right] \right\} - c\lambda \quad (1)$$

$$U_T^R(\lambda) = w_T - e(1 - \lambda) + r \left\{ uw_0 + (1 - u) \left[\frac{w_P + w_T}{2} - e(1 - \lambda p) \right] \right\} - c\lambda \quad (2)$$

where the superscript (I, R) indicates the type of project and the subscript (T) the type of labor contract. The first and second terms on the r.h.s. of equations (1) and (2) measure E 's payoff when he is employed in t_1 —where $w_T \geq 0$ is the temporary wage and $e > 0$ measures the cost of effort; the third term measures E 's payoff when he is unemployed in t_2 —where $0 < r < 1$ is the discount rate, $0 < u < 1$ is the unemployment rate and $w_0 \geq 0$ is E 's reservation wage; the fourth and fifth terms measure E 's payoff when he is employed in t_2 —where we have assumed that E has the same probability = $1/2$ of finding a temporary and a permanent job, where $w_p > w_T$ is the permanent wage; and the sixth term measures the cost of learning, so that $c > 0$. In what follows, we impose the following normalizations: $w_T = w_0 = 0$ and $w_p = w > 0$.

Our first assumption, that learning reduces the cost of effort when E works for F , is captured by the second term in equations (1) and (2), where we have specified the cost of effort in t_1 — $e(1 - \lambda)$ —as a decreasing function of λ . Our second assumption, that routine skills are always portable outside the firm, is captured by the fifth term in equation (2), where we have specified the expected cost of effort in t_2 — $re(1 - u)(1 - \lambda p)$ —as a decreasing function of λ and p , where $0 \leq p \leq 1$ measures the portability of human capital or, alternatively, its degree of generality. Our third assumption, that innovative skills are portable outside the firm only when the dominant innovation regime is “routinized”, is captured by the fifth term in equation (1), where we have specified the expected cost of effort in t_2 — $re(1 - u)(1 - \delta \lambda p)$ —as a decreasing function of λ , p and δ , where $\delta = 1$ indicates a “routinized” regime and $\delta = 0$ indicates an “entrepreneurial” regime.

Similarly, when E is offered a permanent contract, we assume that she chooses $\lambda \in (0,1)$ to maximize:

$$U_p^I(\lambda) = U_p^R(\lambda) = w_p - e(1 - \lambda) + r[w_p - e(1 - \lambda)] - c\lambda \quad (3)$$

where the superscript (I, R) indicates the type of project and the subscript (P) the type of labor contract. The interpretation of equation (3) is analogous to equations (1) and (2).

The following Proposition analyzes the different learning incentives across the different combinations of types of projects and labor contracts:

Proposition 1—*Permanent contracts lead to greater human capital investments than temporary contracts, and routine projects lead to greater human capital investments than innovative projects. In particular:*

- (i) *Assume that F chooses the innovative project, that she offers the temporary contract and that the innovation regime is entrepreneurial. In this case, E invests in human capital if $c \leq e$;*
- (ii) *Assume that that F offers the temporary contract, and the innovation regime is routinized. In this case, E invests in human capital if $c \leq e[1 + r(1 - u)p]$, regardless of the type of project chosen by F .*
- (iii) *Assume that F chooses the routine project and offers the temporary contract. In this case, E invests in human capital if $c \leq e(1 + r)$, regardless of the innovation regime.*
- (iv) *Assume that F offers the permanent contract. In this case, E invests in human capital if $c \leq e(1 + r)$, regardless of the type of project and innovation regime.*

Proof: See the Appendix.

The next step is to analyze F 's investment and hiring decision at stage 2 given E 's learning decision at stage 1.

3.2. *F*'s decision: equilibrium project and equilibrium labor contract

At stage 1, *F* chooses the type of project and labor contract. Formally, we assume that *F* selects a couple $\tau \in (0,1)$ and $\rho \in (0,1)$ to maximize its payoff given *E*'s investment in human capital at stage 2, where $\tau = 1$ indicates that *F* offers the temporary contract and $\tau = 0$ that it offers the permanent contract; while $\rho = 1$ indicates that *F* chooses the routine project and $\rho = 0$ that she chooses the innovative project. Differently from *E* who makes decisions considering their effects in both t_1 and t_2 , *F* is only interested in t_1 , as wages are paid, and profits are collected at the end of each period.

