R&D, innovation activity, and the use of external numerical flexibility

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A B S T R A C T

We address theoretically and empirically the impact of R&D and innovation activity (IA) on the use of external numerical flexibility (ENF). We build a firm-sided model showing that a first-order stochastic dominance shift in the productivity distribution function decreases the probability of hiring workers with temporary contracts, while a second-order shift has ambiguous effects. Next, using a dataset based on a survey of Italian manufacturing firms, we find that R&D and IA increase the extensive and intensive margins of employing workers with temporary contracts. Moreover, we disentangle the impact of different types of R&D and IA, finding that extra muros R&D always has a positive effect, while the effect of intra muros R&D is generally null. Also the effect of IA changes according to the type of activity: positive with product innovation, null with process innovation.

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1. Introduction

In this paper we study the effect of undertaking R&D and innovation activities (IA, hereafter) on the use of external numerical flexibility (IA, hereafter). R&D and IA are considered risky activities, i.e., they are associated with higher but more volatile returns. By ENF, we mean labor contracts with no cost incurred by their non-renewal. Since firing costs are an adjustment cost and since R&D and IA imply higher uncertainty, one may expect a positive relation between these activities and the use of flexible employment. However, other considerations may suggest a negative relation. First, R&D and IA should improve firm performance, thus reducing the conditional expectation of future dismissals and the related firing costs. Second, these activities may perform better in the presence of a commitment to a long-lasting labor relationship, since they may induce workers to enhance their firm-specific human capital. Hence, from a theoretical standpoint, the sign of the relation between R&D and ENF is not clear.

We address this issue both theoretically and empirically. We begin with a model in which a firm has to choose between a permanent and a temporary labor contract, and we study how the probability of opting for a temporary contract changes if the firm is engaged in R&D and IA. We show that while first-order stochastic shifts of the probability distribution of the firm productivity have a positive impact on the probability of hiring workers with permanent contracts, second-order shifts have ambiguous effects on this probability. Since undertaking R&D and IA implies both higher and more volatile expected returns, the effect on the labor contract choice is not theoretically predictable.

We then proceed to address this issue empirically. Specifically, using a dataset of Italian manufacturing firms, we estimate the impact of R&D and IA on both the probability of using at least one temporary contract and on its share in the firm workforce. We start looking at the aggregate of R&D and IA and find that both increase the extensive and intensive margins of using flexible employment. When we disaggregate among different types of R&D and IA, we find some differences. Extra muros R&D has always a positive impact on ENF, while the effect of extra muros R&D is generally not statistically significant. 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 loss implied by a negative scenario; 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 has always a positive impact on the use of ENF, process innovation activity has no influence. This could be due to the fact that product innovation typically implies higher uncertainty, while process innovation is generally associated with cost rationalization, whose effects are not as 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

1 Hereafter, the term flexibility will be used to refer to external numerical flexibility, thus excluding for instance internal numerical flexibility (part-time contracts) and functional flexibility (changing workers’ tasks).

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2. Review of the literature

2.1. ENF

By ENF, we refer to the possibility of changing the numbers of employed workers by using temporary contracts with no firing costs. Of these, the most frequently used are fixed-term contracts and temporary work agency (TWA, hereafter) workers. Even if with some differences, these contracts were originally introduced to meet firm-specific needs, e.g., the adjustment of the production capacity to peaks of production. Subsequently, the use of flexible employment has gone beyond this original scope and nowadays it is sometimes intended as a common practice in the management of the workforce: firms may systematically use flexible employment as a buffer to reduce the costs of downsizing (see Foote and Folta, 2002).

One stream of the literature assumes that temporary and permanent workers have the same productivity. Because of the difference in firing costs, this implies that 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 then introduce the possibility of hiring flexible employment, the newly hired being all given 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 Alonso-Borrego (2009) and Caggese and Cullat (2008) attribute a higher labor-augmenting factor to permanent workers than to temporary workers. In a similar vein, Albert et al. (2005) find a negative relation between flexible employment and firm-provided training activities, probably with negative effects on the 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, the price of this real option being a lower productivity.

Finally, studies that use cross-country industry-level data (Bassanini et al., 2008; Damiani and Pompei, 2010; Lisi, 2009) find that the incidence of flexible employment may dampen TFP growth. In the light of the above, the assumption of our model that permanent contracts are associated with higher productivity than temporary contracts seems well supported.

2.2. R&D and IA

Broadly speaking, firm R&D and IA aim at gaining market power by improving the quality of the product and/or upgrading the production process efficiency. It is difficult to disentangle these effects empirically since datasets generally report firm revenues and not prices, quantities, or product quality, separately. When these activities are studied, they are generally considered a kind of investment possessing higher mean returns and more uncertainty. A cornerstone in this strand of the literature is Griliches (1979), where the 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 relation between R&D and productivity. They stress that the accumulation of knowledge is not deterministic, assuming that firm TFP follows a stochastic process influenced by firm R&D expenditure. Their estimation results show that R&D expenditure has net returns significantly higher and more volatile than those deriving from physical capital.

