Labour Flows and R&D: A Quantile Regression Analysis

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Abstract

Does R&D affect hirings, separations or both? Different answers to this question imply different behavioral responses of firms to innovation. Using a sample of Italian manufacturing firms, this paper explores the effects of R&D intensity on hiring, separation and churning rates. Based on quantile regression models, the results indicate that initial R&D intensity has a positive impact on subsequent hirings and churning and a negligible effect on separations. The results remain stable when the estimates are based on the two- and three-year averages of the labour flow rates and when we account for lagged R&D intensity, for different sub-periods and for an alternative measure of the hiring, separation and churning rates.

Keywords: *Labour flows; R&D; Quantile regression.*

JEL codes: *J63; L25; M51; O33.*

1.Introduction

The present study is aimed at investigating the relationship between labour flows and innovation at the firm level. Competing through innovation may trigger organizational changes possibly leading to contractions or expansions of the workforce of firms. Theoretical contributions suggest that both the kind and strength of innovation strategies pursued by firms are likely to produce different outcomes in terms of changes in firm size and labour flows, with an overall effect of innovation on employment that still remains unclear[1](Van Reenen, 1997). From a policy standpoint, such ambiguity becomes relevant for the appropriate design of innovation policies and the evaluation of their effectiveness. Thereby, the understanding of what to expect from more or less innovation is an empirical task that has received a lot of attention among academics. Nonetheless, the empirical evidence of the relationship between employment growth and innovation is rather mixed. Studies based on output measures of innovation often investigate the impact of product and process innovations. While product innovation is often found to have a positive impact on growth (Lachenmaier and Rottmann, 2011; Hall et al., 2008; Dachs and Peters, 2014; Calvo, 2006), process innovation has been associated not only to employment growth (Lachenmaier and Rottmann, 2011), but also to employment reductions (Dachs and Peters, 2014) and employment stability (Hall et al., 2008). Other studies, instead, concentrate on the effects of input measures of innovations, mostly R&D activities, on employment changes. From this standpoint, both Yasuda (2005) and Falk (2012) finds that R&D has a positive impact on growth, while Brouwer et al. (1993) report a negative relationship between R&D expenditures and employment, but when the authors refine their R&D measure as the percentage of R&D dedicated to product development, they find a positive impact on employment growth. Differently, Klette and Førre (1998) do not find any clear-cut relationship between job creation and R&D intensity.

All of these studies mostly concentrate on net employment changes, while no authors, to the best of our knowledge, have dealt with the impact of innovation on the components of the employment growth rate, namely hiring and separation rates. As recently noted by Lazear and Spletzer (2013), "*among the key issues in personnel economics, none is more important than understanding the factors behind the hiring and separation decisions*". Thus, the first goal of this study is to investigate whether it is possible to associate firms R&D to variations in the rates at which firms hire new workers, separate from existing ones or both.

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[1] Surveyingtheliterature, a keydistinction is alwaysmadebetweenproductandprocessinnovation. Theformerfostersemployment as morelabour is neededtoproducenewgoodsorimprovethequality of existingones. On

Firms grow and contract by manipulating the number of hires, the amount of separations, or both. These choices are non-random and, at least in principle, can be affected by R&D strategies. Indeed, since in R&D companies knowledge is intensively used, an increase in the number of hires could reflect the need to enrich or replace the endowment of skills. Lower separations could depend upon the need to retain skills and knowledge belonging to existing employees. Thus, observed hirings and separations can eventually be thought of as the result of optimal personnel policies that take into account the commitment to innovation pursued by firms.

From the definitions of job and worker flows, it is clear that hires and separations can be seen as the natural consequence of both job creation and job destruction. A growing firm must hire at least as many workers as needed to reach the desired level of employment, although firms often hire more employees in order to replace workers who separate. Analogously, contracting firms very often have more separations than those needed to reach the desired contraction. As a result, hirings and separations may reflect an excess of worker turnover over the net job creation/destruction (i.e. churning), rather than actual changes in firm size. In a context of innovating firm, churning can arise from the reassessment of the quality of existing workers, meaning that existing matches are re-evaluated as an optimal personnel policy. In general, innovation could imply worker flows even in the absence of net employment changes. Very often, indeed, technological progress requires labour reallocation within firms (Bauer and Bender, 2004), but not necessarily a change in firm size. In this respect, this paper has a second goal and aims at offering a novel contribution to the characterization of churning in connection to R&D practices. Up to now, indeed, the literature has mainly focused on cross sectional and time series features of churning along dimensions such as employer size, firm age and industry[2]. Few scholars have attempted to quantify the extent to which more or less churning can be explained by other factors. Notable exemptions are Bauer and Bender (2004) and Askenazy and Galbis (2007) who assess the role played by organizational and technological changes (in the form of ICTs) on churning dynamics.

