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What role for innovation in job creation, destruction and churning?

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Abstract

This paper explores the effects of product innovation, process innovation and R&D expenditure on job creation, job destruction and churning using a sample of Italian manufacturing firms. The results indicate that product and process innovations tend to amplify both job creation and destruction, while R&D tends to work in the opposite direction. We also find that churning increases as firms engage in R&D activities, while it decreases when firms introduce product and/or process innovations.

1 Introduction

Competing[1] through innovation may lead to organisational changes which are likely to translate into contractions or expansions of the workforce of firms. The theory suggests that the kind of innovation strategies implemented by firms may have different repercussions in terms of changes in firm size and labour flows, with an overall effect of innovation on the employment dynamics that is still unclear (Van Reenen, 1997).

This paper aims at taking part to this debate by investigating the effects of output and input measures of innovation on job creation and destruction and,

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particularly, on the corresponding churning flows at the firm level. The analysis presented here is based on the idea that innovation strategies may have different effects on firms size depending on whether firms experience positive or negative growth rates. Numerous scholars, indeed, have recently found that, at a micro level, the effects of innovation activities may vary substantially along the conditional distribution of the employment growth (Falk, 2012)[2].

This paper also contributes to the characterisation of excess worker turnover at the firm level with a specific focus on innovation strategies. As it has been already documented in the literature, much of hirings and separations in the labour market reflect churning rather than actual changes in the size of firms. Moreover, innovation may imply worker flows even in the absence of net employment changes. Very often, indeed, technological change require labour reallocation within firms (Bauer and Bender, 2004), but not necessarily a firm size variation. To the best of our knowledge, this is the first study attempting to assess whether different innovation strategies can be associated to different levels of churning and, in particular, if there are systematic differences in churning that can be statistically associated to different innovation practices.

To answer these questions, the present study uses Italian data collected by Unicredit-Mediocredito Centrale. These data have been already exploited by several scholars[3] in this field of research, thus we believe that our results can be complementary to those already found in the literature.

Our main findings can be summarised as follows. Product and process innovations foster job creation, regardless of whether they are carried out together or individually, but with the effect of product innovations being stronger. Process innovations amplify job destruction, while, if carried out together with product innovation, the effect is milder. We also find that investments in R&D have sizeable effects on job creation and job destruction but, differently from product and process innovation, R&D activities reduce both of them. Moreover, while R&D has a negligible effect on churning for growing firms and a positive impact for shrinking firms, the churning rate is negatively affected by product and process innovation.

Our findings suggest the presence of asymmetric responses of churning to innovation strategies. In particular, when product and process innovations are implemented together, they have a smaller effect in reducing churning compared to product innovation for growing firms. While, process innovation has a negligible

[2]Kaiser (2009) finds that there is a sign reversal of the impact of innovations, measured in terms of patents, on firm growth, measured as the ratio of profit to sales, when moving from lower to upper quantiles of the distribution.

[3]See, for instance, Piva and Vivarelli (2005).

effect. Differently, for shrinking firms, the larger effect is due to process innovation but we do not find evidence of a relation when product and process innovation are implemented together.

The structure of the paper is organised as follows. Section 2 discusses the theoretical underpinnings of the analysis in light of the existing empirical results; section 3 describes the choice of the econometric modelling; section 4 describes the dataset and the variables used in the analysis along with summary statistics; section 5 summarises the results and includes some robustness checks; section 6 concludes.

2 Background and related literature

While a large number of empirical studies have thoroughly investigated the financial growth of firms due to innovation activities, i.e. the Gibrat's Law (Coad and Rao, 2008; Cucculelli and Ermini, 2012), this paper focusses on the effects of innovation on aspects related to firms' human resources, more precisely job creation, job destruction and churning.

In terms of employment changes, process innovation modifies the relative productivity of production factors and, to the extent that this kind of innovation is of a labour-saving kind, it reduces employment. At the same time, if process innovation is associated with lower production costs, firms tend to increase production and their workforce via price reductions and increased demand. Also, the implementation of new processes could require the external acquisition of new skills. In this case, firms could opt for new hirings, and process innovation would bring about firm expansion. In the empirical literature, process innovation has been associated to employment growth (Lachenmaier and Rottmann, 2011), but also to employment reductions (Dachs and Peters, 2014) and employment stability (Hall et al., 2008), leaving open the debate on the empirical assessment of the employment effects of this kind of innovation. Our idea is that the strength of the causal link between innovation and employment changes can differ between growing and shrinking firms. For instance, growing firms could pursue process innovation strategies to lower production costs more intensely than shrinking firms, which, instead, could be more engaged in a labour-saving kind of process innovation. In such situation, process innovation would be simultaneously associated to both higher job creation and destruction.

Product innovation fosters employment as more labour is needed to produce new goods or improve the quality of existing ones. On the other hand, firms introduce new and/or more differentiated products to strengthen their market power. In this situation, firms can set higher prices, ultimately leading to output and employment contractions. Most empirical studies agree that the relationship between product innovation and employment growth is positive (Lachenmaier and Rottmann, 2011; Hall et al., 2008; Dachs and Peters, 2014). Nevertheless, the empirical literature has mostly provided evidence of average effects across firms and industries, but it still lacks on possible asymmetric responses of firms size in terms of job creation and destruction.

Also the R&D effort may have implications in terms of employment changes and labour flows. R&D uses knowledge intensively and this might require additional workers, but it could also simply require a reallocation of the internal workforce towards innovative activities. R&D could imply a high labour turnover as it becomes more difficult to find good matches in the labour market that meet the firm skill requirements. In addition, R&D investments are a large financial effort distorting resources from other scopes, such as investments in other production factors, and this could result in lower growth rates. R&D activities also increase risk and, given the irreversible nature of this kind of investment, firms could be less willing to increase the workforce. A strand of the literature has empirically examined the extent to which R&D activities lead to employment growth. 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 the R&D intensity.