The choice of engaging in R&D and IA 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 with high employment protection (as have most European countries) should prefer the latter because it implies a lower probability of paying the firing costs associated with the 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 their workforce without bearing firing costs. In Koenger (2005) the relation 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 increases the expected returns required to start a business, but, on the other hand, it pushes incumbent firms to innovate in order to avoid dismissal costs.

These contributions analyze the role of labor market institutions, such as employment protection legislation (EPL), on a firm’s choice to undertake R&D and IA. ² Alternatively, other contributions are more interested in how the performance of R&D and IA is affected by different labor contracts. Zhou et al. (2011) review some of the reasons that might induce a negative or a positive relation between the R&D and IA with 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 firm returns from innovation by making higher wage claims in case of success. On the other hand, the use of ENF may impair the organizational learning process, may reduce employee loyalty and effort in acquiring firm-specific knowledge, and may reduce the firm’s incentive to provide training. Kleinhechen et al. (2006) estimate the impact of the use of workers with temporary contracts and of TWA workers on both firm employment and sales, distinguishing between innovating and non-innovating firms. They find that the use of workers with temporary contracts has no significant effect on sales, but a positive effect on employment in non-innovating firms (suggesting a negative effect on productivity). Furthermore, they find that the use of TWA workers has a positive effect on employment growth and sales in innovating firms, while the opposite effect emerges in non-innovating firms.

Finally, Malgarini et al. (2011) address our same topic. They estimate the effect of aggregate IA on the probability of using flexible employment using a database of Italian firms over the period 2006–2010, finding a positive impact only when the Italian economy is in a downturn. They try to get rid of unobserved firm-specific characteristics using a sequential set of firm decisions while we use a large set of control variables. However, both papers share the view that the engagement in R&D and IA is a firm strategic or long-run choice, taken before the choice of labor contracts. ³ In fact, it is quite hard to see how the presence of at least one flexible employee could affect the choice concerning the engagement in R&D and IA.

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² Focusing on the effect of TWA workers on firm productivity, Hirsch and Muller (2012) find an hump-shaped relation: the effect of employing TWA workers is initially positive but, for intensive levels of use, it becomes negative.

³ On the interactions between EPL and labor market performance, see Saltari and Tilli (2009, 2011).

⁴ For example, Av 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.
3. The model

In this section, we first describe the choice between temporary and permanent labor contracts by a firm employing a single worker. We then analyze how this choice changes if the firm decides to undertake R&D and IA. With these activities, one would expect that the firm will have higher than average profits even if at the cost of a higher volatility. However, instead of using the traditional tools of mean and variance, we will employ the more general concept of stochastic dominance shifts. We will proceed in two steps, first by looking at first-order stochastic dominance and then at second-order stochastic dominance.

3.1. Labor contracts and value functions

Every firm can create a job and fill the position by employing either a permanent or a temporary worker. Firms draw their productivity \( y \) from a general distribution whose cumulative is \( G(y) \) with support in the range \( y \in [y_{\min}, y_{\max}] \) with \( y_{\max} > 0 \), discount the future at a constant rate \( r \), and bear a constant production cost \( k \).

For each \( y \), the productivity of a permanent worker is assumed to be higher than that of a temporary worker. \(^5\) Specifically, if the firm decides to hire with a permanent contract, its output is equal to \( y \), whereas it is \( ay \), where \( a \) is a positive constant lower than unity, if the firm hires with a temporary contract. \(^6\) However, while closing a temporary job does not imply any cost, laying-off a permanent worker involves a firing cost \( F \).

Firm productivity changes with the arrival of an idiosyncratic shock which occurs at a Poisson constant rate \( \lambda \), as in Blanchard and Landier (2002), when the shock occurs, if the position is filled with a permanent contract the firm must choose between continuing or closing the position, whereas if the position is filled with a temporary contract, the firm must choose between transforming the temporary contract into a permanent position or closing it.\(^7\)

The expected present value of the profit from a position filled as a permanent job \( rV_P(y) \) is given by

\[
rV_P(y) = y-k + \lambda \int_{y_{\min}}^{y_{\max}} [V_P(y)-V_F(y)]dG(s)-\lambda G(y)F + V_F(y). \tag{1}
\]

The left hand side of Eq. (1) represents the return required by the market for a permanent job, \( rV_P(y) \). The right hand side is the return the firm gets from the job. Current profits are given by \( y-k \). When the idiosyncratic shock arrives (an event whose probability is \( \lambda \)), the firm has to give up the current value of the job, \( V_P(y)* \). If productivity is in the range \( 0 \leq y \leq y_{\min} \), the firm closes the job and pays the firing cost \( F \). But if the productivity is higher than \( y_{\min} \), the firm keeps the permanent worker at the new level of productivity. Hence \( y_{\min} \) indicates the productivity threshold below which the firm lays off permanent workers, i.e., \( y_{\min} \) satisfies the reservation property, \( V_F(y_{\min}) = -F \).