Our main findings can be summarized as follows. Initial R&D acts positively on subsequent hirings and churning, leaving unchanged separations. Moreover, the effect becomes more pronounced when moving from the lower quantiles of the hiring rate distribution to the upper ones. This is an important characterization of personnel policies driven by innovation because it implies that R&D produces new entrants at the firm level but, also, an excess of worker movements. Obviously, our results are confined to a partial equilibrium approach typical of micro econometric studies. Nevertheless, we believe that our results are still informative for the ongoing debate in the growth-innovation literature.

The remainder of the paper is organized as follows. Section 2 describes the data and the variables used in the analysis along with summary statistics; section 3 outlines the methodology; section 4 discusses the results; section 5 concludes.

2. Data and model specification

The analysis in this study draws on firm level data contained in the *Survey of Italian Manufacturing Firms* (SIMF) collected by Unicredit-Mediocredito Centrale. These data have been already exploited by other scholars in the growth-innovation literature. Del Monte and Papagni (2003) report that the growth rate of sales is positively correlated with R&D intensity. Hall et al. (2008) show that both product and process innovation contribute to the growth of firms. Piva and Vivarelli (2005) find a significant, but small in magnitude, positive relationship between innovation and employment. We believe that our results can be complementary to those already found in the literature and can contribute to widen the overall picture gained so far.

The survey has been conducted from 1992 to 2007 every three years and delivers information on the three years prior to the interview. Each wave includes both a stratified sample[3] of firms with up to 500 workers - with no less than 11 employees - and all firms above this threshold.

Even if each wave contains around 9000 records, exploiting the panel dimension of the data is arguable, since the sample overlapping across waves is rather small[4]. Firms that participate in the survey were asked to fill out a questionnaire eliciting information on labour force, innovation activities, export and finance. The data have the main advantage of providing detailed information on annual hires and separations, as well as employment

[2]See, forinstance, theworks of Burgess et al. (2000), Burgess et al. (2001) andDavisandHaltiwanger (1999).
[3]Stratification is based on industry, geographicareaandfirm size.
[4]Bymergingthesecondandthirdwaves, PivaandVivarelli (2005) areabletobuild a panel of 575 manufacturingfirms.

stocks and R&D personnel. In this way, it is possible to recover labour flow rates and a measure of R&D intensity based on R&D personnel, which is often used in the literature.

In the present study, we consider the 2001 and 2004 waves of the available surveys. By merging these waves, we build a dataset of around 19900 records over the period 1998-2006. We cleaned the data from inconsistent data and missing values, ending up with slightly more than 13800 observations, including both innovative and non-innovative firms.

The empirical model is implemented on three key dependent variables, the hiring, separation and churning rates. Specifically, hiring and separation rates at time t are defined in equations 1 and 2 respectively, as the total number of hires (H) or separations (S) between $t-1$ and t, divided by total employment[5] (E) at time $t-1$:

$$HR_{it} = \frac{H_{i;t,t-1}}{E_{i;t-1}} * 100 \quad (1)$$

$$SR_{it} = \frac{S_{i;t,t-1}}{E_{i;t-1}} * 100. \quad (2)$$

As far as the churning rate is concerned, we closely refer to the definition found in the seminal contribution of Burgess et al. (2000). In particular, churning is measured as the amount of worker turnover in excess of that required for a firm to achieve its desired employment change[6]. Algebraically, it is computed as the difference between the sum of hires and separations, i.e. the worker flow, and the job reallocation, where the latter is defined as the absolute value of the net employment change, i.e. the job flow. Then, we compute the churning rate by dividing this amount over the initial level of employment:

$$CR_{it} = \frac{H_{i;t,t-1}+S_{i;t,t-1}-|E_{i,t}-E_{i;t-1}|}{E_{i;t-1}} * 100. \quad (3)$$

We further compute two- and three-year averages of the hiring, separation and churning rates to check the robustness of our results. Despite all these rates are widely used in empirical studies, one could still argue that they are biased towards small firms. Think, for instance, at two companies, each hiring five employees. If the initial size of the two companies is, respectively, 10 and 100, the former will exhibit a 50% hiring rate, while the latter a 5% hiring rate. Thus, small firms are much more likely to experience higher rates. For this reason, we develop an alternative measure of the hiring, separation and churning rates in the spirit of the growth indicator used by Birch (1981). This measure is less sensitive to initial firm size and is obtained by multiplying the rates as defined in equations 1, 2 and 3 by the level of employment at time t. We use this measure to check the robustness of our results.