Another question we address in this study concerns the extent to which different innovation practices produce differences in the excess of worker reallocation over the net job creation/destruction, i.e. churning. In a context of innovating firm, churning can arise from the reassessment of the quality of existing workers. Existing matches are re-evaluated as optimal personnel policies. Process innovation often requires new work practices which can in turn imply the replacement of old workers with newer ones and technological change increases the demand for skills. Thus, even if firms do not experience a net employment change, innovation could still play a role for labour flows. Also a change in the product mix sold by the firm could lead to a replacement of workers (Lachenmaier and Rottmann, 2011). Moreover, the high degree of uncertainty related to R&D investments could induce firms to be more cautious in their hiring and firing strategies, or to screen workers more thoroughly, leading to higher churning but not necessarily to employment growth. On the other hand, the R&D effort may induce firms to retain knowledge and this could lower churning.

Up to now, the literature has mainly focussed on cross sectional and time series features of churning along dimensions such as employer size, firm age and industry[4]. 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 organisational and technological changes (in the form of ICTs). Centeno and Novo (2012), from a different perspective, quantify the impact of more employment protection on the excess of worker turnover of fixed-term workers. There is no evidence of the role played by innovation strategies on the amount of churning.

3 Estimation approach

This study uses two methods to evaluate the conjecture that innovation may have an asymmetric impact on firm size. The first one is a multinomial analysis[5], in which we contrast the job creation and destruction categorical outcomes with the reference category of stable size. With this model we aim at identifying what are the odds that a firm experience a change in its size following previous innovative strategies. In particular, we consider a model where the probabilities of job creation, job destruction or absence of growth depend on a vector of covariates associated with the i-th firm.

We next turn to the validation of the results by running two separate tobit models, respectively, on the job creation and the job destruction rates. In this way, the effects of innovation can be investigated separately for firms experiencing positive and negative growth. By construction, the job creation rate is left censored, while the job destruction rate is right censored. It would seem misleading to use the terminology of censoring, however we interpret our dependent variable as a corner solution response variable. As a matter of fact, we have firms who are solving a maximisation problem and for some of them the optimal choice is the corner solution. Note that in this corner solution application, the issue is not data observability as standard censored model. Differently, we refer to the situation in which the dependent variable takes the zero value with positive probability and it is continuous over strictly positive values. This means that some firms in our sample do not find it optimal to modify the amount of their workforce.

[4]See, for instance, the works of Burgess et al. (2000) and Davis and Haltiwanger (1999).

[5]Alternatively, an ordered probit model could have been applied. Yet, we believe that it is not so straightforward to assume that it is possible to order the outcomes from positive to negative growth rates. Indeed, it could be the case that a firm finds it optimal to reduce its size to reach an efficient scale of production.

4 Database, variables and descriptive statistics

4.1 The survey

The analysis of this study draws on firm level data contained in the *Survey of Italian Manufacturing Firms* (SIMF) collected by Unicredit-Mediocredito Centrale. The survey has been carried out 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[6] of firms with up to 500 workers and all firms above this threshold. Although each wave contains around 5000 records, many of them do not provide complete information on some of the variables relevant to our research. Each firm in the sample is asked to answer a rich questionnaire in order to provide a picture of its business activities, labour practices, innovation strategies, internationalisation status, finance structure and several features of the market in which it operates. Thereby, when available, these data allow us to investigate the response of job creation, job destruction and churning to different innovation practices.

The main limitation of the survey is that it does not provide a picture of the process of entry and exit of firms in the sample. However, the dataset contains a unique combination of self-reported measures of R&D expenditures and information about the different kind of innovation strategies (i.e. product innovation and/or process innovation) which are well suited to analyse the effect of the R&D expenditure and innovation strategies on firms' employment growth.

We consider the 2001, 2004 and 2007 waves of the available surveys. By merging these waves, we build a dataset of 10720 records over the period 1998-2006. Among them, firms with inconsistent data are excluded from the analysis and we also select those firms with a reasonable data (R&D expenditure higher than 10000 euros).

As it will be clarified in the following, we consider only the employment growth rate referring to the last years of each survey. Thus, the estimates are carried out on a sample of 2999 observations.

4.2 Variables and controls

Dependent variables.

This study borrows the definitions of job and labour flows from the existing literature (Burgess et al. 2000; Davis and Haltiwanger 1999; Hamermesh et al. 1996). A job flow at establishment i at time t is defined as the net employment

[6]Stratification is based on industry, geographic area and firm size.

change, thus it can be measured either as the difference between current and past employment or the difference between hirings and separations occurred in a given period. The absolute value of a job flow is called job reallocation. Then, job creation is defined as the job reallocation if the job flow is non-negative, while job destruction is the job reallocation for negative job flows. The corresponding rates are simply obtained by dividing these measures by the employment stock at the beginning of the period[7]. In this study, with a little bit of abuse, we identify firms with job destruction as those for which we observe a non-positive job flow. In this way, both the job creation and destruction rates turn out to be censored at zero and allow us to run two separate tobit regressions.

