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R&D and Innovation Activities and the Use of External Numerical Flexibility

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Abstract

We study the impact of R&D and innovation on the use of external numerical flexibility (ENF). R&D and innovation imply both a higher average and a higher volatile productivity. We investigate this ambiguous effect on the firm preference for using ENF in two steps. First, we use a simple model to show that a first-order stochastic dominance shift in the distribution function increases the probability of hiring permanent workers, while a second-order shift has ambiguous effects. Next, using a dataset based on a survey of Italian manufacturing firms, we run logit regressions to estimate the effect of R&D and innovation on the probability of employing a fixed-term or a TWA worker, finding a positive and always significant effect. We also consider internal and external R&D and different types of innovation. Results show that the former has a positive effect while the latter depends on the type of innovation.

JEL Classification: J41; O33.

Keywords: Flexible employment, Labor contracts, Research and Development, Innovation.

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1 Introduction

In this paper we study the effect of a firm’s undertaking R&D and innovation on its use of external numerical flexibility (ENF). R&D and innovation are considered risky activities, i.e., they are associated with higher but more volatile returns. By ENF we mean labor contracts with a termination date and no cost in case of non-renewal. Of course, both of these features make them different from permanent contracts which are open-ended and entail firing costs in case of dismissal. Since firing costs are an adjustment cost and R&D and innovation imply higher uncertainty, one may expect a positive relationship between undertaking R&D and innovation activities and the use of flexible employment. However, other considerations may suggest a negative relationship. First, R&D and innovation should improve firm performance, thus reducing the conditional expectation of future dismissals and their related firing costs. Second, these activities may perform better in the presence of a commitment to a long-lasting labor relationship, since it may induce workers to enhance their firm-specific human capital.

We address this issue both theoretically and empirically. We begin with a model in which a firm has to choose between a permanent and temporary labor contract and study how the probability of choosing a labor contract changes with changes in the productivity distribution function (as a result of R&D and innovation activities). We show that while a first-order shift in the probability distribution of the idiosyncratic shocks affecting the firm has a positive effect on the firm’s preference for permanent contracts, a second-order stochastic shift has ambiguous effects.

We then proceed empirically to estimate the probability of using ENF. Specifically, using a dataset of Italian manufacturing firms, we estimate the impact of R&D and innovation on the probability of using a non-permanent contract. Initially, we look at the aggregate of R&D and innovation activities and find that both increase the probability of using flexible employment. When we disaggregate among different types of R&D and innovation, we find some differences. R&D always has a positive impact on the probability of using ENF and the higher the impact is, the larger the amount of activity outsourced. An interpretation of this result is that the increase in uncertainty associated with R&D activity boosts the use of flexible employment in order to reduce the expected loss; however, there could be some positive complementarity between R&D activity and long-lasting labor contracts that mitigates this incentive. When we further distinguish between product innovation and process innovation, we get clear-cut results. While product innovation activity always has a positive impact on the probability of using ENF, process innovation activity has no (or a negative) effect. This can be due to the fact that

\[1\] Hereafter, the terms flexibility and flexible will be used to refer to external numerical flexibility, thus excluding for instance internal numerical flexibility (such as part-time contracts) and functional flexibility (changing workers' tasks).
product innovation typically implies higher uncertainty, while process innovation is generally associated with cost rationalization, whose effects are not so uncertain.

The rest of this paper is organized as follows. The next section briefly reviews the literature concerning a firm’s choice between permanent and temporary contracts and the literature concerning the effects of R&D and innovation. The theoretical model of Section 3 investigates how R&D and innovation affect labor contract choice. Section 4 presents the empirical strategy, describes the dataset, and discusses the results of our regressions with different sets of explanatory variables. Section 5 concludes.

2 Review of the Literature

2.1 External Numerical Flexibility (ENF)

The most common definition of ENF refers to the possibility of changing the number of employed workers by using short-term labor contracts with no firing costs. Of these, the most frequently used are temporary contracts and temporary work agency (TWA) workers. Even if with some differences, these contracts were originally introduced to meet firm-specific needs, e.g., the substitution of permanent workers by temporaries or the adjustment of production capacity to peaks of production. Subsequently, the use of flexible employment has gone beyond this original scope and nowadays it has become a way of selecting new employees or a buffer to reduce the costs of possible downsizing.

Some authors assume that short-term and permanent workers are characterized by the same productivity. It follows that, because of the difference in the firing costs, firms should always prefer flexible employment. For example, Cahuc and Postel-Vinay (2002) describe an economy in which both types of employment coexist because of the presence of institutional rules that limit the creation of flexible employment. Similarly, Boeri and Garibaldi (2007) describe an economy that starts with a stock of permanent workers and introduce the possibility of hiring flexible employees, the newly hired being all with temporary contracts. Others instead support the idea that, notwithstanding the firing costs, permanent contracts may be convenient because they have a higher level of productivity. Aguirregabiria and Borrego (2009) and Caggese and Cuñat (2008) endow permanent workers with a higher labor-augmenting factor while Addessi (2011) argues that the most important difference is in the contribution to firm productivity growth. In a similar vein, Albert et al. (2005) find a negative relationship between flexible employment and firm-provided training activities, with likely negative effects on workers’ human capital accumulation. Lotti and Viviano (2011) support the idea that the hiring of temporary workers is a real option allowing firms to adjust the workforce in the case of economic fluctuations and
future demand uncertainty, and the price of this real option is lower productivity.