For simplicity, we assume that both projects require the same amount of initial investments, which are normalized to zero. To model the idea that project-*I* is riskier but potentially more profitable than project-*R*, we follow Acharya et al. (2014) and assume that project-*I* yields greater payoffs than project-*R* when both are successful, while project-*R* yields greater payoffs than project-*I* when both are unsuccessful. Hence, denoting the returns to project *j* when the latter is successful as a_j and the returns to project *j* when the latter is unsuccessful as $b_j, j = I, R$, we assume that $a_I = A; a_R = B; b_R = C; b_I = D$, where the ordering $A > B > C > D$ naturally follows from the above assumptions. To keep things simple and avoid obfuscating the mechanisms at play, we assume that project *j* is successful when *E* decides to learn ($\lambda = 1$) and unsuccessful when *E* does not learn ($\lambda = 0$), $j = I, R$.⁸

The following Proposition analyses *F*'s decision concerning the type of project and labor contract given *E*'s human capital investment:

⁸ Alternatively, we may assume that *E* produces valuable output with probability $s(\lambda)$ and zero output with probability $1 - s(\lambda)$, where *E*'s learning decision affects positively the success probability so that $1 > s(1) > s(0) > 0$. Despite more realistic, this specification adds little to our results.

Proposition 2—*In equilibrium, F does not choose the routine project and offer a permanent contract. In addition:*

- (i) *When learning costs are low— $c < e$ —F chooses the innovative project and offers the temporary contract, while E invests in human capital.*
- (ii) *When learning costs are medium-low— $e < c < e[1 + r(1 - u)p]$ and the innovation regime is routinized, F chooses the innovative project and offers the temporary contract, while E invests in human capital.*
- (iii) *When learning costs are medium-low— $e < c < e[1 + r(1 - u)p]$ —the gains from innovation are large— $A - w > B$ —and the innovation regime is entrepreneurial, F chooses the innovative project and offers the permanent contract, while E invests in human capital.*
- (iv) *When learning costs are medium-low— $e < c < e[1 + r(1 - u)p]$ —the gains from innovation are small— $A - w < B$ — and the innovation regime is entrepreneurial, F chooses the routine project and offers the temporary contract, while E invests in human capital.*
- (v) *When learning costs are medium-high— $e[1 + r(1 - u)p] < c < e(1 + r)$ —F chooses the innovative project and offers the permanent contract, while E invests in human capital.*
- (vi) *When learning costs are high— $c > e(1 + r)$ —F chooses the routine project and offers the temporary contract, while E does not invest in human capital.*

Proof: See the Appendix.

Proposition 1 suggest that firms offering temporary contracts are less likely to invest in innovative projects.; despite this negative effect should be weaker in industries that tend towards a “routinized” innovation regime. The next step is to test these hypotheses by inquiring empirically in the relationship between temporary contracts and innovation.

4. Data, variables and methodology

4.1. Data

The two hypotheses of our theoretical model are tested using three different sources of information. First, to retrieve information on numerical flexibility, we rely on the first three waves (2005, 2007 and 2010) of the Employer and Employee Survey (*Rilevazione Longitudinale su Imprese e Lavoro* [RIL]) conducted by the National Institute for Public Policy Analysis (INAPP). Each of these wave 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. In addition, a subsample of the included firms (around 35%) is followed over time, making the RIL dataset partially panel over the period under study. For obvious reasons, individual firms with less than 1 employee have been excluded from the analysis.

To introduce balance-sheet information in our dataset, we use the firms' tax number to merge the RIL with the AIDA database by Bureau van Dijk. The data included in AIDA offer comprehensive information on the balance sheets of almost all the Italian corporations operating in the private sector, except for the agricultural and financial industries. From this archive, we draw information on R&D expenditures.

Finally, we use the OECD REGPAT dataset to draw information on the firms' patent-filing activities applications to the European Patent Office are extracted for the period 2002-2013. This has been merged with balance sheet data following the matching procedure developed by Lotti and Marin (2013).