To investigate the role of innovation strategies on churning, we use the ratio of churning over worker flows. Churning is measured as the amount of worker turnover in excess to that required for the firm to achieve its desired employment change. Algebraically, it is computed as the difference between the sum of hires and separations, i.e. the worker flow, and the job reallocation. Then, dividing this measured by the worker flow, it is possible to express churning as a percentage. Thus, the churning rate is equal to zero when the worker flow is equal to the job reallocation and is equal to one when, given a positive worker flow, the job reallocation is equal to zero. This measure has the obvious advantage of being independent from firm size and it facilitates the interpretation of the results.

Main regressors.

Our main regressors are dummy variables capturing the types of innovation introduced in the three years prior to the interview, a lagged indicator variable for firms involved in R&D activities and the lag of the R&D expenditure. We use an exclusive definition of product and process innovators, thus we include three dummies in the regressions, one for product and process innovators, one for product-only innovators and one for process-only innovators.

While in most studies innovation is captured either by input-based or output-based measures, our analysis aims at taking both into account. In particular, we use the R&D expenditure as an indicator of the strength of firms' innovative effort and we use information on the introduction of new products and/or processes during the reference period to account for the successfulness of past innovative investments. Moreover, while in most studies firms are considered either as product or process innovator, our dataset let us identify also firms that innovate along both dimensions.

[7]Alternatively, the job creation and destruction rates can be obtained as the ratio of job creation and destruction levels by the average employment. As it turns out, both measures produce very similar results in the present study.

Among our regressors, we include a dummy variable for R&D activities and a measure of the R&D expenditure. The idea, here, is to account first for the choice of investing or not and then to control for how much firms are willing to spend in R&D. The sample distribution of the R&D expenditure is skewed and the standard solution to this problem is to take a log transformation. That brings all of the extreme values closer to the middle and it is easier to control for non linearities. Nevertheless, the log transformation comes with a cost. Since the log is defined only for strictly positive values, all zeros must be dealt with a discretionary assignment, either one or, as found in similar studies, with the minimum strictly positive value. Yet, this is an arbitrary data imputation that, in some case, can lead to very different estimation, especially when there is a large number of zeros. Instead, one can use the inverse hyperbolic sine transformation (IHS). The IHS is defined as the $log(y_i + (y_i^2 + 1)^{\frac{1}{2}})$. Therefore, except for very small values of y, the IHS is approximately equal to $log(2) + log(y_i)$, and so it can be interpreted in the same way as a standard logarithmic variable but, unlike a log variable, the IHS is also defined at zero.

Control variables.

Since investments in physical capital can be considered as an indicator of process innovation inputs, especially for large firms (Vaona and Pianta, 2008), we include investments among our regressors. In particular, we use the IHS transformation of the investments and its lagged value. Our estimates also include firm and industry characteristics. In particular, because size reflects access to finance, scale economies and differences in the organisation of work, we include the size of each firms measured by the number of employees at the firm (lagged value). Firms in more technology-intensive industries may have a higher propensity to conduct R&D than those in more labor-intensive sectors. Thus, we make use of the Pavitt taxonomy. This includes traditional sectors, scale sectors, specialised sectors and high-technology sectors. We also include time dummies to control for shocks common to all firms in the sample.

Product and process innovation may also be related to the early stages of firms' technological life cycle. In other words, young firms could be more prone to engage in product innovation and more likely to link their employment growth to the success of these strategies (Brouwer et al., 1993), thus we use a dummy for young company to purge the estimates from their specific behaviour. Finally, firm's location and age are included in the model.

We implement three different specifications of the empirical models to keep track of changes in point estimates. The first one includes, among the main regressors, the dummies for product innovation, process innovation, product/process innovation, the dummy for R&D and its expenditure level plus investments in physical capital and lagged values of R&D and investments in order to check the link between employment growth rate (JCR and JDR separately) and innovation strategies. Also, the base specification model includes age and size of each firm plus time dummies. The second specification adds the firm's location. The last specification also considers dummy variables for Pavitt sectors.

4.3 Descriptive statistics

Table 1 reports average job creation and destruction rates (panel a and d), along with standard deviations and frequencies for all firms in our sample. We breakdown these measures by types of innovation (panel a and d) and, further, by engagement in R&D activities (panel b, c, e and f). This exploratory analysis highlights some differences among sample means. First, the numbers reported in panel a and d suggest that both job creation and destruction rates tend to be slightly higher for those firms reporting some process and/or product innovation. Compared to the JCR of non innovators, the average JCR is 24.4% higher for firms reporting process and product innovations, 25.13% higher for product innovators and 29.7% higher for process innovators. Analogously, we find higher JDRs for innovators, but the differences are smaller in magnitude. This suggests that the response of employment changes to innovation might be asymmetric for growing and shrinking firms. Nevertheless, standard deviations are often as twice as their respective mean, indicating a high level of dispersion and, thus, a low descriptive power of sample means. Also note that standard deviations tend to be higher in presence of product and/or process innovations and, for this reason, we prefer to calculate bootstrapped standard errors in the estimates. Another striking fact is that, when we look at the job creation and destruction rates by engagement in R&D activities (but holding constant the type of innovation), we observe that, in six out of eight cases, job creation and destruction rates tend to be lower if firms are R&D active.