Some studies that use cross-country industry-level data (Bassanini et al., 2008; Lisi, 2009; Damiani and Pompei, 2010) find that the incidence of flexible employment may dampen total factor productivity (TFP) growth. While these studies focus on fixed-term contracts, Hirsch and Mueller (2010) investigate the effect of TWA workers on firm productivity and find a hump-shaped relationship: the effect of employing TWA workers is initially positive but, for intensive levels of use, it becomes negative. In light of the above, the assumption of our model that permanent contracts are associated with higher productivity than temporary contracts seems well supported. Notice that, even if this literature addresses the relationship between the type of labor contract and productivity, to the best of our knowledge there is no analysis of how R&D and innovation affect the firm’s choice of the labor contract. That is, whether the choice of undertaking R&D and innovation shifts preferences in favor of employment flexibility.

2.2 R&D and Innovation

Broadly speaking, firm R&D and innovation aim at gaining market power by improving the quality of the product and/or at upgrading the efficiency of the production process. It is difficult to disentangle these effects empirically since datasets generally report firm revenues and not prices, quantities, and product quality, separately. When these activities are studied, they are generally considered a kind of investment characterized by higher mean returns and more uncertainty. A cornerstone in this strand of the literature is Griliches (1979), where R&D expenditure generates “knowledge capital” that increases firm productivity and has a depreciation rate just as does physical capital. Recently, Doraszelski and Jaumandreu (2009) relax some assumptions concerning the relationship between R&D and productivity. They stress that the accumulation of knowledge is not deterministic, assuming that a firm’s TFP follows a stochastic process influenced by its R&D expenditure. Their estimation results show that R&D expenditure is characterized by net returns significantly higher than net returns to physical capital. They also estimate that engaging in R&D roughly doubles the degree of uncertainty, i.e., R&D introduces a further source of uncertainty into the production process. In terms of the effect of R&D on the productivity distribution function, they find that in some industries stochastic dominance emerges. This is because the distribution for performers is to the right of that of non-performers, while in others sectors, the probability of being in the lowest levels of productivity is higher for performers, even if the average value of productivity is still higher for performers.

The choice of engaging in R&D and innovation may be related to labor market institutions. Saint-Paul (2002) distinguishes between “primary innovation” (the introduction of new
products) and “secondary innovation” (the upgrading of existing products). The former is considered a riskier activity because the demand facing a producer of new goods is more volatile; consequently, firms operating in labor markets characterized by high employment protection (as in most European countries) should prefer the latter because it implies a lower probability of paying the firing costs associated with a reduction of the workforce. In countries such as the U.S., where employment protection is low, firms are less scared of starting a riskier activity because in case of a non-performing outcome they can adjust the level of workforce without bearing firing costs. In Koeniger (2005) the relationship between firing costs and innovation is more ambiguous. Employment protection, on the one hand, deters the entry of new innovating firms because the presence of these costs decreases the expected returns required to start a business, but, on the other, pushes incumbent firms to innovate in order to avoid dismissal costs.

Previous research has assumed that labor market institutions such as employment protection legislation (EPL)\(^2\) are given when the firm has to choose whether or not to undertake R&D and innovation. Alternatively, other research has been more interested in how the performance of R&D and innovation is affected by different labor contracts. Zhou et al. (2011) review some of the reasons that may induce a negative or a positive relationship between R&D (and innovation) and the use of flexible employment. Permanent employees may be reluctant to adapt to new technologies, may hamper or make the reallocation of labor services very expensive, and may reduce the firm’s returns from innovation by making higher wage claims in case of success. On the other hand, the use of ENF may impair the learning organizational process, may reduce employee loyalty and effort in acquiring firm-specific knowledge, and hence the firm’s incentive to provide training. Kleinkecht et al. (2006) estimate that the use of TWA workers has a positive effect on employment growth and sales among innovating firms, while the opposite effect emerges among non-innovating firms.\(^3\)

Even if at an aggregate level it is reasonable to assume labor market institutions as given, when we look at the relationship at the firm level it seems more appropriate to investigate the reverse causality. Indeed, the engagement in R&D and innovation is a strategic or long-run choice of the firm, hence taken before the choice of labor contracts.\(^4\) This explains why we think that no endogeneity problem will arise from our estimations as it is quite hard to see how the presence of at least one flexible employee should affect the choice concerning the engagement in

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\(^2\)On the interactions between EPL and labor market performance, see Saltari and Tili (2009 2011).

\(^3\)The opposite occurs referring to temporary workers, but the estimated coefficients are not significantly different from zero.

\(^4\)For example, Aw et al. (2009) investigate the effect of R&D and export activities on firm productivity. In their model firms choose whether to engage in R&D and/or export activities assuming that labor services will be chosen optimally.
R&D and innovation. Thus, our aim is to investigate whether the decision of engaging in R&D and innovation activities affects the use of flexible employment.

3 The Model

In this section, we describe the labor demand for permanent and temporary contracts when firms are subjected to revenue shocks. For convenience, we dub temporary worker the worker employed with a temporary contract while we designate permanent worker the worker employed with a permanent contract.

