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Innovation and Employment Churning: The Dynamics of Labour Market Adjustment in Innovating Firms

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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 job creation, while they reduce job destruction. Conversely, R&D tends to work in the opposite direction, reducing job creation and amplifying job destruction. We also find that employment churning increases with firms' engagement in R&D activities, while it decreases when firms introduce new products and/or process innovations. Crucially, the study identifies asymmetric responses of worker flows and churning to innovation strategies, depending on firms' growth trajectories and whether product and process innovations are implemented separately or simultaneously.

Keywords: Churning, Excess worker turnover, Job creation and destruction, R&D, Innovation

1. Introduction

Innovation remains a critical driver of economic growth, productivity, and competitiveness in advanced economies. While its importance for long-term economic development is well-established, innovation's effects on employment patterns extend far beyond simple job creation or destruction metrics, encompassing complex dynamics of worker reallocation within and across firms. Economic theory suggests that different innovation strategies can yield heterogeneous effects on firm size and labour market dynamics, with potentially profound implications for both managerial decision-making and public policy design. Despite significant scholarly attention to the relationship between innovation and firm level net employment changes, the impact of innovation on worker flows and reallocation remains theoretically ambiguous and empirically contested in the economic literature (Dachs et al., 2017; Van Reenen, 1997; Van Roy et al., 2018).

This paper investigates a particularly understudied dimension of this relationship to understand how different innovation strategies—product innovation, process innovation, and R&D expenditure—affect not only job creation and destruction but specifically worker churning at the firm level. Worker churning—defined as the share of worker turnover in excess of what is needed for net employment changes—constitutes a substantial portion of labour market dynamics with significant economic consequences. In developed economies, churning can accounts for over 70% of all worker flows (Burgess et al., 2000; Davis et al., 2012), generating considerable adjustment costs for both firms and workers through recruitment, training, and transitional productivity losses.

Despite its economic significance, the relationship between firm-level innovation strategies and churning remains largely unexplored in the economic literature. While extensive research has examined churning in relation to business cycles at the aggregate level (Centeno & Novo, 2012; Davis et al., 2012), the firm-level determinants of churning—particularly how innovation strategies drive excess worker turnover—have received remarkably little attention.

Our study addresses this critical gap by investigating three key questions: (1) How do product innovation, process innovation, and R&D investments affect job creation and destruction rates at the firm level? (2) Do these innovation strategies increase or decrease churning rates? (3) Do these effects vary depending on whether product/process innovations are implemented separately or in combination, and whether firms are experiencing positive or negative employment growth? By focusing specifically on churning—rather than merely net employment changes—we provide a more comprehensive understanding of how innovation reshapes labour markets at the microeconomic level. This approach acknowledges that innovation often requires labour reallocation within firms (Bauer & Bender, 2004), but not necessarily firm size variation, creating worker flows even in the absence of net employment changes. The analysis presented here represents an important advance in understanding labour market dynamics by recognizing that innovation strategies may have different effects on employment depending on whether firms experience positive or negative growth rates. This perspective builds on recent findings indicating that innovation's effects on employment vary substantially along the conditional distribution of employment growth (Falk, 2012). Our approach allows us to identify asymmetric effects that might be obscured in analyses focusing solely on average effects across all firms.

Using rich firm-level data from Italian manufacturing companies collected by Unicredit-Mediocredito Centrale, we employ censored regression models to account for the asymmetric effects of innovation on growing versus shrinking firms. This methodological approach allows us to capture complexities that might be missed in analyses focusing solely on average effects or net employment changes. For growing firms, we can detect how innovation affects the pace of expansion, while for shrinking firms, we can identify how innovation mitigates or accelerates contraction dynamics. Our empirical results are consistent with a framework in which innovation strategies affect firms' skill requirements and internal adjustment mechanisms, thereby shaping excess worker turnover. By distinguishing between innovation outputs (product and process innovation) and innovation inputs (R&D), the analysis provides empirical building blocks that future research can integrate into more comprehensive theoretical models linking innovation, competencies and organizational dynamics.