Table 2 reports average churning to worker flows ratios along with standard deviations and frequencies. Also these measures have been disaggregated by innovation types and R&D engagement. First, we notice that also in our data there is evidence of a large amount of worker movements in excess of the net job creation/destruction. These figures are very close to those reported in previous studies. For instance, Burgess et al. (2000) report a 61.9% rate for the Maryland manufacturing sector. The table suggests that product and/or process innovations are associated to slightly lower churning rates, while firms engaged in R&D

Table 1: Means (per 100 workers) and standard deviations of JC and JD rates by innovation and R&D strategies

	Job creation								
	(a)			*(b) - R&D*			*(c) - no R&D*		
	Mean	Std dev	Freq	Mean	Std dev	Freq	Mean	Std dev	Freq
Product and process innovation	6.78	14.58	868	6.75	14.79	768	6.99	12.95	100
Product innovation	6.82	13.81	426	6.76	14.24	376	7.27	10.06	50
Process innovation	7.07	11.59	418	6.94	11.72	369	8.05	10.58	49
No innovation	5.45	11.21	490	5.36	11.34	419	5.94	10.48	71
	Job destruction								
	(d)			*(e) - R&D*			*(f) - no R&D*		
	Mean	Std dev	Freq	Mean	Std dev	Freq	Mean	Std dev	Freq
Product and process innovation	-3.58	5.91	629	-3.25	5.49	559	-6.26	8.15	70
Product innovation	-4.12	6.01	329	-4.13	6.14	298	-4.07	4.64	31
Process innovation	-4.11	6.97	282	-4.16	7.15	257	-3.66	4.78	25
No innovation	-3.46	6.32	370	-3.26	6.42	304	-4.38	5.80	66

activities tend to have higher churning rates. Thus, output and input measures of innovation seem to have an asymmetric impact also on churning. The table also indicates that churning rates are less dispersed around the mean compared to job creation and destruction rates.

The Appendix contains the table of summary statistics for the main variables included in the analysis.

5 Results

5.1 Multinomial results

In table 3, we report the results of the multinomial analysis based on the pooled sample. The estimated coefficients are relative to the case of constant employment and must be read as relative risk ratios. Bootstrapped standard errors are in parentheses. Columns (1) - (8) refer to different model specifications, where additional control variables have been progressively added[8]. In particular, specification (2) differs in the inclusion of the R&D dummy; model (3) adds indicators of whether R&D is carried out internally, externally or in both ways; model (4)

[8]Note that we control for firm size, investments in physical capital and year dummies in all the specifications.

Table 2: Means (per 100 workers) and standard deviations of the churning rate by innovation and R&D strategies

	Job creation								
	(a)			*(b) - R&D*			*(c) - no R&D*		
	Mean	Std dev	Freq	Mean	Std dev	Freq	Mean	Std dev	Freq
Product and process innovation	0.64	0.38	868	0.66	0.37	768	0.52	0.43	100
Product innovation	0.62	0.39	426	0.64	0.38	376	0.48	0.43	50
Process innovation	0.65	0.37	418	0.66	0.37	369	0.58	0.39	49
No innovation	0.69	0.38	490	0.71	0.37	419	0.57	0.43	71
	Job destruction								
	(d)			*(e) - R&D*			*(f) - no R&D*		
	Mean	Std dev	Freq	Mean	Std dev	Freq	Mean	Std dev	Freq
Product and process innovation	0.73	0.37	629	0.75	0.35	559	0.50	0.45	70
Product innovation	0.65	0.41	329	0.66	0.41	298	0.57	0.45	31
Process innovation	0.69	0.40	282	0.69	0.40	257	0.64	0.44	25
No innovation	0.74	0.39	370	0.77	0.37	304	0.62	0.43	66

includes the (lagged) R&D expenditure; a dummy for human capital is added in model (5); model (6) controls for cash flow effects; model (7) adds regional dummies and model (8) includes three dummies for Pavitt sectors.

The results show that being a process and/or a product innovator is associated with increased odds both of firm expansion and contraction. In particular, the relative probability of growing rather than not growing is 34.7% higher for product and process innovators than for non-innovators, 55.7% higher for product innovators and 44.3% higher for process innovators. At the same time, the relative probability of observing a decrease in firm size rather than stable employment is 27.6% higher for product and process innovators than for non-innovators, 57.9% higher for product innovators and 36.3% higher for process innovators. Overall, innovation seems to foster employment growth among already growing firms but also seems to exacerbate firms contraction among shrinking firms.

Interestingly, the estimates also show that the effect of R&D works in the opposite direction. If a firm is R&D active, the odds of growth relative to stable employment is expected to decrease by a factor of 0.447, given the other variables in the model are held constant. Thus, it is less likely to observe employment growth among R&D firms. At the same time, if two firms have identical characteristics and have the same baseline likelihood to experience a decline, the one with positive R&D is less likely to experience a workforce contraction. Thus, R&D has a mitigating impact on both JCR and JDR.

In the next section, we further explore the relation between innovation and employment changes (as well as churning) through tobit analyses.

5.2 Tobit results

Tables 4 and 5 report the results of, respectively, the job creation and destruction model. The estimated coefficients of the output measures of innovation are all significant at conventional levels and show a positive impact of all types of innovation on job creation, but with the effect of product innovation alone being stronger. Other authors have previously pointed out that the effects of product innovations on employment need time to unfold, as it takes some time for firms to implement new productions and introduce the innovations to the market[9]. Our results partially confirm this hypothesis as the variable used to measure product innovation refers to a period of three years prior to the interview.

The estimates reveal that both job creation and destruction are more responsive to product innovations and that R&D activities tend to mitigate the expansion of already growing firms. This result could be interpreted as evidence of a short run negative impact of R&D on employment growth and could be related to the financial stress associated to such investments. Moreover, coefficients and standard errors remain fairly stable over different model specifications. The only sizeable change concerns the coefficient of the R&D dummy. Once we include the (lagged) R&D expenditure, the coefficient of the R&D dummy jumps from -3.45 to -5.61 and then remains stable.