Every firm can create a job and fill the position by employing a permanent or a temporary worker which yields a flow of profits. For analytical tractability, we suppose that profits are linear in the productivity, \( y \).\(^5\) For each \( y \), the flow of profits deriving from a permanent worker is assumed to be higher than from a temporary worker. Specifically, the profit flow has two components. One is the firm productivity: firms draw their productivity from a general distribution \( G(y) \) with support in the range \( y \in [y_{\text{min}}, y_{\text{max}}] \). Firm productivity changes with the arrival of an idiosyncratic shock which occurs at a Poisson constant rate \( \lambda \). The other component is deterministic and depends on the firm’s choice of the contract: if the firm decides to hire with a permanent contract, its productivity remains at \( y \), whereas hiring with a temporary contract productivity will be \( ay \), where \( a \) is a positive constant lower than unity.\(^6\) However, while closing a temporary job is costless, laying-off a permanent worker involves a firing cost \( F \).

The equations below are the standard valuation equations, deriving from the no-arbitrage principle with perfect capital markets and a constant interest rate \( r \), for permanent and temporary contracts.

The expected present value of profit from a position filled as a permanent job \( V_P(y) \) satisfies

\[
r V_P(y) = y + \lambda \left( \int_{y_P}^{y_{\text{max}}} V_P(s) dG(s) - F \cdot G(y_P) - V_P(y) \right) .
\]  

(1)

The left hand side of Equation (1) represents the return required by the market for a permanent job, \( r V_P(y) \). The permanent worker has a productivity, \( y \). \( y_P^* \) indicates the productivity threshold below which the firm lays off permanent workers. Consequently, if after the realization of the shock the productivity is in the range \( y_P^* \leq y \leq y_{\text{max}} \), the firm keeps the permanent

\(^5\)This requires the existence of a proportional relation between wage and productivity. If we suppose that firms are in long run equilibrium, as it is implicit in the value function formulated below, then almost all theoretical models are consistent with this hypothesis (see for instance Pissarides 2000, p.71).

\(^6\)It is worth noticing that in our framework workers are homogeneous; they differ only in the contract they are employed under. We do not consider differences determined by human capital endowments.
worker at the new level of productivity, otherwise it closes the job and pays the firing cost $F$.

Consider now the asset value of a temporary job. The expected present value of profit $V_T(y)$ satisfies

$$ rV_T(y) = ay + \lambda \left( \int_{y_{TP}}^{y_{max}} V_P(s) dG(s) - V_T(y) \right). \quad (2) $$

Equation (2) states that the return required by the market $rV_T(y)$ must be equal to the flow of profit $ay$ plus the change in value, where $a < 1$ is a constant. If the new level of productivity is between $y_{TP}$ and $y_{max}$, the worker is switched from a temporary to a permanent position, where $y_{TP}$ is defined as the level of productivity in which $V_P(y_{TP}) = V_T(y_{TP})$. If the new level of productivity is below $y_{TP}$, the temporary worker is fired and the job is closed with no costs.\(^7\)

We now make some simplifications to the Bellman equations for the permanent and temporary contracts. First, starting with the permanent position, integrating by parts and rearranging, we get

$$ (r + \lambda) V_P(y) = y + \lambda \left( V_P(y_{max}) - \int_{y_{TP}}^{y_{max}} V'_P(s) G(s) ds \right), \quad (3) $$

where use has been made of the fact that when a permanent job is closed, the firm gives up $V_P(y)$ and pays the firing cost $F$. Hence, a permanent job with productivity $y$ will be closed if $V_P(y) \leq -F$.

Since firm profits are linear in $y$, it is natural to assume that the value function is also linear, say $V_P(y) = Ay + c$, where $A$ and $c$ are constants to be determined. Simple substitutions show that

$$ A = \frac{1}{r + \lambda}, \quad c = \frac{\lambda}{r} A \left( y_{max} - \int_{y_{TP}}^{y_{max}} G(s) ds \right). \quad (4) $$

The value function also allows us to determine the threshold value for the permanent job by employing the reservation productivity property. Indeed, $y^*_P$ is implicitly determined by

$$ -(r + \lambda) F = y^*_P + \lambda \left( V_P(y_{max}) - A \int_{y_{TP}}^{y_{max}} G(s) ds \right). \quad (5) $$

\(^7\)For tractability, we are assuming that temporary contracts cannot be renewed. This is not a strong assumption since in many countries (including Italy) it is not allowed to indefinitely renew temporary contracts. Furthermore, it not an uncommon assumption (see Blanchard and Landier, 2002).
By following similar steps for temporary jobs, we first get

\[(r + \lambda) V_T(y) = ay + \lambda \left( V_P(y_{\text{max}}) - V_P(y_{\text{TP}}) G(y_{\text{TP}}) - \int_{y_{\text{TP}}}^{y_{\text{max}}} V_P'(s) G(s) ds \right). \tag{6}\]

Again, by supposing that the value function is linear, \(V_T(y) = By + d\) (where \(B\) and \(d\) are constants to be determined) and substituting, we obtain

\[B = \frac{a}{r + \lambda}, \quad d = A\lambda \left( A y_{\text{max}} + c - (A y_{\text{TP}} + c) G(y_{\text{TP}}) - A \int_{y_{\text{TP}}}^{y_{\text{max}}} G(s) ds \right). \tag{7}\]

Notice that in this case \(d\) is not known since it depends on the threshold value \(y_{\text{TP}}\), which is obviously unknown. We can however determine this latter variable by making use of the fact that the firm is indifferent between a permanent job and a temporary job at \(y_{\text{TP}}\):

\[V_P(y_{\text{TP}}) = V_T(y_{\text{TP}}) \tag{8}\]

or

\[A y_{\text{TP}} + c = B y_{\text{TP}} + d. \tag{9}\]

Combining this latter equation with the second equation of (7), we determine the values of both \(d\) and \(y_{\text{TP}}\).