4.2. Variables

The purpose of this paper is to investigate the relationship between numerical flexibility and firms' innovation outcomes. These latter are proxied by measures drawing on patent

statistics⁹. Accordingly, we calculate two dependent variables that can provide a reasonable approximation of firm-level innovation dynamics. First, we calculate firms' knowledge stock by applying to patent flows the permanent inventory method (PIM) that assumes a yearly depreciation rate (σ) of 15% (Hall, 1999), as it follows:

$$KNOWLEDGE\ STOCK_{it} = PAT_{it} + (1 - \sigma)PAT_{STOCK_{it-1}}$$

Second, firms' innovation outcomes can be very different from one another as far as their quality is concerned. For this reason, we follow the empirical literature and develop a dependent variable reflecting the technological importance of the patent and the economic value of inventions (Trajtenberg, 1990; Hall et al., 2005). This additional dependent variable, $Citations_{i,t}$, draws upon the OECD patent quality indicators (Squicciarini et al., 2013) and on the forward citations a patent has received in a 7-years window (Colombelli et al., 2020). This is the yearly stock of citations to all of the patents of the firm, deflated using the PIM with a depreciation rate of 15%, 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).

Our focal regressor concerns the share of temporary workers ($SHARET$) hired by the firm at each period. This is calculated as the ratio between the number of employees with temporary contracts and the total number of employees hired by the firm.

Consistently with our focus on the relationship between flexibility and innovation *output*, we proxy the notion of innovation regimes by constructing two indicators. First, we build an Herfindahl-Hirschman index (HHI) that measures the concentration of patents applications in a given industry. This is a key difference with, for example, Kleinknecht et al. (2014), who

⁹ 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 most reliable than R&D statistics or self-reported survey-based information.

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 (RHO). This provides us with a proxy of the stability of the relative positioning of innovators in the sector. According to the extant literature, a turbulent environment is associated with the Schumpeter Mark I regime (RHO close to 0), while a stable environment is associated with a Schumpeter Mark II regime (RHO close to 1).

Finally, to proxy the inputs of the knowledge production function, we include as a regressor in the estimations the R&D intensity ($RDINT$), calculated as the ratio between firms’ R&D expenditures and total employment (Giliches, 1984).

Table 1 provide the descriptive statistics of our main variables, while Table 2 reports the correlation matrix. Unsurprisingly, our sample features a large share of very small firms (30 percent have less than 9 employees), which is line with previous evidence on the system of Italian enterprises (Sestito and Torrini, 2020). There are on average 55 employees per firm and 3 managers, while 13 % of the total workforce is employed on a temporary basis.

>>> INSERT TABLES 1 AND 2 ABOUT HERE <<<

4.3. Methodology

As discussed above, we investigate the effect of temporary workers on the firms’ innovation outcomes by using two different dependent variables. First, we consider how numerical flexibility impacts on the *size* of the knowledge capitals by using data on patent

applications. Second, we follow Colombelli et al. (2020) and assess the effect of flexible labor on the patents' forward citations to control for the *quality* and economic value of inventions (Sandner and Block, 2011). Both relationships are estimated with a Poisson fixed-effects 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). Our baseline estimation strategy is reported in equation (4):

$$P_{it,t+7} = \alpha + \delta SHARET_{i,t-1} + \varphi RDINT_{i,t-1} + \beta X_{i,t-1} + \gamma_t + \eta_i + \varepsilon_{i,t} \quad (4)$$

where $P_{it,t+7}$ refers to either the size or the quality of the knowledge stock of firm i at time t and the subscript $t + 7$ indicates that we consider the patents' forward citations over a 7-year time window (2006-2013). Our parameter of interest is δ , which captures the effect of labour flexibility, proxied by the share of flexible workers, $SHARET_{i,t-1}$, on firms' innovation performances. $X_{i,t-1}$ is a vector of lagged time-variant and invariant characteristics that includes the variables discussed in detail in Section 4.2 and other controls like: 1-digit sector, firm-size (in classes), a dummy indicating if the firm was involved in a merger or acquisition process (M&A) in the year prior the survey and the share of managers over the total firm's workforce. The choice of this list of controls comes from earlier theoretical and empirical studies on the determinants of innovation, (see for instance, Crepon et al. (1998)). Finally, γ_t are time dummies, η_i are firm fixed effects and $\varepsilon_{i,t}$ is the error term.