Consider now the asset value of a temporary job. The expected present value of profit \( rV_T(y) \) is

\[
rV_T(y) = ay-k + \lambda \int_{y_{\min}}^{y_{\max}} [V_T(y)-V_F(y)]dG(s)-\lambda G(y)0), \tag{2}
\]

Eq. (2) states that the return required by the market \( rV_T(y) \) must be equal to the current flow of profit \( ay - k \) plus the expected change in value. When the idiosyncratic shock arrives, the worker is switched from a temporary to a permanent position only if the value of a permanent position is positive, i.e., if the new level of productivity is higher than \( y_{\min} \), where \( y_{\min} \) is defined as the level of productivity in which the value of the permanent contract is zero, \( V_F(y_{\min}) = 0 \). Otherwise, if the new level of productivity is lower than \( y_{\min} \), the temporary worker is fired and the job is closed with no cost.

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

\[
(r + \lambda)V_P(y) = y-k + \lambda \int_{y_{\min}}^{y_{\max}} V_P(y)G(s)ds, \tag{3}
\]

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 \( F \).

Since the firm profits are linear in \( y \), we guess that the value function is also linear, say \( V_P(y) = Ay + c \), where \( A \) and \( c \) are constants to be determined. Substituting the guess function into Eq. (3), we get

\[
A = \frac{1}{r + \lambda}, \tag{4}
\]

\[
c = \frac{1}{r + \lambda} \left[ -k + \lambda A \left( y_{\max} - \int_{y_{\min}}^{y_{\max}} G(s)ds \right) \right]. \tag{5}
\]

The threshold value for the permanent job is still unknown but the value function allows us to determine \( y_p \) by employing the reservation property, \( V_F(y_{p}) = -F \). Indeed, \( y_{p} \) is implicitly determined by the following equation, where the left hand side is the option value of closing a position and the right hand side is the firm value:

\[
-F = Ay_{p} + c. \tag{6}
\]

For temporary jobs, the reservation property gives \( V_P(y_{p}) = 0 \). We can link the two reservation productivities using Eqs. (6) and (4):

\[
y_{p} = y_{p}^* + (\lambda + r)F. \tag{7}
\]

This equation obviously implies \( y_{p} > y_{p}^* \). Given the presence of firing costs, the threshold value for converting a temporary contract into a permanent one is higher than the level of productivity at which a permanent worker is fired.

We can now deduce the value function for temporary jobs. Integrating Eq. (2) by parts and simplifying, we get

\[
(r + \lambda)V_T(y) = ay-k + \lambda \int_{y_{\min}}^{y_{\max}} V_T(y)G(s)ds, \tag{8}
\]

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

\[
B = \frac{a}{r + \lambda}, \tag{9}
\]

\[
d = \frac{1}{r + \lambda} \left[ -k + \lambda c + \lambda A \left( y_{\max} - \int_{y_{\min}}^{y_{\max}} G(s)ds \right) \right]. \tag{10}
\]

Under our assumptions, the advantage in terms of revenues derived from the use of permanent contracts instead of temporary contracts is increasing in the level of firm productivity.

It seems reasonable to assume that the value of the contract, be it temporary or permanent, cannot be positive if productivity is zero.
Looking at Eqs. (5) and (10), this is tantamount to assuming a value of \( k \) such that \( c, d < 0 \). Notice that in our framework, \( d > c \).\(^8\) Hence, for low levels of \( y \), firms prefer temporary to permanent contracts, while the opposite occurs for high levels of \( y \).

We will call \( y_{TP} \) the level of productivity at which the firm is indifferent between the two kinds of labor contracts. That is, for productivity levels below \( y_{TP} \), the firm prefers temporary to permanent contracts. Hence, \( y_{TP} \) is implicitly defined by

\[
V_P(y_{TP}) = V_T(y_{TP}).
\]

or

\[
Ay_{TP} + c = B y_{TP} + d.
\]

Solving Eq. (12), we obtain

\[
y_{TP} = \frac{\Lambda A^{r_0}}{1 - d} \int_{y_0}^y G(s) ds.
\]

As we saw in the Introduction, the labor contract choice depends, on the one hand, on the productivity gap between the permanent and temporary jobs and, on the other hand, on the labor hoarding induced by the presence of firing costs. Indeed, Eq. (13) shows that the threshold value \( y_{TP} \) is a function of the productivity gap \( 1 - a \), and of labor hoarding represented by the integral between the productivity threshold for closing a permanent position and the productivity below which it would be optimal to close a permanent position in the absence of firing costs. As generally understood in the literature, labor hoarding is what happens when a temporary negative shock occurs: because of the existence of adjustment costs, the firm prefers to keep its job position occupied even if currently unprofitable. This is an ex post definition. In our framework, labor hoarding is defined in ex ante terms: it is determined by the probability of drawing a productivity in the range between \( y_0 \) and \( y_{TP} \) which in turn depends on the level of firing costs. The higher the firing costs, the greater the difference between the two productivity thresholds.

Consistently with this definition, an increase in \( a \), i.e., a reduction of the productivity gap between permanent and temporary contracts, induces an increase in \( y_{TP} \). Since there is no change in the distribution function of productivity levels, an increase in \( y_{TP} \) implies an increase in the productivity levels at which temporary contracts are preferred. The same effect follows from an increase in firing costs.\(^9\)

3.2. R&D and IA and the labor contract choice

We now consider the effect of R&D and IA on the two value functions just obtained, and thus on the choice between the two different contracts. We do this by analyzing what happens if the probability distribution \( G(y) \) changes. Our starting assumption is that R&D and IA are associated with higher and more volatile returns. Instead of addressing this issue directly in terms of a higher mean and volatility, we use the more general concept of stochastic dominance.