We now want to compare firms having different (cumulative) probability distributions. To this end, we use the concept of stochastic dominance. Let \(G(s, \rho)\) be a family of distribution functions indexed by \(\rho\). We begin with first-order stochastic dominance: an increase in \(\rho\) indicates a distribution which is first-order stochastically dominant so that the distribution with the higher \(\rho\) also has a greater expected value. In terms of distribution functions, this implies that if \(\rho_2 > \rho_1\), then

\[G(s, \rho_2) - G(s, \rho_1) < 0.\]

Dividing this expression by \(\rho_2 - \rho_1 > 0\) and taking the limit as \(\rho_2 \to \rho_1\), we get

\[\frac{\partial G}{\partial \rho} = G_2(s, \rho) < 0. \tag{10}\]

We first look at what happens to \(y_{\text{TP}}^*\) when \(\rho\) increases in this sense. To begin with, substitute
the value function of the permanent job in (5) and rearrange to get

\[- (r + \lambda) F = y_P^* + \lambda A y_{\text{max}} + \frac{\lambda}{r} A \left( y_{\text{max}} - \int_{y_P^*}^{y_{\text{max}}} y_{\text{max}} - \int_{y_P^*}^{y_{\text{max}}} G(s, \rho) \, ds \right) - \int_{y_P^*}^{y_{\text{max}}} G(s, \rho) \, ds \]

\[= y_P^* + \frac{\lambda}{r} \left[ y_{\text{max}} - \int_{y_P^*}^{y_{\text{max}}} G(s, \rho) \, ds \right]. \tag{11}\]

Now using Equation (11) and performing an implicit differentiation gives

\[\frac{dy_P^*}{d\rho} = \frac{\lambda}{r} \int_{y_P^*}^{y_{\text{max}}} G_2(s, \rho) \, ds \]

\[< 0, \tag{12}\]

which is negative because of (10). Using this result in the second of (4) we obtain

\[\frac{dc}{d\rho} = \frac{-\lambda A}{r} \int_{y_P^*}^{y_{\text{max}}} G_2(s, \rho) \, ds \]

\[+ G(y_P^*, \rho) \frac{dy_P^*}{d\rho}, \tag{13}\]

where the second equality follows by substituting the expression for \( \frac{dy_P^*}{d\rho} \).

We are now ready to see the effect of a first-order stochastic shift on \( y_{\text{TP}} \). Implicit differentiation of Equation (9) gives

\[\frac{dy_{\text{TP}}}{d\rho} = \frac{\lambda A (1 - G(y_{\text{TP}}, \rho)) + \lambda A (A y_{\text{TP}} + c) G_2(y_{\text{TP}}, \rho) + A \int_{y_{\text{TP}}}^{y_{\text{max}}} G_2(s, \rho) \, ds}{A - B + \lambda A (A y_{\text{TP}} + c) g(y_{\text{TP}})}, \tag{14}\]

where \( g(\cdot) \) is the density. Perhaps surprisingly, this derivative does not have a definite sign: the denominator is positive but the first term in the numerator is positive while the other two are negative. The reader might have expected a negative sign since a firm which has a higher probability to get a higher productivity should also offer a permanent contract at a lower level of reservation productivity, and therefore one would expect \( y_{\text{TP}} \) to decrease when \( \rho \) increases. But the model does not confirm this intuition.

However, what really matters is not how the threshold value \( y_{\text{TP}} \) changes in consequence of a first-order stochastic dominance shift but rather how the probability of hiring with a permanent contract changes for a worker with a productivity at least equal to \( y_{\text{TP}} \). In fact, we
are comparing two otherwise identical firms, one of which has better productivity perspectives. We want to know if this firm has also a higher probability of hiring permanent workers. In formal terms, this means that we are interested in the sign of the following total derivative:

$$\frac{dG(y_{TP}, \rho)}{d\rho} = G_1(y_{TP}, \rho) \frac{dy_{TP}}{d\rho} + G_2(y_{TP}, \rho)$$

By definition, the distribution function $G(y_{TP}, \rho)$ represents the probability of drawing a job with productivity up to $y_{TP}$, while its complement with respect to unity refers to jobs with a productivity level at least equal to $y_{TP}$. Thus, a negative sign in (15) means that the firm with higher profit perspectives has also a higher probability of hiring with a permanent contract. Using (14) and after some lengthy algebra, it can be shown that the total derivative of $G(y_{TP}, \rho)$ is in effect negative.\(^8\)

We will now look at the symmetric situation, that is, what happens if we increase the riskiness of the job distribution while leaving the average job productivity unchanged? More precisely, we will look at mean preserving spreads by using second-order stochastic dominance. We reinterpret “increases in the index $\rho$” as increases in riskiness leaving the mean unchanged:\(^9\)

$$\int_{y_{min}}^{y_{max}} (G(s, \rho_2) - G(s, \rho_1)) \, ds \leq 0,$$

with strict inequality for at least some $y$. As before, dividing this expression by $\rho_2 - \rho_1 > 0$ and taking the limit as $\rho_2 \to \rho_1$, we get

$$\int_{y_{min}}^{y_{max}} G_2(s, \rho_2) \, ds \leq 0. \quad (16)$$

We can now repeat the same steps as above. An increase in risk implies as before that the threshold value for permanent contracts decreases while the constant $c$ increases, so that Equations (12) and (13) still hold. Yet, Equation (14) still does not have a definite sign. Increases in riskiness have an ambiguous effect on $y_{TP}$. This is because we do not know the sign of $G_2(y_{TP}, \rho)$, unlike in the case of first-order stochastic dominance: for symmetric probability