Besides the main variables of interest, we find evidence of the positive role played by human capital. Having a share of workers with at least a bachelor degree above the industry average raises job creation slightly more than 2%, while it has no impact on job destruction. Also firms in the technological sector grow around 5% faster compared to firms in other sectors. Higher job creation (but not job destruction) is also associated both to firms exhibiting a higher-than-average revenues growth and younger companies.

Table 5 reports the coefficients for the job destruction model. In this case, we do not find a significant impact of being at the same time a product and process innovator. Instead, the job destruction rate is 2.28 and 2.09 higher when firms are, respectively, product and process innovators.

From the simultaneous inspection of tables 4 and 5, we note that product

[9]See, among others, Lachenmaier and Rottmann (2011).

Table 3: Multinomial analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job Creation								
product & process inno	1.377**	1.424***	1.367***	1.346**	1.342**	1.352**	1.342**	1.347**
	-2.51	-2.6	-2.62	-2.34	-2.38	-2.49	-2.49	-2.48
product innovation	1.593***	1.654***	1.605***	1.575***	1.560***	1.576***	1.571***	1.557***
	-3.1	-3.41	-3.32	-3.28	-3.14	-3.19	-3.04	-3.14
process innovation	1.441***	1.462***	1.440**	1.445***	1.439***	1.436**	1.428***	1.443**
	-2.59	-2.7	-2.57	-2.69	-2.69	-2.56	-2.66	-2.53
dummy R&D (lagged)		0.603***	0.595***	0.426***	0.440***	0.416***	0.417***	0.447***
		(-3.19)	(-3.17)	(-3.24)	(-3.03)	(-3.32)	(-3.21)	(-2.90)
dummy_resINT			0.889	0.887	0.888	0.881	0.884	0.893
			(-0.63)	(-0.66)	(-0.60)	(-0.65)	(-0.60)	(-0.59)
dummy_resEST			0.993	1.012	1.025	1.011	1.015	1.038
			(-0.03)	-0.05	-0.09	-0.04	-0.06	-0.15
dummy_resMIX			1.185	1.168	1.161	1.152	1.159	1.153
			-0.93	-0.85	-0.78	-0.73	-0.72	-0.77
R&D expenditure (lagged)				1.067*	1.061	1.071*	1.070*	1.05
				-1.75	-1.44	-1.77	-1.67	-1.15
dummy human capital					1.217**	1.199*	1.197*	1.212**
					-2.09	-1.82	-1.96	-1.99
revenues growth rate (lagged)						1.461**	1.461**	1.433**
						-2.22	-2.2	-2.22
sectorial revenue growth						1.068	1.07	1.083
						-0.3	-0.33	-0.38
age						0.993***	0.993***	0.992***
						(-2.76)	(-2.79)	(-2.82)
Job Destruction								
product & process inno	1.277*	1.322**	1.300*	1.277*	1.280*	1.279*	1.266	1.276*
	-1.83	-1.99	-1.94	-1.76	-1.72	-1.78	-1.61	-1.74
product innovation	1.550***	1.610***	1.594***	1.560***	1.568***	1.578***	1.571***	1.579***
	-2.75	-3.08	-2.97	-3	-2.79	-2.91	-2.7	-3
process innovation	1.339*	1.360**	1.353*	1.359**	1.360*	1.365**	1.354*	1.363**
	-1.87	-1.97	-1.93	-2.08	-1.87	-1.98	-1.83	-1.97
dummy R&D (lagged)		0.602***	0.612***	0.413***	0.402***	0.399***	0.402***	0.416***
		(-2.81)	(-2.63)	(-3.12)	(-2.96)	(-2.91)	(-2.91)	(-2.80)
dummy_resINT			0.86	0.858	0.856	0.861	0.853	0.86
			(-0.73)	(-0.71)	(-0.77)	(-0.70)	(-0.73)	(-0.74)
dummy_resEST			0.841	0.861	0.851	0.847	0.849	0.852
			(-0.62)	(-0.51)	(-0.55)	(-0.55)	(-0.57)	(-0.57)
dummy_resMIX			0.979	0.963	0.966	0.963	0.958	0.95
			(-0.10)	(-0.18)	(-0.17)	(-0.17)	(-0.19)	(-0.25)
R&D expenditure (lagged)				1.078*	1.083*	1.082*	1.080*	1.07
				-1.86	-1.72	-1.78	-1.69	-1.42
dummy human capital					0.884	0.88	0.884	0.893
					(-1.20)	(-1.21)	(-1.27)	(-1.03)
revenues growth (lagged)						1.335	1.339	1.321
						-0.86	-0.91	-0.81
sectorial revenue growth						0.716	0.721	0.737
						(-1.22)	(-1.19)	(-1.12)
age						1.002	1.001	1.001
						-0.76	-0.53	-0.43
Pavitt	No	No	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No	Yes	Yes
Size, investments and time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a categorical variable indicating changes in firm size. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Nominal variables are in millions of 2006 euros.