As discussed above, to control for R&D intensity, we use the balance-sheet information provided by AIDA. Moreover, to deal with the selection problem arising from the fact that only a limited number of firms undertake formal R&D activities, we predict R&D intensity using a selection equation that follows the Wooldridge's (1995) approach in a panel settings. This method has been used in several studies (see, e.g., Colombelli et al. 2020) and it allows potential R&D intensity to be predicted for non-reporting firms.

5. Estimation results

Table 3 reports our main results as concerns the effect of temporary workers on the size of the firms' knowledge stock, while Table 4 considers the same effect on the forward citations received by a patent in a 7-years window (Colombelli et al, 2020). For both outcome variables, we estimate four different specifications of the baseline model presented in equation (1) – see columns 1-4. 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 (HHI) measuring the degree of concentration of patents acquisition. The model in column 3, in turn, adds RHO, i.e. the Spearman rank correlation index of innovators hierarchy in the sectors. Finally, the full model presented in column 4 includes both the HHI and an interaction term that measures the interplay between the latter and the share of temporary workers (SHARET).

>>> INSERT TABLE 3 ABOUT HERE <<<

All of our results are in line with most of the existing literature that supports the view whereby temporary workers are detrimental to innovation (Guarascio et al., 2019; Wachsen and Blind, 2016; Franceschini and Mariani, 2015; Kleinknecht et al., 2014; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; Michie and Sheenan, 2003).¹⁰ Starting from knowledge stocks, we observe that temporary workers have a negative and statically significant effect on patents applications across all specifications considered – see Table 3. In addition, all our controls have intuitive and reasonable signs: larger firms and higher shares of managers, in fact, lead to more patent applications, and this is also true, *ceteris paribus*, for those who engage in M&A operations. In Model 2, the Herfindahl-Hirschman index is positively correlated with the

¹⁰ 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.

number of patent applications, thus suggesting that the degree of patenting concentration has a positive effect on innovation, *ceteris paribus*.

More to the point, it is important to stress that the full specification presented in column 4 of Table 3 confirms a key prediction from our theoretical model, that is, that the negative effect of numerical flexibility on innovation is mitigated in industries that tend towards a “routinized” innovation regime – see section 2.2 for a rationalization. Indeed, while the increase in the share of temporary workers have a direct and negative effect on the knowledge stock of the firm (the effect of *SHARET* is negative and significant), a higher degree of patenting concentration seems to be conducive to more innovation (the effect of *HH* is positive and significant). When we look at the interaction between these terms, however, we see that the negative effect of temporary workers on innovation seems to disappear in industries where the patenting activities are more concentrated (the effect of the interaction term is positive and significant).

>>> INSERT TABLE 4 ABOUT HERE <<<

The relationship between numerical flexibility and the number of citations seems to confirm the picture that we have just described, but for the fact that the interpretation of the interaction term described in the above is now less clear-cut. From a closer inspection of the full specification reported in column 4 of Table 4, in fact, we see that once we include both the direct effect of patenting concentration and the interaction term between temporary workers and the latter, the negative effect of numerical flexibility on the quality of the firms’ knowledge stock is still negative but not significant anymore, while the coefficient of the Herfindahl-Hirschman index is still both positive and significant. In addition, the interaction between these terms is now negative but not statistically significant. Despite these results are less robust than those obtained in the previous section, they are loosely in line with the idea that the negative

effect of temporary workers on innovation is mitigated by the industry-specific concentration of knowledge.

5.1. Are temporary workers all alike? Some additional evidence

The evidence discussed so far provides a clear picture in which increasing shares of temporary workers in firms' boundaries hinders the unfolding of innovation capacity. This is consistent with our theoretical model in which firms decide to hire using open-ended contracts when they are prone to carry out innovative projects. Indeed, according to the resource-based theory of the firm, successful innovation dynamics require the accumulation of firm-specific capabilities via learning dynamics. On the contrary, workers with fixed-term contracts have less incentives to commit time and efforts to develop firm-specific skills because of their lower portability outside firm's boundaries.