\^8\) To see this note that the inequality can be written as \( d < \frac{1}{\Lambda + r} \left[-k + \Lambda \int_{y_{max}}^{y_{TP}} \frac{G(s) ds}{s} \right] < c \) or \( -k + \Lambda \int_{y_{max}}^{y_{TP}} \frac{G(s) ds}{s} > c \).\(^9\) Using this result in Eq. (13), we get

\[
\frac{dy_{TP}}{dp} = \frac{\Lambda A^{r_0}}{1 - d} \int_{y_0}^y G(s) ds.
\]

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 a 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

\[
\frac{dG}{dp} = G_2(s, \rho) < 0.
\]

We first look at what happens to \( y_{TP} \) when \( \rho \) increases in this sense. Implicit differentiation of Eq. (6) gives\(^10\)

\[
\frac{dy_{TP}}{dp} = \frac{\lambda \int_{y_{max}}^{y_{TP}} G(s; \rho) ds}{1 + \frac{\lambda}{\Lambda} G(y_{TP}; \rho)} < 0,
\]

which, by Eq. (14), is negative.

We are now ready to see the effect of a first-order stochastic shift on \( y_{TP} \). Using Eq. (12) and noticing that because of Eq. (7), we have

\[
\frac{dy_{TP}}{dp} = \frac{dy_{TP}}{dp} = \frac{\lambda \int_{y_{max}}^{y_{TP}} G(s; \rho) ds}{1 + \frac{\lambda}{\Lambda} G(y_{TP}; \rho)} < 0.
\]

which, by Eqs. (15) and (14), is negative. This implies that a higher expected productivity should encourage firms to offer permanent contracts.

However, what really matters is not how the threshold value \( y_{TP} \) changes as a consequence of a first-order stochastic dominance shift, but rather how the probability of hiring with a temporary contract changes. In formal terms, this implies that we are interested in the sign of the total derivative

\[
\frac{dG(y_{TP}; \rho)}{dp} = G_1(y_{TP}; \rho) \frac{dy_{TP}}{dp} + G_2(y_{TP}; \rho) = g(y_{TP}; \rho) \frac{dy_{TP}}{dp} + G_2(y_{TP}; \rho),
\]

where the distribution function \( G(y_{TP}; \rho) \) represents the probability that the firm prefers a temporary to a permanent contract. Thus, a negative sign in Eq. (17) would imply that the firm with a higher productivity perspective also has a lower probability of hiring with a temporary contract. Using Eq. (16), it is easy to see that in the case of first-order stochastic dominance, the total derivative of \( G(y_{TP}; \rho) \) is negative since, by definition, \( G_2(y_{TP}; \rho) \) is negative.

Consider now the effect of a higher uncertainty of productivity, which is also a by-product of undertaking R&D and IA. We look at the symmetric situation, that is, what happens if we increase the riskiness of the \( y \) distribution while leaving its mean unchanged? More precisely,

\[
\frac{dy_{TP}}{dp} = \frac{\lambda \int_{y_{max}}^{y_{TP}} G(s; \rho) ds}{1 + \frac{\lambda}{\Lambda} G(y_{TP}; \rho)} > 0.
\]

Using this expression, we obtain the derivative in the main text.
we will look at mean preserving spreads by using the second-order stochastic dominance. We reinterpret increases in the index $\rho$ as increases in riskiness leaving the mean unchanged: \[ \int_{\gamma_1}^{\gamma_2} (G(s, \rho_2) - G(s, \rho_1)) ds \leq 0 \]

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

\[ \int_{\gamma_1}^{\gamma_2} G_2(s, \rho_2) ds \leq 0. \quad (18) \]

We can now repeat the same steps as above. An increase in risk implies, as before, that the threshold value for permanent contracts decreases, so that Eq. (15) still has a negative sign. But, perhaps surprisingly, Eq. (16) does not have a definite sign. Indeed, a riskiness increase has now an ambiguous effect on $y_{TP}$. This is because, unlike the case of first-order shifts, we do not know how uncertainty affects labor hoarding, i.e., we do not know the sign of \[ \int_{\gamma_1}^{\gamma_2} G_2(s, \rho_2) ds. \]

It is straightforward to see that for just the same reason, the total derivative of the distribution function in this case has an ambiguous sign.

To sum up, Eq. (17) shows that a first-order stochastic shift in the productivity distribution decreases the probability of hiring with a temporary contract. Contrariwise, a second-order stochastic shift has an ambiguous effect.

3.3. A numerical example

To give some of the flavor of these results, let us assume that the unit time period is a year and that the parameters of the economy have the following values: $r = 0.05$, $\lambda = 0.1$, $a = 0.95$, and $F = 2k$, i.e., the firing costs are equal to two years of unit cost. As in Blanchard and Landier (2002), we adopt the uniform probability distribution with extrema $y_{min} = m - \frac{1}{2} \sigma$, $y_{max} = m + \frac{1}{2} \sigma$, where $m$ is the mean and $\sigma$ (equal to the inverse of the support of the distribution function) is in reverse if it is written in terms of the upper bound of the support in the upper limit of integration, as in the main text.

\[ \int_{\gamma_1}^{\gamma_2} (G(s, \rho_2) - G(s, \rho_1)) ds \leq 0 \]

where we use $\sigma$ in place of $\rho$ as a measure of riskiness. The non-monotonicity implies that the two addends should have opposite signs, at least in the neighborhood of the maximum of the probability distribution. Under our parameterization, as uncertainty rises, the productivity threshold $y_{TP}$ monotonically increases, i.e., $\frac{dy_{TP}}{d\sigma} > 0$.