To shed light on the relationship between labour flows and innovation, we use the R&D intensity. According to previous research, R&D intensity can be measured both in financial and organizational terms. From the first point of view, scholars commonly use the R&D intensity computed as the ratio of R&D expenditure over either total sales or total assets. Sales or capital evaluation, though, are flow variables which can be highly associated with rapidly changing economic conditions (Stam and Wennberg, 2009). Moreover, in our data, reported R&D expenditure includes both internal and external R&D. While we believe that this measure is worth investigating, we prefer a more conservative measure to describe the R&D effort. In this respect, a better proxy reflecting the accumulated knowledge stock within a firm is the number of employees engaged in internal R&D activities. So, we compute R&D intensity (in percentage points) as the fraction of R&D personnel over total employment at the firm level.

In line with the literature on firm growth, we model our dependent variables as a function of age and firm size. Our estimates also include time dummies to control for shocks common to all firms in the sample, geographical indicators, sectorial dummies and investments in physical capital per employee. Hence, the model specification is $r = \alpha_0 + \alpha_1(R\&D\ intensity) + \alpha_2(age) + \alpha_3(size) + \alpha_4(physical\ capital) + \sum\beta(sector) + \sum\gamma(region) + \sum\delta(time) + \epsilon$, where the dependent variable (r) is, alternatively, the hiring, separation and churning rate.

Table 1reports means and standard deviations of hiring, separation and churning rates at selected quantiles of their distributions. For each distribution, we also report the average R&D intensity, age and initial employment.

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[5]Theresultsarerobustto an alternativedenominator, averageemploymentovertheyear, which is alsoused in theliterature.
[6]Whilethegrowth rate is a measure of thenecessaryworkermovementstoreach a desiredfirm size, thechurning rate is oftenlooked as a measure of theunnecessarymovementstoachieve a givenchange in thefirm size.

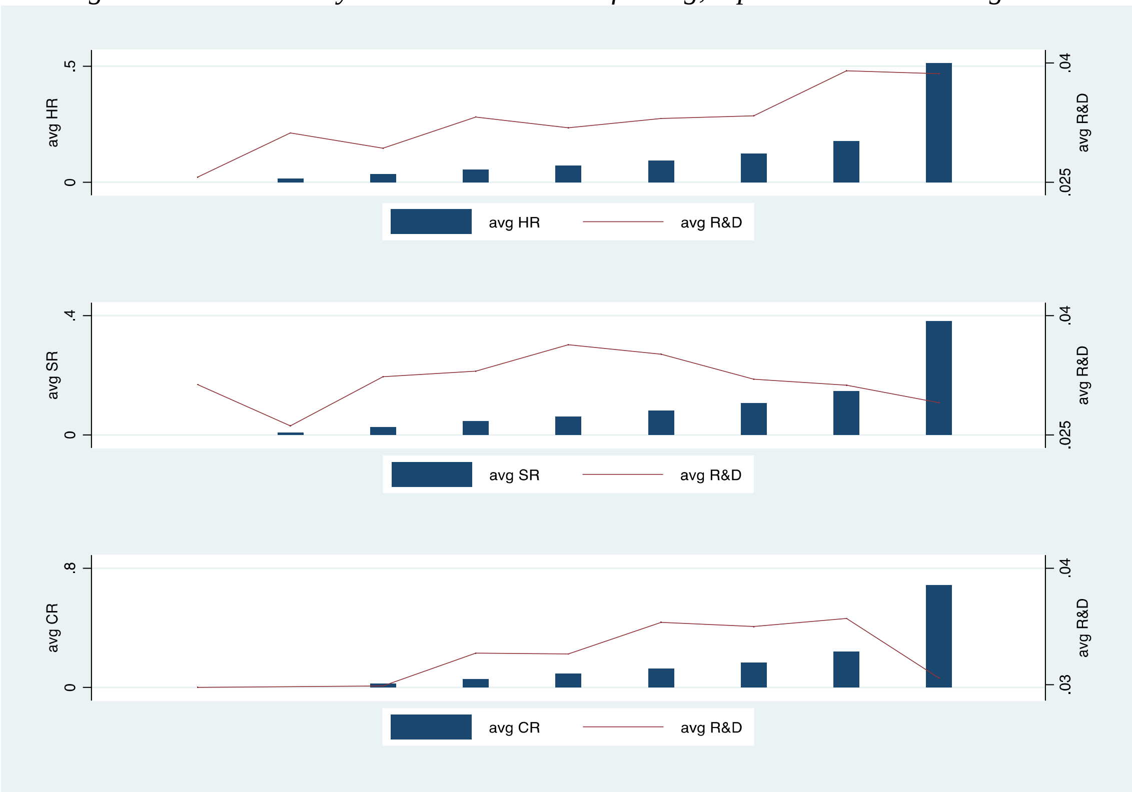
Figure 1provides a more intuitive representation of our key variables. The figure shows that, as commonly found in the data, exceptionally large hiring and separation rates can be observed at the right tail of the distribution, motivating numerous studies on the performance and role of high -growth firms in the economy (see, among others, Hölzl, 2009 and Goedhuys and Sleuwaegen, 2010). Moreover, the figure clearly shows that also in our data there is a considerable amount of churning, even if in the first two bins of the distributions there is no churning. Indeed, the average churning to worker flow ratio computed on the overall sample is around 63%. This is not surprising, since other scholars have reported similar patterns. For instance, in Bauer and Bender (2004), churning is between 47% and 70% of total worker flows for shrinking and growing establishments[7], Burgess et al. (2000) document a 61.9% churning rate for the Maryland manufacturing sector, and Lazear and Spletzer (2012) find that 65% of hiring is churn. Another feature of our data is that, similarly to what found in Lazear and Spletzer (2013), the correlation between hirings and separations is quite high, almost 70%, indicating that hirings and separations tend to move closely.