However, it is important to stress that firms in Italy, like in other countries, may choose different typologies of fixed-term contracts, i.e. apprenticeship or temporary contracts (Picchio and Staffolani, 2019; d'Agostino et al., 2019). Accordingly, we further decompose the overall measure into two main components: one attributable to pure fixed-term contracts only, and another one related with apprenticeship, training and work contracts and job insertion contracts. This decomposition offers two important advantages. First, it enables us to provide a more accurate picture of the Italian labour market, characterized by a large variety of contractual arrangements¹¹. Second, it allows us to shed some light on the mechanisms that some specific type of temporary contracts, like those related with job training, might generate on the innovative process of a firm. Indeed, apprenticeship, training and work contracts and job

¹¹ The process of labor market deregulation started in the mid-1990s (with the "Treu package" in 1997, the Legislative Decree 368 of 2001, and the Law 30 of 2003) in Italy, has introduced various types of temporary contracts with fixed-term contracts being amongst the most popular, accounting for around 7% of the workforce, but also other forms of contractual arrangements like for instance apprenticeship, at approximately 3% of the workforce (see Devicienti et al. 2008).

insertion contracts normally involve programs of on-the-job training and they can often be viewed as “ports of entry” into regular contracts. Conversely, more standard fixed-term contracts do not receive on-the-job training, and are associated to lower transition probability to permanent jobs (Picchio and Staffolani, 2019; Berton et al., 2011).

In tables 5 and 6 we provide estimations of the differential impact of temporary vis-à-vis apprenticeship contracts on innovation, focusing respectively on firms’ knowledge stock, and on citation-weighted knowledge stock as outcome variables. To carry out these estimations we have proceeded as follows. We have first calculated the ratio between apprenticeship and temporary contracts. The value of interest of this variable is one, which signals a perfect balance in the use of the two types of fixed-term contracts. Then we have built two symmetric dummy variables: *SHARE_A* takes value 1 if the ratio between apprenticeship and temporary contracts is greater than, or equal to, 1, zero otherwise; *SHARE_TC* takes value 1 if the ratio between apprenticeship and temporary contracts is lower than 1, zero otherwise. Finally, we have interacted these two dummy variables with the variable *SHARET*, so as to ascertain the differential impact of *SHARET* when fixed-term jobs are biased towards temporary or apprenticeship contracts. The estimations are therefore restricted to firms in the sample hiring at least one employee with a fixed-term contract.

>>> INSERT TABLE 5 ABOUT HERE <<<

In table 5 we report the results of the baseline estimations of the impact of fixed-term jobs on firms’ knowledge stock, by disentangling the differential effect of temporary and apprenticeship contracts. For what concerns our control variables, one can observe that the coefficient of R&D intensity is positive and significant in two out of the three estimated models, in line with our expectations. The same applies to the dummy for merger and acquisitions (M&A). The variables proxying the innovation regime show coefficients that are consistent with

the previous estimations, i.e. HHI has a positive and significant coefficient, while the coefficient of RHO is not significant.

Let us turn now to the variables of interest, i.e. the interactions between SHARET on the one hand, and SHARE_A and SHARE_TC on the other hand. The econometric results suggest that the negative impact of fixed-term jobs on innovation is driven by apprenticeship contracts, while temporary contracts seem not to have any significant impact. This result is apparently surprising, in view of the main characteristic of apprenticeship contracts, i.e. the compulsory training of hired personnel to favour the accumulation of human capital via formalized or non-formalized training. Actually, the extant literature suggests that people hired with these contracts are more likely to get a permanent job than people hired with temporary contracts. However, the literature also stresses that after the 2003 “Biagi reform”, the training of human capital within apprenticeship contracts has substantially lost the general component, so as to privilege the accumulation of firm-specific competences. Moreover, since these contracts imply substantial lower costs of hiring, in many cases they are not used to address real firms’ need, but to cope in a cheap way with demand fluctuations (Berton et al., 2011; Picchio and Staffolani, 2019; d’Agostino et al., 2019). Another important aspect is that, overall, the share of temporary jobs that are transformed into open-ended contracts seems to be only about 29% (Picchio and Staffolani, 2019). These considerations suggest that the real issue with people hired with apprenticeship contracts could be the low rate of transformation of these jobs into permanent jobs. Actually, the human capital accumulation favoured by these kind of contracts make the loss of apprentices more costly for the firm than the loss of people hired with simple temporary contracts. This impact is particularly severe because of the firm-specific content of training activities, which implies the loss of skills and competences that can feed innovation dynamics from the factory floor (Waeyenbergh and Pintelon, 2002; Alsyouf, 2007; Kukla, 1983; Sohal et al, 2001; Deivanayagam, 1992; Consoli et al., 2021).