The contribution of our paper lies also in connecting two previously separate strands of literature: studies of innovation-induced employment changes (Dachs et al., 2017; Harrison et al., 2014) and analyses of labour market churning (Burgess et al., 2000; Davis et al., 2012). To the best of our knowledge, this is the first study systematically assessing whether different innovation strategies can be associated with different levels of churning and whether systematic differences in churning can be statistically associated with different innovation practices. By demonstrating how different innovation strategies drive excess worker turnover at the firm level, we provide a more granular understanding of innovation's labour market impacts that can inform both theoretical models and practical policy design.

Our results reveal that product and process innovations tend to amplify job creation and reduce job destruction, with product innovations showing stronger effects both on job creation and destruction. In contrast, R&D expenditure works in the opposite direction, reducing job creation and amplifying job destruction. Regarding churning, we find that it increases as firms engage in R&D activities but decreases when firms introduce product and/or process innovations, with effects varying significantly if firms are growing rather than shrinking.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundations and empirical evidence on innovation and labour market dynamics. Section 3 describes our econometric approach, highlighting how censored regression models account for asymmetric effects. Section 4 presents the dataset and variables, discussing the advantages and limitations of our survey data. Section 5 summarizes the results and includes robustness checks. Section 6 concludes with implications for theory development, managerial practice, and policy design.

2. Background and Related Literature

Economic theory suggests that innovation can affect employment through multiple channels with potentially offsetting effects. Process innovation typically increases labour productivity, potentially reducing labour requirements per unit of output—the "displacement effect" described in the literature by Vivarelli (2014) and Calvino and Virgillito (2018). However, if productivity gains translate into lower prices, increased demand may stimulate production and employment—the "compensation effect." The net impact depends on market structures, demand elasticities, and the nature of technological change.

Product innovation generally has a more straightforward positive effect on employment, as firms require additional workers to produce new goods or services. Harrison et al. (2014) provide extensive cross-country evidence supporting this positive relationship, particularly in manufacturing sectors. However, this effect may be attenuated if new products cannibalize existing ones or if increased product differentiation allows firms to exercise market power, potentially leading to higher prices and reduced output, as noted by Dachs et al. (2017). R&D investments represent inputs to the innovation process rather than innovation outputs and may affect employment through different mechanisms. R&D activities are typically knowledge-intensive and may increase demand for skilled labour. However, R&D also represents a significant financial commitment that may divert resources from other investments, including workforce expansion. Additionally, the inherent uncertainty of R&D outcomes may lead firms to adopt more cautious employment strategies, as suggested by Di Cintio and Grassi (2017). Recent research has increasingly recognized that innovation's employment effects may vary across the distribution of firm growth rates. Falk (2012) demonstrates that innovation has stronger positive effects on high-growth firms than on others. These findings suggest that examining average effects across all firms may mask important heterogeneities—our study directly addresses such gap by examining innovation's effects conditional on firms' growth trajectories.

Regarding R&D investments, the empirical evidence remains inconclusive. Some studies report positive impacts on employment growth (Falk, 2012; Yasuda, 2005), while others find negative relationships (Brouwer et al., 1993) or no clear association (Klette & Førre, 1998). More recent analyses by Van Roy et al. (2018) suggest that R&D's employment effects depend on complementary factors such as industry characteristics, firm capabilities, and institutional contexts.

While these studies provide valuable insights into how innovation affects net employment changes, they typically overlook a critical dimension of labour market dynamics: worker flows in excess of what is needed for net employment changes, or churning. Worker churning represents a significant yet understudied dimension of labour market dynamics with substantial economic implications. Conceptually, churning occurs when firms simultaneously hire and separate workers beyond what is needed for net employment changes (Burgess et al., 2000).

The existing literature on churning has primarily focused on its relationship with business cycles at the aggregate level. Davis et al. (2012) document that churning tends to be procyclical in the United States, increasing during economic expansions and decreasing during recessions. Similar patterns have been observed in other developed economies by Centeno & Novo (2012). This procyclicality suggests that churning is partly driven by workers voluntarily moving to better job matches when labour markets are tight. In addition to cyclical movements, recent work documents pronounced shifts in worker turnover over time and across institutional settings. Pries and Rogerson (2022) use US Quarterly Workforce Indicators data for 1999 to 2017 and show that the secular decline in worker turnover is largely accounted for by a reduction in very short employment spells of one or two quarters across industries, firm size classes and worker groups, which they interpret as the outcome of more intensive employer screening that raises the quality of newly formed matches. Flórez et al. (2021) compare worker and job flows in Colombia and the United States and report that, while job creation and destruction rates are similar or even higher in Colombia, worker flows and churning are roughly half as large, which they attribute to stricter employment protection and higher separation costs. These contributions stress that churning reflects long run changes in labour market fluidity and institutions, not only business cycle conditions.