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\(^8\)Details available upon request.  
\(^9\)The usual form in which second-order stochastic dominance is written is

$$\int_{y_{min}}^{y_{max}} (G(s, \rho_2) - G(s, \rho_1)) \, ds \geq 0$$

It is straightforward to show that the inequality is reversed if the upper limit of integration is the upper bound of the support.
distributions, like the uniform and the normal, $G_2(y_{TP}, \rho)$ will be positive if $y_{TP}$ is greater than the mean, negative otherwise.\footnote{Thus, unlike what happens in the Blanchard and Landier (2002) model, being above or below the productivity mean is relevant.} It is straightforward to see by looking at Equation (15) that for this same motive the total derivative of the distribution function in this case has an unpredictable sign.

To sum up, Equation (15) shows that first-order stochastic shifts in the productivity distribution affects the firm’s contract preferences in the sense that the probability of hiring with a permanent contract increases. Contrariwise, a mean preserving spread has an indefinite effect. In light of these ambiguous results about the effects of changes in firm’s productivity distribution on labor contract choice, the empirical analysis developed in the next section is especially relevant.

4 Empirical Analysis

4.1 Dataset

We estimate the relationship between a firm’s engagement in R&D and innovation and its use of ENF using a survey conducted by the MedioCredito Centrale—Capitalia—Unicredit Research Centre, on a sample of Italian manufacturing firms over the period 2001–2003. This dataset includes information about firm structural characteristics and workforce composition, the R&D and innovation undertaken, and the sources of financing.\footnote{More details on the implementation of the survey can be found in the report of the Research Centre of the Unicredit Corporate Banking and at the website http://www.unicreditcorporate.it/media/rapporto_corporate.htm. This dataset has been used in other studies (see Caggese and Cuñat, 2008 and Hall et al., 2006).} The dataset provides annual information for many variables while for others the answers refer to the entire period. For this reason we choose to perform a cross-section analysis.

Table 1 gives some descriptive statistics of our sample. The definition of ENF is strictly related to the type of labor contract. We consider flexible (flex) both the temporary contracts (tm) and the TWA workers (ag). Even if Italian aggregate data shows that the number of TWA workers is lower than the number of workers with fixed-term contracts, Table 1 shows that the use of TWA workers is more spread across firms. As to firm activities, in our sample less than half of the firms are engaged in R&D (rd) while more than 63% are engaged in innovation (in). Overall, it is worth noticing that both the spread of flexible employment and the engagement in R&D and innovation split the sample in almost equal parts. Thus, addressing the topic as\footnote{In the survey R&D is defined as creative activities undertaken to increase the stock of knowledge and to use this stock to develop new applications. Innovations is classified in four categories: product innovation, process innovation, management and organizational innovations related to product innovation, and management and organizational innovations related to process innovation.}
Finally, Table 1 shows that the selected variables are positively correlated among each other thus providing some preliminary evidence of the linkage between these firm choices.

4.2 Benchmark empirical models

We run logit regressions that differ in the number of explanatory variables, where the dependent variable, $fl_{ex}$, is equal to 1 if the firm employed either at least one worker with a fixed-term contract or at least one TWA worker, and equal to 0 otherwise. The main purpose is to evaluate whether undertaking R&D and innovation affects the probability of using ENF. Table 2 (regression $R1$) reports the estimation results when only R&D and innovation are used as explanatory variables. These variables are binary, equal to 1 if the firm carried out these activities and equal to 0 otherwise. The values reported in each cell of Table 2 indicate the estimated values of the regression coefficients, while the standard deviations are inside brackets. Both R&D and innovation have a positive and significant impact on the probability of using flexible employment.\(^\text{14}\)

Since the coefficients are significantly different from 0, it is interesting to evaluate how much the choice of engaging in R&D and innovation would affect the probability of employing at least one flexible worker. We start by observing that 64.6\% of the firms in the sample used ENF, while regression $R1$ predicts that the probability of opting for this choice is 65.3\%. We next calculate how much the predicted probability changes when the value of one independent variable changes, while the other one remains at its average value (as shown in Table 1). We also calculate the 95\% confidence interval for these marginal effects.

Let’s start from the choice of engaging in R&D. Without R&D, the predicted probability of using flexible employment is 59\% and 72.1\% otherwise. This implies a change of 13.1 percentage points, whose confidence interval ranges between 9.9 and 16.3.

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\(^{13}\)The analysis of the impact on the incidence of ENF on total firm workforce would also have been interesting. However, we do not have information about the amount of TWA workers along the entire time period of the survey.

\(^{14}\)There is weak evidence of a higher impact of R&D activity, but the difference between the coefficients is not significant.
Similarly, without innovation activity, the predicted probability of observing ENF is 57.4% and 69.5% otherwise. This implies a change equal to 12.1 percentage points with a confidence interval from 8.7 to 15.5.

At this point, we introduce some variables in order to control for firm and employee characteristics. Table 3 gives, for each control variable, three types of information: i) the incidence among firms in the case of binary variables, and the mean value, otherwise; ii) the correlation with the use of ENF; and iii) the number of available observations in our sample.