Table 4: Tobit - Job creation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
product & process inno	3.736***	3.916***	3.484***	3.384***	3.368***	3.461***	3.425***	3.413***
	-3.24	-3.56	-3.04	-2.94	-2.91	-3.02	-3.04	-3.22
product innovation	4.289***	4.422***	4.110***	4.020***	3.886***	3.913***	4.040***	4.023***
	-3.05	-3.28	-3.1	-2.93	-2.8	-3.14	-2.97	-3.14
process innovation	3.258***	3.255***	3.120***	3.138**	3.121**	2.984**	2.866**	2.943**
	-2.62	-2.95	-2.59	-2.53	-2.54	-2.52	-2.51	-2.52
dummy R&D (lagged)		-3.264***	-3.453***	-5.609**	-5.135**	-5.573***	-5.915***	-5.292**
		(-2.62)	(-2.66)	(-2.56)	(-2.27)	(-2.75)	(-2.64)	(-2.46)
dummy_resINT			-0.515	-0.466	-0.46	-0.836	-0.756	-0.699
			(-0.28)	(-0.24)	(-0.24)	(-0.44)	(-0.42)	(-0.36)
dummy_resEST			-1.062	-0.879	-0.765	-1.047	-1.16	-1.177
			(-0.48)	(-0.37)	(-0.33)	(-0.48)	(-0.57)	(-0.53)
dummy_resMIX			1.562	1.516	1.368	1.068	1.233	1.193
			-0.84	-0.81	-0.74	-0.58	-0.68	-0.63
R&D expenditure (lagged)				0.393	0.325	0.436	0.501*	0.338
				-1.27	-1.03	-1.48	-1.71	-1.13
dummy human capital					2.367***	2.298***	2.161***	2.227**
					-2.75	-2.68	-2.64	-2.57
revenues growth (lagged)						0.255	0.258	0.253
						-0.11	-0.13	-0.12
sectorial revenue growth						4.733**	4.748**	4.716**
						-2.27	-2.32	-2.08
age						-0.141***	-0.138***	-0.141***
						(-5.61)	(-5.75)	(-5.63)
Pavitt	No	No	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No	Yes	Yes
Size, investments and time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

Table 5: Tobit - Job destruction

product & process inno	-1.156	-1.406	-1.420*	-1.343	-1.362	-1.374*	-1.326	-1.367
	(-1.45)	(-1.62)	(-1.67)	(-1.53)	(-1.64)	(-1.68)	(-1.63)	(-1.61)
product innovation	-1.941**	-2.275**	-2.294***	-2.176**	-2.190**	-2.202**	-2.234**	-2.282**
	(-2.18)	(-2.51)	(-2.60)	(-2.54)	(-2.41)	(-2.42)	(-2.57)	(-2.57)
process innovation	-1.852*	-2.061**	-2.059**	-2.086**	-2.103**	-2.089**	-2.017*	-2.095**
	(-1.77)	(-1.97)	(-2.12)	(-1.98)	(-2.01)	(-2.13)	(-1.92)	(-2.25)
dummy R&D (lagged)		3.061***	2.924***	4.747***	4.848***	4.876***	4.886***	4.527***
		-3.44	-3.37	-3.19	-3.2	-2.91	-3.11	-2.87
dummy_resINT			0.743	0.748	0.747	0.742	0.761	0.698
			-0.75	-0.67	-0.71	-0.7	-0.71	-0.67
dummy_resEST			0.561	0.393	0.429	0.426	0.437	0.413
			-0.32	-0.23	-0.25	-0.26	-0.26	-0.23
dummy_resMIX			0.549	0.614	0.616	0.634	0.634	0.693
			-0.54	-0.55	-0.56	-0.58	-0.59	-0.68
R&D expenditure (lagged)				-0.345	-0.367	-0.372	-0.373*	-0.293
				(-1.56)	(-1.60)	(-1.52)	(-1.66)	(-1.31)
dummy human capital					0.632	0.641	0.647	0.555
					-1.1	-1.04	-1	-0.97
revenues growth (lagged)						-0.143	-0.175	-0.148
						(-0.21)	(-0.23)	(-0.16)
sectorial revenue growth						0.389	0.538	0.475
						-0.24	-0.34	-0.28
age						-0.00232	0.000225	-0.000748
						(-0.16)	-0.02	(-0.05)
Pavitt	No	No	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No	Yes	Yes
Size, investments and time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

innovation has the higher positive impact on JCR compared to other types of innovations, while process innovation has the higher negative impact on JDR. R&D reduces both JCR and JDR. Output measures of innovation reduce churning, while R&D has a negligible effect on churning for growing firms and a positive impact for shrinking firms.

Our results are in line with what found in Piva and Vivarelli (2005) on the same dataset, but with different measures of innovations. The authors find a significant but small positive relationship between innovation and employment.

5.3 Sensitivity analysis

In this section, we present the results from tobit estimates carried out on several subsamples. First we repeat the analysis by reducing the sample to the first two waves of the survey and, then, to the last two[10]. Second we restrict the analysis to those firms exhibiting the same path in job creation/destruction as in the previous year. We also repeat the analysis on the subsample of SMEs and the subsample of young companies. Finally, we repeat the analysis by replacing the output measures of innovations with their interaction with the lagged R&D dummy. In this way, we try to select firms with a higher commitment to innovation strategies.

Overall, most of the results reported in the tables are quantitatively very similar to the previous estimates as well as the level of significance.

6 Conclusions

This paper documents empirical evidence of the effects of input and output measures of innovation on job creation, job destruction and churning for a sample of Italian manufacturing firms over the period 1998-2006. Given the overall theoretical ambiguity of the direction of the effect of innovation on firm size, we focus on whether innovation strategies may have asymmetric effects on growing firms rather than on those experiencing a contraction.

The analysis reveals asymmetric effects for growing or shrinking firms both on what strategies are relevant and in terms of their magnitudes. Product and process innovations foster job creation, regardless of whether they are carried out together or individually, but with the effect of product innovation being stronger. Job destruction is amplified by process innovations, while, if carried out with product innovation, the effect is lower. We also find that investments in R&D have sizeable effects on job creation and job destruction but, differently from innovation, R&D

[10]Dealing with singular waves results in a significant decline of the number of observations.