It is worthwhile to observe that the non-monotonicity of the probability distribution with respect to $\sigma$ is not confined to the uniform distribution. Indeed, one can get very similar results using other distributions. For instance, employing the lognormal distribution and almost the same parameterization, one obtains the same kind of non-monotonicity of $G(y_{TP}, \sigma)$, as shown in Fig. 3. Observe that in this case, $y_{TP}$ also is not monotonic in $\sigma$.14

Recall that $R&D$ and $IA$ presumably give rise to (expected) profits both higher and more volatile. Taking stock of the theoretical results, this means that we do not know how these activities will affect labor contract choices. In the next section we proceed empirically to address this issue.

4. Empirical investigation

4.1. The dataset

We estimate the relation between $R&D$ and $IA$ and the 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 firms’ structure and workforce composition, the $R&D$ and IA undertakings, and the sources of financing.15 In some cases the dataset provides information referring to each year, while in other cases the information refers to the entire time period.

Table 1 gives some descriptive statistics of our sample. It includes more than four thousand firms with 110 employees on average. As often happens when surveys ask for a lot of information, small firms (less than 20 employees) are under represented; indeed they represent one-fifth of our sample even though the Italian production system is mostly composed of small firms. The average sales per employee is 241 thousand euro and does not depend linearly on the firm size: the sales per employee decreases when moving from small to medium size (between 20 and 99 employees) firms, but increases when moving from medium to big (100 or more employees) firms.16 The definition of $ENF$ is strictly related to the type of labor contract. We count as flexible (flex) both a fixed term contract (tm) and a TWA worker (aq). Even if Italian aggregate data show 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 spread across firms. As to firms’ activities, in our sample less than half of the firms are engaged in $R&D$ ($rd$) while more than 63% are engaged in innovation (inn). Finally, Table 1 shows that rd, in and flex (if measured as binary variables) are positively correlated among each other, thus providing a first evidence of the linkage between these firm choices.

12 Thus, unlike what happens in the Blanchard and Landier (2002) model, being above or below the productivity mean is relevant.
13 The only change is in the value of $a$, which in the lognormal case is $a = 0.97$.
14 It is left to future research to investigate how general is this non-monotonicity result of the distribution function.
15 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/sapporto_corporate.htm. This dataset has been used in other studies (see Caggesi and Cubat, 2008 and Hall et al., 2006).
16 This path is not peculiar to our dataset but holds good for the whole structure of Italian firms. For example, taking the data reported in Istat (2012) referring to industry and service firms, it is easy to see that the turnover per employee initially decreases and then increases with firm size.
4.2. Benchmark empirical models

We have run four types of regression, which differ according to the way we deal with the dependent variable and the variable measuring the R&D. First of all, we have to consider that our dependent variable is given by the use of fixed term contracts and the TWA workers. From the survey we can infer the annual number of workers with fixed term contracts, whether the firm has ever (within the three-year period) employed TWA workers, and the number of employed TWA workers in the last year (2003). So, on the one hand, we can build a discrete dependent variable, \( \text{flex} \), that is equal to 1 if the firm has ever employed at least one worker with a fixed term contract or a TWA worker, and equal to 0 otherwise. On the other hand, we can build a continuous variable referring just to 2003. Specifically, we calculate the share of flexible employment in the total employment (given by the sum of firm employees plus the TWA workers used by the firm). When the dependent variable is binary, the explanatory variables are measured as the average value along the entire time period (whenever possible), and the estimation is carried out through logit regressions. In this case, the regressions indicate whether undertaking R&D and IA affects the probability of using ENF. When the dependent variable is continuous, the value of the explanatory variables is that reported in 2003. In this case, we run Tobit regressions to take into account that the share of flexible employment has a lower (0) and an upper (1) bound. Since the share of flexible employment is not normally distributed, we use the log-transformation of this variable as the dependent variable.\(^{17}\)

The Tobit regressions clarify whether undertaking R&D and IA affects the intensity of the use of ENF. Furthermore, our regressions differ according to the way the R&D variable is measured. It can be just a binary variable (as IA) equal to 1 if the firm carried out this activity and equal to 0 otherwise, or it can be considered a continuous variable given by the expenditure per employee in R&D. Combining the two ways of measuring the dependent variable and the two ways of defining R&D, we get four types of regression.

Table 2 gives the estimated value and the standard error of the coefficients when only R&D and IA are used as explanatory variables. Regressions R1 and R2 are both logit regressions where in the former, R&D is a binary variable while it is continuous in regression R2. Instead, regressions R3 and R4 are both Tobit regressions where in the former, R&D is a binary variable while it is continuous in regression R4. The first two columns of Table 2 show that both R&D and IA have a positive and significant impact on the probability of using flexible employment. The last two columns show a positive and statistically significant effect also on the share of flexible employment.