Table 1: Descriptive statistics

quantiles	*variable*	***Hiring***		***Separation***		***Churning***	
		mean	*sd*	*mean*	*sd*	*mean*	*sd*
p10	*Hiring rate*	0	0	0	0	0	0
	R&D intensity (lagged)	2.565	6.258	3.133	7.294	2.976	6.997
	Age	24.84643	17.66284	22.57961	17.64315	23.62865	18.08838
	Initial employment	49.47946	94.33666	45.24695	91.97603	49.84825	97.24193
p30	*Hiring rate*	3.496	0.67	2.559	0.672	2.334	0.768
	R&D intensity (lagged)	2.928	5.332	3.232	5.338	2.989	4.823
	Age	28.71128	20.91582	28.04619	20.86704	32.56275	26.34833
	Initial employment	145.3882	657.8929	132.62	231.2582	276.9858	516.2991
p50	*Hiring rate*	7.164	0.485	6.146	0.462	9.214	0.94
	R&D intensity (lagged)	3.185	6.393	3.633	6.873	3.264	6.242
	Age	24.08802	17.89127	24.25506	19.01239	25.77965	18.60392
	Initial employment	70.70418	247.129	70.81148	151.9991	130.9828	786.7113
p70	*Hiring rate*	12.469	1.103	10.655	0.858	16.842	1.421
	R&D intensity (lagged)	3.336	6.613	3.2	7.418	3.499	7.216
	Age	22.37782	17.95159	25.07258	20.09833	22.26134	16.05381
	Initial employment	75.25048	206.2873	104.7289	378.4215	74.20014	194.8585
p90	*Hiring rate*	51.358	87.325	38.084	60.396	68.709	123.836
	R&D intensity (lagged)	3.866	8.591	2.904	5.754	3.056	6.429
	Age	19.23072	14.33723	22.32533	15.75346	21.24775	15.34234
	Initial employment	76.03362	282.2893	102.5873	541.1369	78.55917	319.6575

[7]Theauthorsalsofoundthatworkerreplacement is relativelylargerforskilledandunskilledworkersthanforprofessionalsandengineers. Unfortunately, ourdataarelimitedtogrossnumbersand do not allow us toidentifychurningflowsbyworkercategories.