Table 6: Tobit - Churning for growing firms

product & process inno	-0.115**	-0.128***	-0.114**	-0.109**	-0.108**	-0.110**	-0.108**	-0.108**
	(-2.27)	(-2.65)	(-2.31)	(-2.11)	(-2.20)	(-2.15)	(-2.32)	(-2.15)
product innovation	-0.180***	-0.190***	-0.180***	-0.175***	-0.169***	-0.170***	-0.174***	-0.172***
	(-3.22)	(-3.54)	(-3.22)	(-3.01)	(-2.96)	(-3.09)	(-3.13)	(-2.88)
process innovation	-0.113**	-0.113**	-0.108*	-0.109**	-0.108**	-0.107*	-0.103**	-0.106*
	(-2.13)	(-2.03)	(-1.93)	(-2.06)	(-2.06)	(-1.84)	(-1.98)	(-1.89)
dummy R&D (lagged)		0.236***	0.250***	0.367***	0.346***	0.356***	0.367***	0.344***
		-3.91	-3.66	-3.7	-3.49	-3.38	-3.66	-3.41
dummy_resINT			-0.0167	-0.0191	-0.0189	-0.0134	-0.0167	-0.0174
			(-0.22)	(-0.25)	(-0.25)	(-0.18)	(-0.23)	(-0.22)
dummy_resEST			-0.0271	-0.0369	-0.0419	-0.0381	-0.0356	-0.0347
			(-0.27)	(-0.35)	(-0.40)	(-0.40)	(-0.36)	(-0.32)
dummy_resMIX			-0.0791	-0.0763	-0.0696	-0.0663	-0.0729	-0.0696
			(-1.03)	(-1.05)	(-0.97)	(-0.88)	(-1.01)	(-0.86)
R&D expenditure (lagged)				-0.0213	-0.0183	-0.0206	-0.0227*	-0.0169
				(-1.58)	(-1.38)	(-1.49)	(-1.75)	(-1.26)
dummy human capital					-0.105***	-0.104***	-0.0998***	-0.102***
					(-2.91)	(-2.99)	(-2.90)	(-2.91)
revenues growth (lagged)						-0.00504	-0.00515	-0.00503
						(-0.07)	(-0.06)	(-0.07)
sectorial revenue growth						-0.0678	-0.0687	-0.0694
						(-0.89)	(-0.81)	(-0.89)
age						0.00286***	0.00277***	0.00284***
						-2.92	-2.7	-2.91
Pavitt	No	No	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No	Yes	Yes
Size, investments and time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

Table 7: Tobit - Churning for shrinking firms

product & process inno	-0.0853	-0.115	-0.118	-0.108	-0.109	-0.108	-0.105	-0.11
	(-1.02)	(-1.34)	(-1.51)	(-1.24)	(-1.26)	(-1.31)	(-1.19)	(-1.25)
product innovation	-0.241***	-0.278***	-0.285***	-0.270***	-0.270***	-0.270***	-0.276***	-0.287***
	(-2.70)	(-2.92)	(-3.02)	(-2.97)	(-2.91)	(-2.96)	(-2.82)	(-2.99)
process innovation	-0.228**	-0.251**	-0.252**	-0.256**	-0.257***	-0.253***	-0.246**	-0.255**
	(-2.35)	(-2.48)	(-2.52)	(-2.50)	(-2.66)	(-2.66)	(-2.46)	(-2.46)
dummy R&D (lagged)		0.342***	0.316***	0.557***	0.565***	0.558***	0.560***	0.518***
		-3.57	-3.22	-3.3	-3.5	-3.43	-3.43	-3.29
dummy_resINT			0.179	0.181	0.18	0.181	0.182	0.176
			-1.48	-1.53	-1.57	-1.44	-1.56	-1.45
dummy_resEST			0.248	0.225	0.228	0.229	0.233	0.234
			-1.45	-1.32	-1.35	-1.39	-1.39	-1.31
dummy_resMIX			0.145	0.154	0.154	0.16	0.158	0.169
			-1.19	-1.29	-1.36	-1.28	-1.35	-1.39
R&D expenditure (lagged)				-0.0456*	-0.0472**	-0.0457*	-0.0462**	-0.0373
				(-1.94)	(-2.11)	(-1.96)	(-2.00)	(-1.60)
dummy human capital					0.0479	0.046	0.0471	0.0356
					-0.78	-0.78	-0.78	-0.55
revenues growth (lagged)						-0.0108	-0.0139	-0.0127
						(-0.11)	(-0.13)	(-0.13)
sectorial revenue growth						0.114	0.131	0.118
						-0.71	-0.81	-0.71
age						-0.00192	-0.00169	-0.00176
						(-1.46)	(-1.16)	(-1.25)
Pavitt	No	No	No	No	No	No	No	Yes
Regional dummies	No	No	No	No	No	No	Yes	Yes
Size, investments and time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