>>> INSERT TABLE 6 ABOUT HERE <<<

In table 6 we report instead the results of the estimations looking at the drivers of citation-weighted firms' knowledge stock. Also in this case, the evidence is much in line with the results of the previous estimations. For our purposes, it is worth stressing that when one looks at the differential impact of temporary vis-à-vis apprenticeship contracts, these latter seem to drive the negative effect of temporary jobs not only on the size, but also on the quality of innovation. Once again, we speculate that this evidence is attributable to the loss of specific human capital that is entailed by the low rate of transformation of temporary jobs into permanent jobs. Firms therefore miss the opportunity to permanently hire people with skills, competences and tacit knowledge that can be fruitful for the introduction of innovation in production processes, because of the capacity of these workers to bring new ideas in the organization (Rosenberg, 1976; Rosenberg and Steinmuller, 2016; Lewis, 2020a and Lewis, 2020b).

6. Conclusions

In this paper, we have studied the effect of temporary workers on firms' innovation performances, 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 highlighted a mechanism according to which longer labor contracts are conducive to larger human capital investments. Second, by elaborating upon the idea whereby the skills developed in innovative, firm-specific projects are often of little use outside the boundaries of the firm (Neal, 1995; Poletaev and Robinson, 2008; Zangelidis, 2008; and Suleman and Lagoa, 2013), we have drawn attention to a channel that rationalizes why workers may face greater learning incentives when employed in routinary activities. Third, by drawing on different though highly communicating

theories of the firm (Penrose, 1959; Barney, 1991; Foss, 1997, 1998; Teece et al., 1997; Makadok, 2001), 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. Fourth, we have remarked on the fact that the Schumpeterian notion of innovation regimes (see Malerba and Orsenigo, 1996) is not neutral when it comes to evaluate the workers' incentives to invest in human capital. More specifically, we advanced the working hypothesis whereby, as industries approach maturity, innovation becomes less erratic. The upshot is that innovative skills should be more portable in a "routinized" than in a "entrepreneurial" innovation regime, conversely to what postulated by previous studies (Kleinknecht et al., 2014; Wachsen and Blind, 2016).

To put together these different insights, we have then developed a simple game-theoretic model that analyzes how the workers' incentives to invest in firm-specific skills depend on the type of contract and investment project chosen by the firm. Our key theoretical finding is that firms hiring on a temporary basis are less likely to invest in innovative projects, despite this effect is weaker in industries that tend towards a "routinized" innovation regime.

Our theoretical predictions are then tested using firm-level data on employment composition and patents acquisition in Italy. In line with previous findings (Guarascio et al., 2019; Wachsen and Blind, 2016; Franceschini and Mariani, 2015; Kleinknecht et al., 2014; Dekker et al., 2011; Lucidi and Kleinknecht, 2009; Michie and Sheenan, 2003), we find that temporary workers are detrimental to innovation. Differently from Kleinknecht et al. (2014) and Wachsen and Blind (2016), however, we also find that this negative effect does not survive once we consider the type of innovation regime, as industries characterized by higher degrees of patenting concentration seem immune to the negative effect of numerical flexibility. Moreover, we have investigated whether a differential impact of temporary vs. apprenticeship contracts can be observed. Our findings, though preliminary, show that the negative effect of

temporary jobs is driven by apprenticeship contracts. Our suggested interpretation is that, since these contracts are often used by firms as a cheap way to cope with demand fluctuations, and that a small share of temporary jobs are transformed in permanent ones, separations of apprentices are more harmful than separations of workers hired with simple temporary contracts. Actually, apprentices develop firm-specific knowledge via formalized and non-formalized training activities, which they bring with themselves once outside of the firm. This latter therefore misses the important of opportunity to activate innovation dynamics originating by ideas and competences developed at the factory floor.

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-term contracts on innovation, by explicitly accounting for separations and transformations in permanent contracts. Second, future research should make an effort in developing an empirical framework able to assess the causal relationships between the dependent variable and the focal regressors. 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.