At the firm level, employment churning has been studied primarily in relation to structural characteristics such as firm size, age, and industry. Lane et al. (1996) find that large firms typically experience higher churning rates than small ones, possibly due to internal labour markets that facilitate worker reallocation. Haltiwanger et al. (2013) document that young firms tend to have higher churning rates as they experiment with different organizational structures and workforce compositions. Ilmakunnas and Maliranta (2005) find that churning increases with plant size and is higher in younger plants. High-wage plants and those with low wage variability experience less churning, and past employment growth and lower average employee tenure also positively affect churning rates. Further matched employer employee studies emphasise the role of employer policies and compensation structures in shaping churning. Lazear and McCue (2018) use US administrative data to show that churn, defined as replacement hiring, accounts for most worker turnover and that permanent employer differences explain about one third of the variation in churn rates; turnover is lower in high wage firms and in local labour markets with a higher wage level, and higher where within firm wage dispersion is greater. Shiferaw and Söderbom (2023) analyse manufacturing establishments in Ethiopia and find that churning rises in a non linear way with establishment size and is positively related to lagged net employment growth, while higher wages, pension coverage and gain sharing schemes reduce both separation and churning rates. These results indicate that persistent firm characteristics and compensation policies are central for understanding excess worker turnover. A related strand of research links the pattern of job and worker flows to earnings dynamics. Tanaka, Warren and Wiczer (2023) use US matched employer employee data to study job to job transitions and show that earnings growth at the time of a move increases systematically with net employment growth at the destination firm and, to a lesser extent, declines when the origin firm is shrinking. Conditioning on firm age, size and average wage, they find that net employment growth rather than gross hires is the key predictor of earnings gains for movers, which suggests that reallocation of workers toward expanding firms is central to wage progression, whereas excess churning in itself plays a more limited role for average earnings growth.

Spatial dimensions of labour reallocation also matter for employment churning. Gervais (2018) examines multi regional firms in US manufacturing and shows that they account for a disproportionate share of output and employment, and that changes in the set of regions in which they operate generate sizable employment churning as less productive regional operations are closed and new establishments are opened in more productive locations. Bratsberg, Rogstad and Raaum (2021) study Norwegian local labour markets that differ in their reliance on Central and Eastern European migrant workers and find that firms employing a high share of such migrants display very high levels of excess churning, with simultaneous hiring and separations that do not translate into net job creation; they interpret this pattern as the result of easy access to a pool of temporary migrant workers that reduces the cost of replacing incumbents. These findings indicate that geographical mobility and workforce composition can magnify excess churning independently of net job creation.

There exists a striking contrast between the extensive literature on aggregate churning patterns and the limited research on firm-level determinants of churning, particularly innovation strategies. This gap is particularly notable given that innovation often requires significant adjustments in workforce composition and skills, which may generate substantial worker turnover even in the absence of net employment changes. Among the few studies on innovation and firm level employment dynamics, Bauer and Bender (2004) find that organizational changes and new technologies increase both hiring and separation rates in German establishments, with stronger effects on separation rates, leading to net employment reductions. Similarly, Askenazy and Galbis (2007) report that ICT implementation in French firms increases worker turnover, particularly for less skilled workers. These studies suggest that innovations may render some existing skills obsolete while creating demand for new ones, leading firms to replace rather than retrain some workers. Additionally, the uncertainty associated with technological change may lead to more experimentation in hiring, potentially increasing mismatch rates and subsequent separations. However, these studies focus primarily on specific types of technological changes (mainly ICT adoption) rather than providing a comprehensive assessment of how different innovation strategies affect worker flows. Moreover, innovation strategies could affect churning differently depending on whether firms are growing or shrinking. For instance, growing firms implementing process innovations might experience less churning if they can reallocate existing workers to new tasks. Conversely, shrinking firms adopting process innovations might face higher churning as they struggle to match worker skills with new technological requirements. To our knowledge, no study has systematically examined how product innovation, process innovation, and R&D investments affect churning rates at the firm level, particularly with attention to potential asymmetries based on firms' growth trajectories.