The list of control variables is the following. The Pavitt classification indicates that a firm’s activity pertains to a sector that is supplier dominated, scale intensive, specialized supplier, or science based (pv1, pv2, pv3, and pv4, respectively).

The average (along the three years of the survey) level of employment (em) and the average ratio of sales over employment (se) should control for firm size and labor productivity. The incidence of employees with secondary high school (hs) and a graduate degree (gd) is used to control for employee education, and the average number of employees used in R&D activity (er).

The source of investment financing distinguishes between risk capital (c0), self-financing (c1), short-term bank loans (c2), medium/long-term bank loans (c3), medium/long-term bank loans at subsidized rates (c4), government grants (c5), fiscal benefits (c6), leasing (c7), group firms’ loans (c8), and other firms’ loans (c9). The dataset reports the incidence of each financing source on the total amount.

In the following regressions we use these variables as binary variables (equal to 1 if the financing source has been used and equal to 0 otherwise) but we ran the same regressions maintaining the incidence share and the results do not change significantly.\(^{15}\)

\(^{15}\)In more than one case we could have treated regressors as continuous variables but we generally preferred treating them as dummy variables. The choice is due to the fact that we are studying the discrete choice of using or not using ENF and not the intensity of the use of ENF. Then, we should refer to the marginal condition for
Finally, two other elements reported in the dataset are considered. The first is still related to the financial side. Firms are asked to answer whether they would have desired further credit (cr), where a positive answer may be interpreted as a signal of credit rationing. The last control we include is related to export activity, exp, equal to 1 if the firm exported and zero otherwise. This kind of activity introduces another source of uncertainty related to the behavior of foreign markets.

The first column of Table 4 gives the results concerning the logit regression (R2) which includes all the control variables listed in Table 3. Only the variables whose coefficients are significant at 10% or less are reported.

All the reported coefficients, except one, are positive. This implies that the selected variables increase the probability of using flexible employment. The firm size is relevant while the sales per employee are not. Even if Table 3 suggests a significant correlation between the Pavitt classification and the use of flexible employment, no significant relationship emerges in our regressions. Similarly, the average number of workers employed in R&D activity does not have a significant impact and the same is true for employee education level. Just two sources of firm investment financing, short-term bank loans and leasing, have coefficients significantly different from zero.

Furthermore, export activity has a positive effect while the self declaration of being financially constrained is the only variable which reduces the probability of using ENF. The use of at least one flexible employee. Since the weight of an employee in the firm structure is low, it should be sufficient to detect the presence of the different elements among the firm characteristics, independently of their relative relevance, without incurring the higher measurement errors implied by more detailed data.

16 The presence of financial constraints is expected to shift the labor demand towards flexible types of labor contracts in order to avoid the coexistence of binding financial constraints and firing costs (see Caggese and Cunat, 2008).
table 4 Logit regressions with control variables

<table>
<thead>
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<th>R3</th>
<th>R4</th>
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<tbody>
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<td>(.09)</td>
<td>(.08)</td>
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<tr>
<td>exp</td>
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<td>.30</td>
<td>.29</td>
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<td>(.09)</td>
<td>(.08)</td>
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<td>em</td>
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<td>cr</td>
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<td></td>
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<td>(.11)</td>
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<tr>
<td>c2</td>
<td>.22</td>
<td>.24</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.12)</td>
<td>(.11)</td>
<td></td>
</tr>
<tr>
<td>c7</td>
<td>.23</td>
<td>.25</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.08)</td>
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<tr>
<td>LR</td>
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<td>280</td>
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<tr>
<td>χ²</td>
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<tr>
<td>n. obs.</td>
<td>2,981</td>
<td>3,387</td>
<td>4,076</td>
</tr>
</tbody>
</table>

*Significant at 10% in R2, not significant in R3.

All other coefficients significant at 5% or less.

Introduction of these control variables has reduced the estimate of the coefficients of the independent variables we are interested in. The decrease is higher for the role of innovation and the impact on the confidence interval of its coefficient is quite relevant, even if it is still statistically significant at 5%.

In the middle of Table 4 (R3), we give the estimates obtained by regressing over only the variables which emerged as significant at 10% or less in regression R2. Again, the coefficients of both R&D and innovation are positive and strongly significant. Also, the other variables have a significant impact, except for the indicator of credit rationing. In particular, the estimated value for the coefficient of export activity increases while the estimated standard deviation remains stable.

Regression R₄, in the last column of Table 4, does not include the indicator of credit rationing and the source of investment financing. The results highlight that the selected variables have a significant influence on the dependent variable. The coefficient of innovation activity emerges as particularly high. The choice of excluding variables whose coefficients are not statistically significant is due to the decrease in the number of observations which would ensue, and it is supported by the application of the Bayesian Information Criterion (BIC). The number of observations in regression R₄ is equal to 4,076 but it falls to 3,429 if we include the variables.
related to the source of financing, and to 3,387 when we include also the indicator of credit rationing (whose coefficient is not always significant). Furthermore, even if we nullify the effect of the number of observations, i.e., referring to the smallest sample size when we compare different regressions with a different number of observations, the BIC suggests excluding cr, c3 and c7. Indeed, comparing regressions R4 and R3, the difference in the BIC is equal to 8.241, providing strong support for logit R4. If we consider a regression that excludes just cr, the difference in the BIC is equal to 1.715, still providing weak support for logit R4.