Table1: Descriptive statistics

	Obs.	Mean	Std. Dev.
<i>Innovation characteristics</i>			
Knowledge stock	58896	0.246	6.443
Citations	88600	0.014	0.269
RDINT	50960	0.072	0.235
HHI	36649	0.175	0.166
<i>Personnel characteristics</i>			
Total workforce	58822	55.453	794.191
SHARET	58821	13.361	23.066
Share of managers	58822	3.216	11.277
<i>Others</i>			
RHO		0.180	0.550
M&A (0/1)		12.76%	

Table2: Spearman's rank correlation coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1) Knowledge stock	1.000							
2) Citations	0.825*	1.000						
3) Share of managers	0.134*	0.127*	1.000					
4) RDINT	-0.033*	-0.024*	-0.150*	1.000				
5) HHI	-0.056*	-0.048*	0.016*	-0.006	1.000			
6) Rho	0.102*	0.088*	0.033*	0.053*	-0.376*	1.000		
7) SHARET	0.032*	0.020*	0.032*	-0.030*	0.012*	0.039*	1.000	
8) Total employment	0.200*	0.181*	0.365*	-0.296*	0.032*	0.023*	0.213*	1.000

The asterisks identify all correlation coefficients significant at the 5% level or lower.

Table 3: Fixed effects Poisson estimations: knowledge stock

Knowledge stock	(1)	(2)	(3)	(4)
SHARET	-0.0087*** (0.0018)	-0.0101*** (0.0020)	-0.0096*** (0.0019)	-0.0152*** (0.0037)
Share of managers	0.0122** (0.0054)	0.0173*** (0.0058)	0.0145** (0.0057)	0.0202*** (0.0061)
RDINT	0.4467** (0.2251)	1.1097*** (0.3191)	1.1688*** (0.3145)	1.1272*** (0.3195)
M&A	0.0310 (0.0451)	0.1127** (0.0531)	0.0676 (0.0505)	0.1332** (0.0545)
HHI		1.1808*** (0.2972)		0.9237*** (0.3339)
Rho			-0.2450*** (0.0848)	
Temporary & HH (interaction)				0.0519* (0.0308)
<i>N</i>	702	502	538	502
<i>AIC</i>	3062.5339	2230.2507	2389.3687	2229.4123
<i>BIC</i>	3153.6125	2310.4041	2470.8380	2313.7843

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; R&D intensity is predicted using Wooldridge (1995); all models include (i) time fixed effects, (ii) sector fixed effects; (iii) controls for firm size.

Table 4: Fixed effects Poisson estimations: citation-weighted knowledge stock

Citations	(1)	(2)	(3)	(4)
SHARET	-0.0141** (0.0062)	-0.0146** (0.0066)	-0.0141** (0.0067)	-0.0112 (0.0134)
Share of managers	0.0120 (0.0233)	0.0110 (0.0258)	0.0089 (0.0254)	0.0095 (0.0262)
RDINT	-0.2261 (0.4457)	1.3261 (0.8662)	1.2435 (0.8536)	1.2941 (0.8729)
M&A	0.0688 (0.1356)	0.2376 (0.1564)	0.2298 (0.1502)	0.2308 (0.1581)
HHI		2.5528** (1.0311)		2.7182** (1.1783)
Rho			-0.3130 (0.2744)	
Temporary & HH (interaction)				-0.0342 (0.1175)
<i>N</i>	702	502	538	502
<i>AIC</i>	3062.5339	2230.2507	2389.3687	2229.4123
<i>BIC</i>	3153.6125	2310.4041	2470.8380	2313.7843

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; R&D intensity is predicted using Wooldridge (1995); all models include (i) time fixed effects, (ii) sector fixed effects; (iii) controls for firm size.

Table 5: Fixed term vs. vocational contracts, knowledge stock

Knowledge stock	(1)	(2)	(3)
SHARET*SHARE_TC	0.0022 (0.0033)	0.0065 (0.0039)	0.0036 (0.0039)
SHARET*SHARE_A	-0.0252*** (0.0037)	-0.0251*** (0.0039)	-0.0226*** (0.0036)
Share of managers	0.0063 (0.0129)	0.0327** (0.0162)	0.0167 (0.0156)
RDINT	0.2448 (0.2368)	0.9552*** (0.3690)	1.0199*** (0.3682)
M&A	0.0639 (0.0495)	0.1521** (0.0594)	0.1079* (0.0562)
HHI		1.9134*** (0.3598)	
Rho			-0.1311 (0.1023)
<i>N</i>	513	354	381
<i>AIC</i>	2262.9493	1644.1120	1779.0696
<i>BIC</i>	2351.9951	1717.6286	1850.0400

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; R&D intensity is predicted using Wooldridge (1995); all models include (i) time fixed effects, (ii) sector fixed effects; (iii) controls for firm size.