3. Estimation Approach

To capture the potentially asymmetric effects of innovation on labour market dynamics, we employ censored regression models. For job creation, we estimate:

$$\begin{aligned} JC_i &= \max(g_i, 0) = \beta_{JC} X_i + \varepsilon_{JC,i} \quad && if \quad g_i > 0 \\ JC_i &= 0 \quad if \quad g_i = 0 \end{aligned} \tag{1}$$

where JC_i represents the job creation rate for firm *i*, defined as positive employment growth g_i when it occurs, and zero otherwise. Similarly, for job destruction, we estimate:

$$\begin{aligned} JD_i &= \max(-g_i, 0) = \beta_{JD} X_i + \varepsilon_{JD,i} \quad && if \quad g_i < 0 \\ JD_i &= 0 \quad if \quad g_i = 0 \end{aligned} \tag{2}$$

where JD_i represents the job destruction rate for firm *i*, defined as the absolute value of negative employment growth when it occurs, and zero otherwise. These censored specifications explicitly recognize that job creation occurs only in growing firms, while job destruction occurs only in shrinking firms, providing a natural framework for capturing asymmetric effects of innovation strategies across different growth regimes.

To capture potential asymmetries in how innovation affects churning across growth regimes, we also estimate separate models for growing and shrinking firms:

$$\begin{aligned} CH_i^{grow} &= \beta_{CH}^{grow} X_i + \varepsilon_{CH,i}^{grow} \quad && if \quad g_i > 0 \\ CH_i^{shrink} &= \beta_{CH}^{shrink} X_i + \varepsilon_{CH,i}^{shrink} \quad && if \quad g_i < 0 \end{aligned} \tag{3}$$

where CH_i represents the churning rate for firm i.[1] Our main regressors are (1) dummy variables capturing the types of innovation (product and/or process innovations) introduced in the three years prior to the interview and (2) a lagged indicator variable for firms involved in R&D activities and the lag of the R&D expenditure.

This approach allows innovation strategies to affect job creation, job destruction and churning differently depending on whether a firm is expanding or contracting, addressing a key aspect of asymmetry identified in the theoretical literature.

Since job creation, job destruction and churning are censored variables, we perform our estimations under separate Tobit regressions.

4. Data, Variables and Descriptive Statistics

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[2] 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 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. Thus, the results should be interpreted with caution, particularly in rapidly changing industries where entry and exit play a significant role in market dynamics. Future research could complement survey findings with business registry data to better capture firm entry and exit dynamics.

Although the analysis relies on cross-sectional survey data, the timing of innovation variables allows us to capture medium-term effects of innovation strategies on employment dynamics. Future research could complement this approach with fully longitudinal matched employer–employee data to explore also the internal organizational mechanisms underlying the observed churning patterns. Specifically, we consider the 2001, 2004 and 2007 waves of the available surveys. By merging these waves, we build a dataset of 10,720 records over the period 1998-2006. Among them, firms with inconsistent or missing data with respect to relevant variables of our analysis are excluded from the analysis and we also select those firms with a meaningful data, i.e. R&D expenditure higher than 10,000 euros. Since the innovation dummies refer to the three years period prior to the interview, we are constrained to consider only the employment growth rates referring to the last years of each survey. Thus, reducing the final sample to 2,999 observations.

As explained in the previous section, this study borrows the definitions of job and labour flows from the existing literature (Burgess et al., 2000; Davis & Haltiwanger, 1992; Hamermesh et al., 1996). At time t, a job flow at establishment i is defined as the net employment change, thus it can be measured either as the difference between current and past employment or, alternatively, as the difference between hirings and separations occurred in each 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[3]. In this study, we identify firms with job destruction as those for which we observe a non-positive job flow.