Focusing on regression R4, the empirical model predicts that the probability of opting for ENF is 66.6%. Without R&D activity this probability is 62.4% and 71.4% otherwise. This implies a change equal to 9 percentage points whose 95% confidence interval is between 5.7 and 12.4. Without innovation activity, the predicted probability of using flexible employment is 59.8% and 70.3% otherwise. This implies a change equal to 10.4 percentage points whose confidence interval is between 7 and 13.8.

Furthermore, it is worth noting that if we run the previous regressions also as probit, we obtain very similar results in terms of the statistical significance of the regression coefficients and marginal effects on the probability of using ENF. In each case, comparing the regression performance, the BIC always provides support for logit regression (weak in R1, positive in R2, strong in R3, and very strong in R4).

Before extending our analysis to include the different types of R&D and innovation activities, we provide some further information concerning logit R4 of Table 4.

4.2.1 Goodness of fit

The goodness of fit of the model is generally quite poor. However, these types of empirical models can hardly explain the adoption of flexible employment; rather, they can verify whether there is a statistically significant relationship between the dependent and independent variables.

McFadden’s $R^2$ is given by the ratio of the difference of deviance between the model with only the constant term and the model with the independent variables, over the deviance of the model with only the constant term, where the deviance is defined as $-2$ times the log of the likelihood. This statistic is equal to 0.053. McFadden’s Adjusted $R^2$, which takes into account the number of parameters, is equal to 0.051.

Another statistic is Efron’s $R^2$, which is given by 1 minus the ratio of the sum of squared difference between the observed and predicted values over the sum of the squared differences between the observed data and their mean. Efron’s $R^2$ is equal to 0.069.

The maximum likelihood $R^2$, which measures the geometric mean square improvement per observation, is equal to 0.066. The number of correctly classified observations over the total
number of observations is 64.7%.

4.2.2 Tests of significance

We start by testing the hypothesis that all the coefficients of the independent variables are zero versus the alternative hypothesis that at least one coefficient is different from zero. In logistic regression the likelihood ratio chi-square test is generally used. The deviance of our model is equal to 5,016.923 while the deviance of the model with only the constant term is equal to 5,296.796. This implies that the reduction in the deviance induced by introducing our selected variables is equal to 279.873. This difference has a chi-square distribution with four degrees of freedom since the constraints are equal to the number of independent variables. The test clearly induces the rejection of the hypothesis that all the parameters are null.

We also tested the relevance of each variable. The Wald tests and log likelihood tests confirm the relevance of each selected variable. Just one aspect is worth noting. Generally, the BIC provides strong support for preserving each variable, except for export. The difference in the BIC with and without exp is 1.8 providing weak support for the model that includes it.

We also checked whether there is some multicollinearity between the independent variables. No suspicious correlation emerges. The tolerance indexes, given by 1 minus the $R^2$ between each variable and the other variables, are always next to unity. The lowest value belongs to rd and is equal to 0.76.

4.3 Extensions

Our dataset allows us to disentangle different types of R&D and innovation activities. R&D can be run inside the firm (rdi) and/or outside (rde). Innovation activity can concern product innovation (in1), process innovation (in2), management and organizational innovations related to product innovation (in3), and management and organizational innovations related to process innovation (in4). Since they are all binary variables, Table 5 gives the incidence among firms.\textsuperscript{17} Furthermore, it gives the correlations with the use of flexible employment which are all positive and significant.

Table 6 gives the estimates of logit models which take into account the previous classification of R&D and innovation activities, but differ in the number of independent variables included,\textsuperscript{17}

\textsuperscript{17}For internal and external R&D we have also the share of incidence. Regressions with shares, instead of binary variables, have been run with no qualitatively significant change in the results. Furthermore, BIC provides very strong support for logit with dummy variables.
just as in Table 4. \( R_5, R_6, \) and \( R_7 \) include the same variable as \( R_2, R_3, \) and \( R_4, \) respectively. The main results are as follows.

Both ways of carrying out R&D (inside and outside) always have a positive effect on the probability of using ENF and the interaction with external structures seems to produce a higher impact. These results provide support for the idea that the positive relationship between R&D and the use of flexible employment is not due to some technological reasons. Even when the firm delegates the R&D activity to an external entity, the probability of using ENF increases. Consequently, it seems reasonable to interpret the empirical results in favor of our theoretical model that keeps constant the revenue gap between permanent and temporary contracts after a change in the productivity distribution. Perhaps a complementarity between R&D and permanent contracts could be introduced (since the coefficient of \( rdi \) is always lower than that of \( rde \)).

More complex is the interpretation of the results about the role played by the different types of innovation, even if some clear evidence still emerges. First of all, product innovation always has a positive and significant effect on the probability of using ENF while the impact of process innovation is not significant or negative. This difference can be explained in the light of our interpretation of the linkage between these strategic choices on the part of a firm and its labor contract choice. Indeed, product innovation can be considered a risky activity while process innovation is more related to the rationalization of costs, which can be hardly associated with an increase in uncertainty. More puzzling is the interpretation of the difference between the effect of management and organizational innovations related to product innovation, and the effect of management and organizational innovations related to process innovation. Further qualitative information may be helpful for a better understanding.