Figure 1: R&D intensity and the distribution of hiring, separation and churning rates



3. Estimation approach

Quantile regressions have increasingly gained the attention of scholars in the literature based on the growth-innovation relationship, allowing numerous authors to find that, at a micro level, the effects of innovation vary substantially along the conditional distribution of the employment growth[8]. In the present study, we adopt this methodology to disentangle the impact of R&D on hiring, separation and churning rates. In particular, we estimate a model[9] of the form specified as

$$y_i = x_i^{'}\beta_\theta + u_{\theta i} \quad \text{with} \quad Quant_\theta(y_i|x_i) = x_i^{'}\beta_\theta \qquad (i = 1, \ldots, n), \tag{4}$$

where $Quant_\theta(y_i|x_i)$ denotes the quantile of y_i, conditional on the regressors x_i, θ indicates the quantiles, n is the sample size, β_θ is the vector of coefficient to be estimated and $u_{\theta i}$ is the error component. In particular, the estimator for β_θ solves the problem

$$\min_{\beta} \frac{1}{n}\left\{\sum_{i:y_i \geq x_i^{'}\beta} \theta \left|y_i - x_i^{'}\beta\right| + \sum_{i:y_i < x_i^{'}\beta} (1-\theta) \left|y_i - x_i^{'}\beta\right|\right\}. \tag{5}$$

Quantile regression has several advantages. First, it can be used to characterize the overall distribution of a dependent variable given a set of regressor. In this sense, it allows to quantify the effects of a variable in a more accurate way than standard linear regression techniques based on conditional mean functions. Moreover, we retain that, in our study, the use of linear regression can be misleading also because of the heterogeneity that firms have been found to show in innovation activities. As noted by Vezzani and Montresor (2015), firms with different characteristics show different abilities of developing (introducing, appropriating and exploiting) innovations. Accordingly, quantile regression is a useful analytical tool that directly tackles firms' heterogeneity and can help us detect how much the effect of the R&D intensity varies along different quantiles of the flow variables. Second, quantile regression techniques have been proved to be robust in the presence of heteroskedastic and nonnormally distributed errors. In our case this is important, since the Jarque-Bera test rejects the null hypothesis that our dependent variables are normally distributed. Finally, the quantile regression objective function is a weighted sum of absolute deviations, so that the estimated coefficients are not sensitive to outliers.

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[8]See, amongothers, GoedhuysandSleuwaegen (2010) andFalk (2012).
[9]SeeKoenkerandBassettJr (1978), KoenkerandHallock (2001) andBuchinsky (1998).

4. Results

The firm level quantile regressions are estimated from a sample of 13808 observations for the pooled sample, 8785 observations when we use lagged R&D intensity at $t-2$, 8339 and 3141 when we use, respectively, the two- and three-year averages of our dependent variables, and 7226 and 6582 when we carry out the estimates separately on each wave included in the sample. Table 2 reports the results of our first set of estimates. The quantiles were chosen from 10% to 90% (with incremental steps of 10%) of the distributions of each rate considered as dependent variable. The table lists coefficients for the main regressor and bootstrapped standard errors with 399 replications [10].

The first result of the quantile estimates is that R&D intensity matters for the hiring rate with a varying positive impact across the conditional distribution of hirings. Quantitatively, an increase in R&D intensity generates an increase in the annual average hiring rate between 0.049 at the 0.2 quantile and 0.21 at the 0.9 quantile. In other words, a 10 percentage point increase in R&D intensity leads to a 2 percentage point increase in the hiring rate at the highest quantile. The effect becomes more pronounced when moving to the upper quantiles of the hiring rate distribution, indicating that R&D intensity has a larger impact in firms with already large hiring rates.A second result is that, when looking at the separation rate, the coefficients of the R&D variable are not statistically significant (except for a slightly significant coefficient at the 0.4 quantile). Together, these results suggests that, overall, the positive effect on hirings is likely to result in the opening of additional vacant slots, generating transitions into newly created jobs.This is an important result for at least two reasons. First, innovating firms have different personnel strategies compared to non-innovating firms. In particular, the need to increase the endowment of skills pushes the hiring rate upwards. Since knowledge is largely embodied in workers, we suppose that the positive effect of R&D on hiring could be interpreted in the sense that firms, which aim at becoming more innovative, may also benefit from additional knowledge embodied in new workers.Second, if we consider the amount of resources devoted by governments to stimulate private R&D investments, the fact that those firms require additional workers tend to increase the benefits of such policies.