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 and it underscores a key distinction between hires that actively drive the firm's expansion and those that merely fill positions left by separating employees. Algebraically, it is computed as the difference between the worker flow (i.e. the sum of hires and separations) and the job reallocation.[4] Then,

1 We provide the algebraic formulation in the next section.

2 Stratification is based on industry, geographic area and firm size.

3 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.

4 For example, a firm that hires 15 workers and separates 10 experiences a net job creation of 5, with churning accounting for 20.

dividing this measured by the worker flow, it is possible to express churning as a percentage. This measure has the obvious advantage of being independent from firm size and it facilitates the interpretation of the results.

As far as innovations are concerned, we refer to three dummies, one for product and process innovators, one for product-only innovators and one for process-only innovators. Thus, differently to most existing studies where firms are considered either as product or process innovators, we can identify also firms that innovate along both dimensions. On the other hand, with respect to input-based innovations measures, we use the R&D expenditure as an indicator of the strength of firms' innovative effort. So that it is possible to account for both input- and output-based measures of innovation. Moreover, we include a dummy variable for R&D activities to capture a firm's decision of whether to invest in R&D. Since the sample distribution of the R&D expenditure is usually skewed, the standard solution to this problem is to take a log transformation. That brings all 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 are many zeros. Instead, one can use the inverse hyperbolic sine transformation (IHS). Specifically, the IHS is defined as the $log\left(y_i + (y_i^2 + 1)^{\frac{1}{2}}\right)$. 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.

Since investments in physical capital can be considered as an indicator of process innovation inputs, especially for large firms (Vaona & Pianta, 2008), we include investments among our regressors. We use the IHS transformation of the investments and its lagged value. Our estimates also include firm and industry characteristics. Because size reflects access to finance, scale economies and differences in the organisation of work, we include the size of 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 labour-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 stage 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 companies to purge the estimates from their specific behaviour. Finally, firm's location and age are included in the model.

We employ three different empirical model specifications to monitor any shifts in the point estimates. The first (baseline) specification includes dummies for product innovation, process innovation, and joint product/process innovation, as well as a dummy for R&D, its expenditure level, investments in physical capital, and lagged values of both R&D and investments. This setup enables an examination of how these factors affect the employment growth rate—captured separately by JCR and JDR—through different innovation strategies. The baseline specification further accounts for firm age, firm size, and time dummies. The second specification expands the model by incorporating the firm's location, while the third adds dummy variables for Pavitt sectors.

Table 1 presents the average job creation (JCR) and destruction rates (JDR), along with their standard deviations and frequencies, for all firms in our sample (Panels a and d). In both panels, these rates are further disaggregated by innovation type. Meanwhile, Panels (b, c) and (e, f) distinguish between R&D and non-R&D firms. This exploratory overview reveals certain differences in the sample means. Specifically, the figures in Panels a and d indicate that both job creation and destruction rates tend to be slightly higher for firms reporting process and/or product innovation. Compared to non-innovators, the average JCR is 24.4% higher among firms with process and product innovations, 25.13% higher for product innovators, and 29.7% higher for process innovators. Likewise, while innovators also show higher job destruction rates, the differences are smaller in scale. 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 (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 1. JCR and JDR by innovation and R&D strategies

Job creation									
	(a) – all firms			(b) - R&D			(c) - no R&D		
Innovation	Mean	S.D.	Freq	Mean	S.D.	Freq	Mean	S.D.	Freq
Product & 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) – all firms			(e) - R&D			(f) - no R&D		
Innovation	Mean	S.D.	Freq	Mean	S.D.	Freq	Mean	S.D.	Freq
Product & 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

Table 2 reports average churning to worker flows ratios along with standard deviations and frequencies for all firms in our sample, distinguishing between growing (panel a) and shirking (panel d) firms. Also, these measures have been disaggregated by R&D engagement (panels b, c, e and f). 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 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.

Table 2. Churning rate by innovation and R&D strategies

Growing firms									
	(a) – all firms			(b) - R&D			(c) - no R&D		
Innovation	Mean	S.D.	Freq	Mean	S.D.	Freq	Mean	S.D.	Freq
Product & 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
Shrinking firms									
	(d) – all firms			(e) - R&D			(f) - no R&D		
Innovation	Mean	S.D.	Freq	Mean	S.D.	Freq	Mean	S.D.	Freq
Product & 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

5. Results

This section presents the empirical results of our analysis on the relationship between innovation strategies and labor market dynamics. We investigate how product innovation, process innovation, and R&D expenditure affect job creation, job destruction, and worker churning at the firm level.