Focusing on regression \( R_7 \), the predicted probability of opting for ENF is 66.9%. Firms not running inside R&D activity have a probability equal to 64.9% that rises to 69.6% otherwise. This implies a change equal to 4.7 percentage points whose 95% confidence interval is between 1.1 and 8.4. Firms not running outside R&D activity have a probability equal to 64.7% that rises to 74.7% otherwise. This implies a change equal to 9.9 percentage points whose 95%
## Table 6: Logit regressions with different types of R&D and innovation

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<th>R6</th>
<th>R7</th>
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<td>.23** (.10)</td>
<td>.19** (.09)</td>
<td>.21** (.09)</td>
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<td>.43*** (.12)</td>
<td>.40*** (.11)</td>
<td>.47*** (.11)</td>
</tr>
<tr>
<td>in1</td>
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<td>.39*** (.10)</td>
<td>.38*** (.09)</td>
</tr>
<tr>
<td>in2</td>
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<td>-.15* (.09)</td>
<td>.02 (.08)</td>
</tr>
<tr>
<td>in3</td>
<td>-.01 (.13)</td>
<td>-.07 (.12)</td>
<td>-.02 (.11)</td>
</tr>
<tr>
<td>in4</td>
<td>.38*** (.12)</td>
<td>.40*** (.11)</td>
<td>.43*** (.10)</td>
</tr>
<tr>
<td>exp</td>
<td>.17** (.10)</td>
<td>.27*** (.09)</td>
<td>.26*** (.08)</td>
</tr>
<tr>
<td>em</td>
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<td>.002*** (.0004)</td>
<td>.002*** (.0004)</td>
</tr>
<tr>
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<td>-.21* (.11)</td>
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<tr>
<td>c2</td>
<td>.21* (.12)</td>
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<tr>
<td>c7</td>
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<td>229</td>
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<td>3,387</td>
<td>4,076</td>
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*Significant at 1%, 5%, 10% respectively

Standard error in parenthesis
confidence interval is between 5.9 and 14. Without product innovation activity the predicted probability of using ENF is 63.4% and 71.6% otherwise. This implies a change equal to 8.3 percentage points whose confidence interval is between 4.5 and 12.

Finally, some statistics concerning logit $R7$ are reported. McFadden’s $R^2$ is equal to 0.061 while McFadden’s Adjusted $R^2$ is equal to 0.058. Efron’s $R^2$ is equal to 0.077 and the Maximum Likelihood $R^2$ is equal to 0.076. The proportion of correctly classified observations over the total number of observations is 64.9%. The deviance of our model is equal to 4,973.61 which implies a reduction in the deviance induced by introducing our selected variables equal to 323.019. Consequently, we can reject the hypothesis that all the parameters are null.

Furthermore, it is worth noting that using the BIC to compare $R7$ and $R4$, the difference is equal to 10.062 providing very strong support for the former model that takes into account the different types of R&D and innovation activities.

4.4 Robustness analysis

We previously stated that it is reasonable to expect that the engagement in R&D and innovation affect the use of labor inputs (both the type and the amount), because the former is a long-lasting strategic choice while the latter can be changed with lower adjustment costs. Consequently, we believe that our analysis does not suffer a reverse causality problem. However, we cannot exclude that in some (rare) cases labor relationships within firms are so rigid that they become a constraint, affecting the choice concerning the engagement in R&D and innovation. In order to overcome this issue, we run our benchmark regressions ($R4$ and $R7$, respectively, with and without the different types of R&D and innovation) but restricting our sample by including only the firms which changed the amount of labor input between 2001 and 2003. The remaining firms are not constrained in the use of labor input and, consequently, not constrained in the R&D and innovation choice. Specifically, we take into account both firms which changed the level of employment (see regressions $R8$ and $R9$ in Table 7) and firms which changed the number of workers employed with permanent contracts (see regressions $R10$ and $R11$). The estimates reported in Table 7 confirm the results seen above.

5 Conclusions

In this paper we studied the impact of R&D and innovation on the probability of using external numerical flexibility.

We presented a theoretical model to analyze how a firm’s demands for permanent and temporary labor contracts are affected by first and second order shifts in the distribution function of
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<tr>
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<td></td>
<td>(0.10)</td>
<td></td>
</tr>
<tr>
<td><strong>rdi</strong></td>
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<td>0.22**</td>
<td></td>
<td>0.22**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.11)</td>
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<td>(0.11)</td>
</tr>
<tr>
<td><strong>rde</strong></td>
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<td>0.46***</td>
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<td>0.47***</td>
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<tr>
<td></td>
<td></td>
<td>(0.13)</td>
<td></td>
<td>(0.13)</td>
</tr>
<tr>
<td><strong>in</strong></td>
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<td></td>
<td>0.44***</td>
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<td></td>
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<td>(0.10)</td>
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<td>0.36***</td>
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***, **, *Significant at 1%, 5%, 10% respectively. Standard error in parenthesis
firm productivity. We interpreted such changes as induced by R&D and innovation. We showed that while first-order stochastic shifts in the productivity distribution affect on the firm contract preference in the sense that the probability of hiring with a permanent contract increases, second-order stochastic shifts have ambiguous effects.

We next estimated the impact of R&D and innovation on the probability of employing a fixed-term or a temporary agency worker using a sample of Italian manufacturing firms. We found that R&D, performed either inside and outside the firm, always has a positive impact, which is particularly high in the latter case. In our view, the volatility of returns generates the link between R&D and ENF regardless of the production process. This is confirmed by the fact that external R&D activity has a stronger impact on the probability of use ENF than the internal one. Innovation activity has a significant and positive effect in the case of product innovation, while it has no, or negative, impact in the case of process innovation.

References


Hirsch, B., and S. Muller (2010): “Temporary agency work and the user firm’s productivity: First evidence from German panel data,” Nuremberg discussion paper n. 68.


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