To give a demonstrative example, we evaluate how much the choice of engaging in R&D and IA would affect the probability of employing at least one flexible worker (with reference to regression R1). The dataset indicates that 64.6% of 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 is 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 activity. Without R&D activity, the predicted probability of using flexible employment is 59.0%, but 72.1% otherwise. This is a change of 13.1 percentage points, the confidence interval of which is the range from 9.9 to 16.3.

Similarly, without IA, the predicted probability of observing ENF is 57.4%, but 69.5% otherwise. This is a change equal to 12.1 percentage points, with a confidence interval from 8.7 to 15.5.

4.3. The control variables

In this section, we introduce some variables in order to control for firm and employee characteristics. The list of control variables is the following. The average (along the three years of the survey) level of employment (\( \text{em} \)) and the average ratio of sales over employment (\( \text{se} \)). The former should control for firm size and it seems reasonable to assume that the higher the level of employment, the higher the probability of using at least one form of flexible employment, while it is difficult to see a priori the sign of the effect on the share of ENF. The latter is a rough measure of labor productivity and, consequently, should be negatively related to the use of ENF. Another firm characteristic that we consider particularly interesting concerns its export activity, \( \text{exp} \), equal to 1 if the firm exported and to 0 otherwise. This kind of activity introduces another source of uncertainty related to the behavior of foreign markets. Furthermore, the dataset provides a wide range of information related to the financing side. We are particularly interested in the presence of financial constraints. Firms are asked to answer whether they would have desired further credit (\( \text{cr} \)), where a positive

---

\(^{17}\) The distribution of the log-transformation of the share of flexible employment without the extreme values has a skewness equal to \(-0.14\) and kurtosis equal to 3.53. Moreover, since the share of flexible employment is truncated at zero, we decided to follow Cameron and Trivedi (2009, p. 532) and carry out the log-transformation.
answer may be interpreted as a signal of credit rationing. The other variables related to the financing side regard the source of investment financing, distinguishing between: risk capital, self-financing, short-term bank loans, medium/long-term bank loans, medium/long-term bank loans at subsidized rates, government grants, fiscal benefits, leasing, group firms’ loans, other firms’ loans. Other control variables can be drawn from the dataset. The firm localization is distinguished in four macro-areas. The Pavitt classification indicates that a firm’s activity pertains to a sector that is supplier dominated, scale intensive, specialized supplier, and science based. The incidence of employees with secondary high school and a graduate degree to control for employee education, and the average number of employees used in R&D activity.

Even if in the following regressions all the previous variables will be included, Table 3 focuses on just the first four cited variables that we consider particularly interesting from a theoretical point of view, and whose regression coefficients will be reported hereafter. Table 3 provides for each variable: i) the incidence among firms in the case of binary variables, and the mean value, otherwise; ii) the correlation with the use of ENF.

Table 1
Sample descriptive statistics.a

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>n. of firms</td>
<td>4103</td>
<td>% Firms with flex</td>
</tr>
<tr>
<td>Average n. of workers</td>
<td>110</td>
<td>% Firms with tm</td>
</tr>
<tr>
<td>% Small firms</td>
<td>21</td>
<td>% Firms with ag</td>
</tr>
<tr>
<td>% Medium firms</td>
<td>55</td>
<td>% Firms with rd</td>
</tr>
<tr>
<td>% Big firms</td>
<td>24</td>
<td>% Firms with in</td>
</tr>
<tr>
<td>Sales per worker (small firms)</td>
<td>280</td>
<td>corr (flex, rd)</td>
</tr>
<tr>
<td>Sales per worker (medium firms)</td>
<td>222</td>
<td>corr (flex, in)</td>
</tr>
<tr>
<td>Sales per worker (big firms)</td>
<td>248</td>
<td>corr (rd, in)</td>
</tr>
</tbody>
</table>

a All the correlations are significant at 1 percent. Small firms have less than 20 employees; medium firms have between 20 and 99 employees; big firms have 100 or more employees. Sales per worker are in thousands of 2001 euro.
4.4. Regressions with control variables

We ran the same four types of regression including all the cited control variables. The estimated coefficients and the standard errors are reported in Table 4. First of all, it can be noticed that, even if the estimated values are lower than in the absence of the control variables, the effect of engaging in innovation is always positive and statistically significant at 1% both on the probability of using ENF and on the share of flexible employment. With regard to the effect of engaging in R&D, it is still positive and significant at 1% if it is defined as a binary variable. Otherwise, when it is defined in terms of expenditure per worker, it is significant at 5% in the logit regression, while it is not significant in the Tobit regression. Concerning the control variables we are interested in, it can be noticed that just the firm size is always statistically significant, engaging in export activity turns out to boost the use of ENF in three out of four regressions, while neither turnover per employee nor credit constraints are ever significant.

4.5. Extensions

Our dataset allows us to disentangle different types of R&D and IA. R&D activity can be run inside the firm (rdi) and outside (rde). The IA 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). The statistics given in Table 5 are obtained when treating all these variables as binary variables. Specifically, Table 5 shows the incidence among firms and the correlation with the use of flexible employment. It emerges that all the correlations are positive and significant.