Table 6: Fixed term vs. vocational contracts, citation-weighted knowledge stock

Citations	(1)	(2)	(3)
SHARET*SHARE_TC	0.0021 (0.0117)	0.0103 (0.0151)	0.0044 (0.0147)
SHARET*SHARE_A	-0.0390** (0.0154)	-0.0324** (0.0141)	-0.0288** (0.0128)
Share of managers	0.0528 (0.0424)	0.0606 (0.0475)	0.0409 (0.0458)
RDINT	-0.0465 (0.4784)	1.5799* (0.9485)	1.4887 (0.9407)
M&A	0.1561 (0.1483)	0.3916** (0.1768)	0.3725** (0.1693)
HHI		3.4648*** (1.2692)	
Rho			-0.3949 (0.3074)
<i>N</i>	323	238	250
<i>AIC</i>	473.7995	334.6249	355.5523
<i>BIC</i>	545.5749	390.1812	411.8957

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; R&D intensity is predicted using Wooldridge (1995); all models include (i) time fixed effects, (ii) sector fixed effects; (iii) controls for firm size.

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Appendix: Proofs

1. Proof of Proposition 1

Evaluate equations (1), (2) and (3) at $\lambda = 0$ and $\lambda = 1$. From equation (1), we see that $U_T^I(\lambda = 1) \geq U_T^I(\lambda = 0)$ iff $c \leq e$ and $\delta = 1$, while $U_T^I(\lambda = 1) \geq U_T^I(\lambda = 0)$ iff $c \leq e[1 + r(1 - u)p]$ and $\delta = 0$; from equation (2), we see that $U_T^R(\lambda = 1) \geq U_T^R(\lambda = 0)$ iff $c \leq e[1 + r(1 - u)p]$; from equation (3), we see that $U_p^j(\lambda = 1) \geq U_p^j(\lambda = 0)$ iff $c \leq e(1 + r)$, $j = I, R$. Given the ordering $e(1 + r) < e[1 + r(1 - u)p] < e$ and applying the tie-breaking rule for which E chooses $\lambda = 1$ when indifferent between $\lambda = 0$ and $\lambda = 1$ —see Kräkel (2016)—the results follow ■

2. Proof of Proposition 2

When $c < e$, E chooses $\lambda = 1 \forall \rho \in (0,1)$ and $\forall \tau \in (0,1)$. Given Lemma 1, point (i) follows. When $e < c < e[1 + r(1 - u)p]$ and $d = 0$, E chooses $\lambda = 1 \forall \rho \in (0,1)$ and $\forall \tau \in (0,1)$. Given Lemma 1, point (ii) follows. When $e < c < e[1 + r(1 - u)p]$, $\delta = 1$ and F offers $\tau = 0$, E chooses $\lambda = 1 \forall \rho \in (0,1)$. Conversely, when $e < c < e[1 + r(1 - u)p]$, $\delta = 1$ and F offers $\tau = 1$, E chooses $\lambda = 1$ if F chooses $\rho = 0$ and E chooses $\lambda = 0$ if F chooses $\rho = 1$. Given Lemma 1, this implies that if F chooses $\rho = 1$, it will offer $\tau = 1$; if it chooses $\rho = 0$, it will offer $\tau = 0$. Hence, we must compare F 's returns between choosing $(\rho, \tau) = (0,0)$ —given by $A - w$ —and F 's returns from choosing $(\rho, \tau) = (1,1)$ —given by B . Points (iii) and (iv) immediately follow. When $e[1 + r(1 - u)p] < c < e(1 + r)$ and F offers $\tau = 0$, E chooses $\lambda = 1 \forall \rho \in (0,1)$. Conversely, when $e[1 + r(1 - u)p] < c < e(1 + r)$ and F offers $\tau = 0$, E chooses $\lambda = 0 \forall \rho \in (0,1)$. Given Lemma 1, point (v) follows. Finally, when $c > e(1 + r)$, E chooses $\lambda = 0 \forall \rho \in (0,1)$ and $\forall \tau \in (0,1)$. Given Lemma 1, point (vi) follows ■