Table 2: Quantile estimates of R&D intensity on labour flow rates

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.000298*	0.0487***	0.0690***	0.0612***	0.0898***	0.106***	0.129***	0.155***	0.211***
	(1.65)	(3.39)	(6.98)	(4.56)	(6.18)	(5.81)	(6.55)	(4.72)	(3.58)
SR	-0.00000884	-0.0000821	0.0132	0.0148*	-0.000366	-0.0113	-0.0117	-0.013	-0.039
	(0.23)	(0.02)	(1.42)	(1.93)	(0.05)	(1.10)	(0.87)	(0.74)	(1.44)
CR	0.000	0.0000479	0.0207	0.0674***	0.0780***	0.0533***	0.0476**	0.0378	0.00555
	(0.00)	(0.71)	(0.88)	(3.04)	(4.17)	(2.62)	(2.41)	(1.16)	(0.12)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis (399 replications). The sample includes 13808 observations.

By addressing the question of how R&D affects churning, we initially abstract from net employment growth or contraction. By looking at the third row in Table 2, we notice that the coefficients of the R&D intensity are positive and statistically significant from the 0.4 to 0.7 quantiles. This indicates that the optimal level of churning chosen by firms is partially affected by R&D strategies. Probably, a higher amount of churning means that R&D firms are more interested in adjusting their workforce to maintain high levels of competitiveness.

At first, the effect of R&D on churning may seem at odds with what found in the cases of hirings and separations, but we can interpret it by considering the definition of churning and the fact that the sample includes both growing, shrinking and stable firms. Having found that separations are not statistically associated with R&D intensity, we expect the impact of R&D on churning to be related to the inclusion in the sample of firms with non-positive job flows. As noted by Burgess et al. (2001), an alternative way to compute the churning rate is $CH_{it} = 2 * min(HR_{it}, SR_{it})$. This means that $CH_{it} = 2SR_{it}$ for positive job flows, $CH_{it} = 2HR_{it}$ for negative job flows and $CH_{it} = HR_{it} + SR_{it}$ for null job flows.

[10]Wealsoobtainedstandarderrorsthatarerobusttointra-clustercorrelation (Parente et al., 2013).Unreportedresultsaresimilartothoselisted in thetablesandareavailableuponrequest.

Table 3: Quantile estimates of R&D intensity on churning rates for firms with positive/non-positive job flows

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
CR (JF>0)	0.000	-0.000154	0.00162	0.0186	0.047	0.0444	0.0267	0.00068	-0.0652
	(0.00)	(0.42)	(0.09)	(0.67)	(1.43)	(1.4)	(0.62)	(0.02)	(0.66)
CR (JF ≤ 0)	0.000	0.000138	0.0344	0.0994***	0.0853***	0.0617***	0.0668**	0.0767	0.0755
	(0.00)	(0.47)	(1.22)	(5.26)	(3.37)	(3.22)	(2.27)	(1.49)	(1.39)
Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis (399 replications). The sample includes 13808 observations.									

To check that the results on churning are driven by firms with non-positive job flows, we run separate quantile regressions both for these firms and for those with positive job flows. Results are presented inTable 3. We find that churning and R&D intensity are statistically associated only for shrinking and stable firms. Moreover, similarly to the benchmark results in Table 2, the coefficients are significant from the 0.4 to 0.7 quantiles. Hiring new workers, even in the presence of a personnel reduction, may be seen as a mechanism to acquire or replace skills. As a consequence, firms benefit from knowledge inflows and suffer from knowledge outflows at the same time. Therefore, for shrinking and stable R&D firms, the positive relation between R&D and churning may indicate that the knowledge outflows, due to separations, is compensated both by a higher R&D intensity and a higher hiring rate.

4.1. Robustness

A number of checks have been implemented in order to assess the robustness of our results. First, given that R&D activities might deploy their effects on a wider horizon[11], we re-estimate the model using the R&D intensity at $t-2$. Table 4reports the estimated coefficients. The results are in line with those presented in the previous table and corroborate the idea that firms with higher R&D intensity are also those with higher hiring rates and that R&D intensity has no significant impact on separations. We also find that R&D intensity has an impact only on some quantiles of the churning distribution, but with lower significance levels compared to the benchmark estimates presented inTable 2. Probably, this is because R&D activities need faster organizational adjustments and, thus, require an initial, more conspicuous, labour replacement.