For internal and external R&D activity we have also the share of incidence. Then, combining this information with the total expenditure on R&D, we can run regressions in which the different types of R&D are also measured as continuous variables.

The estimation results in Table 6 come from the same four types of regressions previously illustrated. The first two columns refer to logit regressions, while the third and the fourth refer to Tobit regressions. The same control variables are included. The main results are as follows.

Striking differences emerge between the different types of R&D and innovation. Starting from the former, all the regressions suggest a positive and significant influence of external R&D on ENF. On the contrary, internal R&D turns out to have a significant effect (at 10%) only in the case in which both the dependent and the R&D variables are handled as binary variables. In the other cases, the R&D run inside the firm does not show a significant influence. We interpret this result in the following way: The uncertainty associated with R&D activity induces the use of flexible employment, but if the R&D is run inside the firm, it could be more convenient to establish a long-term labor relationship and, consequently, in the case of internal R&D the two forces compensate each other, producing no significant effect on the use of ENF. This suggests that there could be a complementarity between internal and permanent contracts.

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 and on its share, while the impact of process innovation is not significant. Indeed, product innovation can be considered a risky activity while process innovation is more related to the rationalization of costs, generally not implying 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. Finally, the role of the selected control variables is similar to that which emerged from Table 4.

4.6. Robustness analysis

In this section, we restrict our dataset by including only the firms which changed the amount of permanent workers between 2001 and 2003. This choice is mostly related to the idea that the adjustment costs associated with permanent labor contracts may affect a firm’s choice to engage in R&D. On the one hand, the expected costs implied by a risky activity increase in the presence of adjustment costs, determining a negative influence of the firing costs on the choice of engaging in R&D (Saint-Paul, 2002). On the other hand, just to avoid the adjustment costs associated with a downturn, firms may be induced to exert more effort in R&D and innovation activities (Koeniger, 2005). We recognize that labor market institutions and labor relations may affect a firm’s strategic choice also in further and complex ways. Notwithstanding, we think that our specific questions do not suffer a reverse causality.

---

Table 2
Descriptive statistics of control variables.

<table>
<thead>
<tr>
<th></th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
</tr>
</thead>
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<tr>
<td>rd</td>
<td>0.58***</td>
<td>0.06***</td>
<td>0.76***</td>
<td>0.05***</td>
</tr>
<tr>
<td>(0.07)</td>
<td>(0.01)</td>
<td>(0.14)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>in</td>
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<td>0.70***</td>
<td>1.00***</td>
<td>1.20***</td>
</tr>
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<td>(0.07)</td>
<td>(0.15)</td>
<td>(0.14)</td>
<td></td>
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<td>127</td>
<td>106</td>
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<td>4099</td>
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</table>

Table 3
Descriptive statistics of control variables.

<table>
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<th>em</th>
<th>se</th>
<th>exp</th>
<th>cr</th>
</tr>
</thead>
<tbody>
<tr>
<td>% firms</td>
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<td>240.5***</td>
<td>74.1***</td>
<td>14.6***</td>
</tr>
<tr>
<td>corr</td>
<td>.12***</td>
<td>-.02</td>
<td>-.13***</td>
<td>-.02</td>
</tr>
</tbody>
</table>

a Average number of employees.
b Thousands of 2001 euros.
*** Significant at 1%.

Table 4
Logit and Tobit regressions with control variables.

<table>
<thead>
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<th>R7</th>
<th>R8</th>
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</thead>
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<td>0.46***</td>
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</tr>
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<td>(0.09)</td>
<td>(0.02)</td>
<td>(0.16)</td>
<td>(0.02)</td>
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<td>0.63***</td>
<td>0.75***</td>
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<td>(0.08)</td>
<td>(0.17)</td>
<td>(0.16)</td>
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<td>(0.09)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td></td>
</tr>
<tr>
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<td>0.004***</td>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td>(0.0006)</td>
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<td>(0.0003)</td>
<td>(0.0004)</td>
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<td>-0.00</td>
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<td>(0.00)</td>
<td>(0.00)</td>
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</table>

Standard error in parentheses.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Table 5
Different types of R&D and innovation activities.

<table>
<thead>
<tr>
<th></th>
<th>rdi</th>
<th>rde</th>
<th>in1</th>
<th>in2</th>
<th>in3</th>
<th>in4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% firms</td>
<td>41.6</td>
<td>20.6</td>
<td>41.7</td>
<td>42.8</td>
<td>20.4</td>
<td>27.2</td>
</tr>
<tr>
<td>corr</td>
<td>.179</td>
<td>.164</td>
<td>.172</td>
<td>.122</td>
<td>.121</td>
<td>.138</td>
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</tbody>
</table>

* All the correlations are significant at 1% or less.
Table 6
Logit regressions with different types of R&D and innovation.