Table 8: Robustness

Dependent variable	JCR 2000-2003	JDR	JCR 2003-2006	JDR	JCR Path dep	JDR	JCR SME	JDR	JCR Large	JDR	JCR Young	JDR	JCR Old	JDR
product & process inno	3.033**	-0.813	3.007**	-1.682*	4.008***	-1.341	2.488**	-1.159	8.872***	-3.859**	3.308	-2.481	2.979**	-1.22
	-2.27	(-0.82)	-2.2	(-1.69)	-2.91	(-1.30)	-2.06	(-1.26)	-2.83	(-2.29)	-0.94	(-1.17)	-2.5	(-1.31)
product innovation	4.158**	-2.201**	2.956**	-2.938***	4.199**	-3.172***	3.474***	-2.289**	7.325	-4.445**	11.01**	-3.752	2.526*	-2.198**
	-2.5	(-2.06)	-2.1	(-2.81)	-2.41	(-2.98)	-2.64	(-2.27)	-1.64	(-2.41)	-2.09	(-1.53)	-1.93	(-2.34)
process innovation	2.659**	-2.024*	3.555**	-2.836**	3.389**	-2.067*	2.702**	-1.129	4.073	-6.620***	4.867	-3.294	2.332*	-1.832*
	-1.98	(-1.84)	-2.26	(-2.29)	-2.35	(-1.72)	-2.2	(-1.03)	-1.22	(-2.84)	-1.38	(-1.05)	-1.79	(-1.72)
dummy R&D (lagged)	-5.784**	6.550***	-5.924**	2.937*	-5.412**	6.271***	-6.077**	0.251	-0.682	11.66***	-12.94*	7.434*	-4.615**	3.806**
	(-2.08)	-3.4	(-2.32)	-1.74	(-2.07)	-2.93	(-2.43)	-0.13	(-0.09)	-3.2	(-1.83)	-1.84	(-2.09)	-2.21
N	1737	1289	1201	1016	1780	1204	1941	1423	261	187	380	250	1822	1360

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

Table 9: Robustness

Dependent variable	CHR JC 2000-2003	CHR JD	CHR JC 2003-2006	CHR JD	CHR JC Path dep	CHR JD	CHR JC SME	CHR JD	CHR JC Large	CHR JD	CHR JC Young	CHR JD	CHR JC Old	CHR JD
product & process inno	-0.0835	-0.0735	-0.109	-0.141	-0.126**	-0.136	-0.0722	-0.0953	-0.240**	-0.236*	-0.077	-0.144	-0.108*	-0.114
	(-1.59)	(-0.91)	(-1.42)	(-1.34)	(-2.34)	(-1.36)	(-1.36)	(-0.90)	(-2.50)	(-1.76)	(-0.67)	(-0.86)	(-1.89)	(-1.23)
product innovation	-0.167***	-0.238***	-0.199**	-0.336***	-0.193***	-0.392***	-0.139**	-0.289**	-0.303**	-0.413**	-0.313**	-0.249	-0.143**	-0.304***
	(-2.81)	(-2.59)	(-2.18)	(-2.90)	(-3.15)	(-3.14)	(-2.35)	(-2.50)	(-2.39)	(-2.51)	(-2.29)	(-1.25)	(-2.18)	(-2.75)
process innovation	-0.0608	-0.238**	-0.231**	-0.351***	-0.114**	-0.307**	-0.0798	-0.201*	-0.196	-0.391**	-0.0929	-0.171	-0.110*	-0.258**
	(-1.12)	(-2.56)	(-2.40)	(-2.74)	(-2.06)	(-2.38)	(-1.32)	(-1.71)	(-1.59)	(-2.52)	(-0.73)	(-0.89)	(-1.78)	(-2.16)
dummy R&D (lagged)	0.271**	0.669***	0.467***	0.320*	0.287***	0.661***	0.341***	0.206	0.431*	0.730**	0.485**	0.578*	0.334***	0.456**
	-2.16	-3.84	-3.26	-1.72	-2.65	-3.28	-2.81	-0.98	-1.68	-2.46	-1.98	-1.72	-2.95	-2.5
N	1737	1289	1201	1016	1780	1204	1941	1423	261	187	380	250	1822	1360

Notes: The dependent variable is the job creation rate. ***, **, * denote, respectively, significance levels at 1%, 5% and 10%. Bootstrapped standard errors are in parenthesis. The sample includes 2999 firms. Among them 1859 firm-year observations, 461 are left-censored. Nominal variables are in millions of euros. Uncertainty has been measured by the standard deviation of past two-years sales per-employee, where firm's sales per-employee are normalised by the average sales per-employee in firm's operating industry. The interaction term is the product of the share of temporary workers times the uncertainty. The size of firms is proxied by a dummy for small (lower than 51 employees), medium (from 51 to 250 employees) and large firms (more than 250 employees). Worker inflow (outflow) rate is the ratio of hirings (separations) over the workforce.

activities reduce both of them. Moreover, while R&D has a negligible effect on churning for growing firms and a positive impact for shrinking firms, the churning ratio has a negative relation with product and process innovation.

We believe that our results are informative for the ongoing debate on incentives for innovative firms. From one standpoint, policy makers should be aware that firms' innovation performance may amplify both positive and negative growth rate and that the incentives to foster R&D investments may be an additional route to increase the excess of worker reallocation over the whole number of workers that each firm hires and fires, i.e. the churning rate.

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Appendix A

Table 10: Summary statistics

	Overall sample (N=2999)		Stable size (N=813)		Increasing size (N=1389)		Decreasing size (N=797)	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
growth rate	2.789	13.415	-	-	10.377	15.378	-7.591	7.007
churning level	18.18	104.45	11.10	24.14	20.70	126.97	20.99	110.99
product & process inno	0.397	0.489	0.376	0.485	0.405	0.491	0.405	0.491
product innovation	0.202	0.401	0.185	0.388	0.199	0.399	0.225	0.418
process innovation	0.186	0.389	0.176	0.381	0.198	0.399	0.174	0.380
no innovation	0.215	0.411	0.263	0.441	0.199	0.399	0.196	0.397
dummy R&D (lagged)	0.872	0.335	0.905	0.293	0.861	0.346	0.856	0.352
R&D expenditure (lagged)	4.853	2.355	4.796	2.045	4.856	2.418	4.906	2.535
employment (lagged)	149.558	450.948	89.454	185.799	148.936	368.752	211.954	697.129
age (lagged)	26.337	18.970	26.664	18.315	24.792	17.877	28.695	21.121