Table 4: Quantile estimates of R&D intensity at t-2 on labour flow rates

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.000102	0.00262	0.0653***	0.0595***	0.0791***	0.0943***	0.116***	0.149***	0.298***
	(0.91)	(0.19)	(4.01)	(3.53)	(4.2)	(4.06)	(5.37)	(4.15)	(3.85)
SR	-0.0000414	-0.0000553	0.00381	0.0125	-0.00024	-0.00174	-0.0016	-0.0189	-0.0453
	(0.70)	(0.12)	(0.29)	(1.24)	(0.02)	(0.11)	(0.11)	(0.87)	(1.50)
CR	0.000	-2.96E-06	0.000581	0.0563*	0.0665***	0.0462*	0.0556*	0.0198	-0.0256
	(0.00)	(0.03)	(0.26)	(1.76)	(3.05)	(1.75)	(1.73)	(0.57)	(0.45)
Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors ar e in parenthesis (399 replications). The sample includes 8785 observations.									

[11]Forinstance, Falk (2012) findsthatthegrowth of firmswith R&D activities in Austriaduringtheperiod 1995-2006 is positivelyrelatedalsotothelag of theinitial R&D intensity.

Table 5: Quantile estimates of R&D intensity on two-year averages labour flow rates

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.00758	0.0652***	0.0739***	0.0909***	0.105***	0.108***	0.125***	0.161***	0.236***
	(0.45)	(5.16)	(4.51)	(6.43)	(5.4)	(5.91)	(5.73)	(5.07)	(3.36)
SR	-0.00021	0.00489	0.00438	0.00658	0.00106	-0.00247	-0.0123	-0.0119	-0.02
	(0.94)	(0.51)	(0.36)	(0.61)	(0.1)	(0.24)	(0.80)	(0.57)	(0.50)
CR	0.000	0.000514	0.0245	0.0580**	0.0689***	0.0576**	0.0449**	0.0578	0.0462
	(0.00)	(0.08)	(1.1)	(2.2)	(3.12)	(2.56)	(2.02)	(1.23)	(0.69)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errorsare in parenth esis (399 replications). The sample includes 8339 observations.

Table 6: Quantile estimates of R&D intensity on three-year averages labour flow rates

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.0273*	0.0282	0.0482***	0.0805***	0.0887***	0.116***	0.113***	0.123***	0.243***
	(1.84)	(1.47)	(2.59)	(3.91)	(2.85)	(3.67)	(4.13)	(3.71)	(3.4)
SR	0.000000512	-0.00559	0.00877	0.0184	0.0146	0.018	0.00374	0.0331	0.0588
	(0.00)	(0.43)	(0.53)	(0.98)	(0.64)	(0.96)	(0.15)	(0.77)	(1.12)
CR	0.000	-0.00272	0.00699	0.0032	0.0399	0.0438	0.0491	0.0516	0.201**
	(0.00)	(0.13)	(0.22)	(0.09)	(0.9)	(0.97)	(0.86)	(0.56)	(2.2)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errorsare in parenth esis (399 replications). The sample includes 3141 observations.

It could also be possible for firms to plan their employment changes and replacements as medium run strategies. In this sense, it could be useful to check if there is a response of the flow rates considered over a wider time window.To this end, we compute the two- and three-year averages of our dependent variables. Table 5and Table 6 present the results based on this idea. As it can be seen, the results for hirings and separations appear aligned with the ones reported in previous tables, even if the sample size reduces significantly to 8339 in Table 5 and 3141 in Table 6. Conversely, evidence of the effects of R&D on churning is present only in the case of the two-year averages of labour flow rates.

To test for the stability of the parameters, we conducted separate estimates for each of the two waves included in the analysis. Of course, the results are not expected to perfectly match those presented inTable 2, but some alignment between them should be considered as satisfactory.

Table 7and

Table 8 present the estimated coefficients. We notice that the overall picture gained so far is still valid. Once again, we find positive and significant coefficients in the hiring model, with the strength of the effect of R&D intensity being less pronounced in the second wave of our sample. The impact of R&D on the separation rate is insignificant in both waves. Moreover, we find evidence that churning reacts more in the second wave.

Table 7: Quantile estimates of R&D intensity on labour flow rates - wave 1

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.131***	0.0784***	0.0609***	0.0644***	0.0991***	0.132***	0.156***	0.180***	0.261**
	(6.51)	(8.24)	(6.9)	(3.64)	(3.83)	(5.36)	(4.32)	(4.65)	(2.53)
SR	-0.00000654	0.00191	0.0135	0.0121	-0.00304	-0.0238	-0.0165	-0.0179	-0.0479
	(0.14)	(0.11)	(0.89)	(0.94)	(0.26)	(1.46)	(1.09)	(0.84)	(1.32)
CR	0.000	0.0000992	0.0581	0.0643**	0.0570**	0.0237	0.0236	-0.00184	-0.00951
	(0.00)	(0.01)	(1.37)	(2.41)	(2.44)	(0.84)	(0.72)	(0.05)	(0.16)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errorsare in parenth esis (399 replications). The sample includes 7226 observations.