<table>
<thead>
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<th></th>
<th>R9</th>
<th>R10</th>
<th>R11</th>
<th>R12</th>
</tr>
</thead>
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<tr>
<td>rdi</td>
<td>0.17**</td>
<td>0.00</td>
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<td>−0.01</td>
</tr>
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<td>(0.02)</td>
<td>(0.17)</td>
<td>(0.03)</td>
</tr>
<tr>
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<td>0.19**</td>
<td>0.55***</td>
<td>0.11***</td>
</tr>
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<td>(0.06)</td>
<td>(0.19)</td>
<td>(0.05)</td>
</tr>
<tr>
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<td>0.35***</td>
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<td>(0.10)</td>
<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>in2</td>
<td>−0.08</td>
<td>−0.04</td>
<td>−0.02</td>
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<td></td>
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<td>(0.09)</td>
<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>in3</td>
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<td>0.13</td>
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<td>(0.12)</td>
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<td>(0.21)</td>
</tr>
<tr>
<td>in4</td>
<td>0.32**</td>
<td>0.11**</td>
<td>0.58**</td>
<td>0.60**</td>
</tr>
<tr>
<td></td>
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<td>(0.11)</td>
<td>(0.20)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>exp</td>
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<td>0.37</td>
<td>0.44</td>
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<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>em</td>
<td>0.004**</td>
<td>0.004**</td>
<td>0.001**</td>
<td>0.001**</td>
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<td>(0.003)</td>
<td>(0.003)</td>
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<td>−0.00</td>
<td>−0.00</td>
<td>−0.00</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>cr</td>
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<td>0.02</td>
<td>−0.11</td>
<td>−0.12</td>
</tr>
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<td>(0.11)</td>
<td>(0.11)</td>
<td>(0.19)</td>
<td>(0.19)</td>
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<tr>
<td>LR χ²</td>
<td>419</td>
<td>420</td>
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<td>278</td>
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<td>n. obs.</td>
<td>3489</td>
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<td>3484</td>
<td>3484</td>
</tr>
</tbody>
</table>

Standard error in parentheses.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

solve the issue, but at least it restricts the analysis to firms with the possibility of changing the number of workers with permanent contracts.

The estimates included in Table 7 confirm the previous results. External R&D, product innovation, and management and organizational innovations related to process innovation, have a positive impact on the extensive and intensive margins of ENF. Internal R&D and process innovation are not associated with a higher use of flexible employment.

5. Conclusions

In this paper we studied the impact of R&D and innovative activities (IA) on the probability of using a firm's using external numerical flexibility (ENF) for at least some of its employment, and on the share of ENF in a firm's total employment. 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 firm productivity. We interpreted such changes as being induced by a firm's engagement in R&D and IA, and showed that the joint effect of these shifts has an ambiguous impact on the choice of labor contract.

Next, we used a sample of Italian manufacturing firms in order to test how the choice to engage in R&D and IA affects the extensive and intensive margins of the use of fixed-term and TWA contracts. Since the issue of reverse causality cannot be excluded, but is difficult to address with the available data, the estimated coefficients should be interpreted as a measure of the linkage between the firm choices we are interested in. We found a positive linkage of ENF with R&D performed outside the firm while, if it is performed inside the firm, the regressions generally exclude a statistically significant linkage. We interpret this result in the light of a positive complementarity between the engagement in R&D and the use of long-lasting labor contracts. R&D is a risky activity and may induce the use of flexible employment in order to reduce downturn costs. Alternatively, when the research activity is developed inside the firm, it could be better to have a stronger commitment with the labor force. The joint presence of these effects makes the engagement in R&D run inside the firm irrelevant to the use of ENF. The estimates concerning the relevance of IA show that it is significant and positive in the case of product innovation, while it is non-significant in the case of process innovation.

Finally, even if our contribution does not provide a policy evaluation analysis, it indicates that public subsidies to firms for engaging in R&D and IA can have ambiguous effects on labor contract composition. The way the incentives are defined can be quite relevant. For example, limiting the financial benefits to R&D expenditures inside the firm may have no impact on labor contract choice, while including also the expenditure for external consulting may (indirectly) encourage the spread of ENF. Similar considerations apply to public subsidies to innovation activities. While process innovation may have no spin-off on labor contract composition, boosting product innovation may increase the use of ENF.

Table 7
Logit regressions with different types of R&D and innovation.

<table>
<thead>
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<th>R14</th>
<th>R15</th>
<th>R16</th>
</tr>
</thead>
<tbody>
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<td>0.02</td>
<td>0.20</td>
<td>−0.02</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.02)</td>
<td>(0.18)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>rde</td>
<td>0.45***</td>
<td>0.12**</td>
<td>0.44**</td>
<td>0.15**</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.08)</td>
<td>(0.19)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>in1</td>
<td>0.30***</td>
<td>0.35***</td>
<td>0.43**</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
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<td>(0.12)</td>
<td>(0.18)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>in2</td>
<td>0.03</td>
<td>0.09</td>
<td>0.17</td>
<td>0.23</td>
</tr>
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<td>(0.12)</td>
<td>(0.18)</td>
<td>(0.18)</td>
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<td>in3</td>
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<td>0.16</td>
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<td>(0.22)</td>
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<td>(0.20)</td>
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<td>(0.18)</td>
</tr>
<tr>
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<td>0.005***</td>
<td>0.0009*</td>
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<td>LR χ²</td>
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</tr>
</tbody>
</table>

Standard error in parentheses.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

References

Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics Using Stata. Stata Press.