Table 8: Quantile estimates of R&D intensity on labour flow rates - wave 2

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.0000565	0.000729	0.0709***	0.0728***	0.0759***	0.0734***	0.123***	0.101**	0.195***
	(1.49)	(0.1)	(3.09)	(3.71)	(4.16)	(3.35)	(4.45)	(2.31)	(2.73)
SR	-0.0000404	0.00016	0.00148	0.00962	0.00197	-0.000139	0.00147	0.0193	-0.041
	(0.45)	(0.36)	(0.15)	(0.92)	(0.15)	(0.01)	(0.07)	(0.68)	(0.92)
CR	0.000	0.0000124	0.000588	0.0435	0.0626*	0.0877***	0.0783**	0.0835	0.099
	(0.00)	(0.16)	(0.1)	(1.34)	(1.88)	(3.11)	(2.37)	(1.5)	(1.19)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parent hesis (399 replications). The sample includes 6582 observations.

Finally, we further check the robustness of our results by using a different measure of the hiring, separation and churning rates. As explained in section 2, we aim at reducing the impact of initial firm size on the labour flow rates. This is done by multiplying the rates as defined in equations 1, 2 and 3 by the level of employment at time t. The results are in **Error! Not a valid bookmark self-reference.** and confirm the findings reported in previous tables. Across the quantiles, R&D intensity is confirmed as an important factor in personnel strategies.

Table 9: Quantile estimates of R&D intensity on labour flow Birch rates

Dep. var.	*q10*	*q20*	*q30*	*q40*	*q50*	*q60*	*q70*	*q80*	*q90*
HR	0.00409**	0.00657***	0.0172***	0.0214***	0.0247***	0.0288***	0.0342***	0.0455***	0.0850***
	(2.03)	(3.29)	(4.27)	(6.31)	(6.04)	(5.66)	(5.18)	(3.59)	(3.22)
SR	-0.0000269	0.00125	0.00359	0.00384*	0.00202	0.00185	0.00158	-0.00018	-0.00367
	(0.04)	(0.53)	(1.47)	(1.92)	(0.98)	(0.69)	(0.46)	(0.06)	(0.66)
CR	0.000	0.00229	0.00889*	0.0168***	0.0216***	0.0165***	0.0145**	0.0157**	0.00436
	(0.00)	(1.54)	(1.87)	(3.87)	(4.95)	(2.89)	(2.21)	(2.06)	(0.32)

Notes: ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthes is (399 replications). The sample includes 13808 observations.

From the inspection of all the tables shown so far, we cannot make a direct inference on the resulting firm growth in our sample. Nevertheless, the only component of the growth rate that seems to react to increasing R&D is the hiring rate. Thus, our estimates, suggest that, overall, new jobs are created and that firms engaged in R&D should grow faster than otherwise.

5. Conclusions

In this paper we sought investigating whether it is possible to associate the R&D intensity, measured as the share of R&D personnel over total employment, to variations in the rates at which firms hire new workers, separate from existing ones or churn them.

While the innovation-growth literature has widely investigated the net employment growth rate, this study explores to what extent innovation is related to the components of the growth rate. Specifically, we shed light on whether R&D affects hirings, separations or both. To this end, quantile regressions were used on a sample of Italian manufacturing firms to disclose heterogenous responses of hiring, separation and churning rates to R&D along their conditional distributions. Results show that R&D intensity has a significant and positive impact on hirings and insignificant effects on separations. Another novel contribution of this study is the characterization of churning conditional on firms R&D intensity. Our empirical evidence suggests that R&D intensity has a positive and significant impact from the 0.4 to 0.7 quantiles of the distribution of churning, indicating that the optimal level of churning chosen by firms is partially affected by R&D strategies. We interpret our results as evidence of different personnel strategies of innovative firms compared to non-innovative firms.

Overall, our findings are mostly confirmed in estimates based on a different lag of the R&D intensity, the two- and three-year averages of the hiring, separation and churning rates, on different subsamples and an alternative measure of the hiring, separation and churning rates.

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