Tables 3 and 4 present the findings from the job creation and job destruction models, respectively. In table 3, the estimated coefficients for the innovation output measures are statistically significant at conventional levels, indicating a positive effect of all types of innovation on job creation, with product innovation exhibiting the strongest impact even when it is implemented together with process innovation. Prior studies suggest that the employment effects of product innovations take time to materialize, as firms need time to implement new production processes and introduce innovations to the market. Our findings partially support this hypothesis, given that our measure of product innovation captures activities from a three-year period prior to the interview.

Differently, when looking at table 4, the results reveal that job destruction rates are negatively correlated to both product and process innovations when carried out separately. Instead, we find the coefficient on simultaneous product and process innovators being statistically not different from zero. Additionally, our estimates remain consistent across different model specifications, with coefficients and standard errors displaying minimal variation. The only notable change concerns the R&D dummy coefficient, which goes from -3.45 to -5.61 once lagged R&D expenditures are incorporated into the model, after which it remains stable. Overall, our estimates signal an asymmetric response of employment growth rates in relation to output measures of innovation.

Also, while R&D reduces job creation, it increases destruction rates. Intuitively, introducing new or improved products can stimulate demand, leading to higher sales and potentially more jobs. Firms that innovate successfully often experience growth, which can reduce the need to cut jobs. Also, innovations often require a more skilled workforce, and firms may invest in training and retraining employees rather than laying them off. This shift can reduce job destruction as workers adapt to new roles or technologies. In the case of process innovation, innovative firms may adopt forward-looking strategies that prioritize long-term growth over short-term cost reductions. These firms are more likely to invest in their workforce and explore new opportunities rather than resorting to layoffs. Conversely, when looking at innovation input, R&D activities appear to amplify the job destruction rate and constrain the expansion of already growing firms. R&D can lead to the development of capital-intensive technologies and impose short-term financial burdens that limit immediate employment growth. Also, R&D projects often have a high level of uncertainty and firms may invest heavily in R&D without guaranteed returns, which can lead to higher perceived instability and limit their ability to expand or even maintain their current workforce.

Table 3. Tobit - Job creation

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product & Process innovation	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)
Internal R&D			-0.515	-0.466	-0.46	-0.836	-0.756	-0.699
			(0.28)	(0.24)	(0.24)	(0.44)	(0.42)	(0.36)
External R&D			-1.062	-0.879	-0.765	-1.047	-1.16	-1.177
			(0.48)	(0.37)	(0.33)	(0.48)	(0.57)	(0.53)
Both Internal & External R&D			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, 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. 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.

Beyond the primary variables of interest, our findings highlight the positive role of human capital in employment dynamics. Firms with a higher-than-industry-average share of workers holding at least a bachelor's degree experience a slight increase of over 2% in job creation, while no significant effect is observed on job destruction. Moreover, firms operating in technological sectors exhibit a growth rate approximately 5% higher than those in other industries. Additionally, higher-than-average revenue growth and younger firm age are positively associated with increased job creation but do not significantly impact job destruction.

Table 4. Tobit - Job destruction

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product & Process innovation	-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)
Internal R&D			0.743	0.748	0.747	0.742	0.761	0.698
			(0.75)	(0.67)	(0.71)	(0.7)	(0.71)	(0.67)
External R&D			0.561	0.393	0.429	0.426	0.437	0.413
			(0.32)	(0.23)	(0.25)	(0.26)	(0.26)	(0.23)
Both Internal & External R&D			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)	(1.00)	(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, time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the job destruction 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. 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.

Conversely, Tables 5 and 6 report the results derived from the Tobit model estimations, using churning rate as the dependent variable. In particular, we estimate the impact of innovation on churning separately by distinguishing between growing and shrinking firms. The empirical findings highlight that measures of innovation outputs contribute to a reduction in churning rate in both expanding and contracting firms. However, the magnitude of the coefficients associated with product and process innovations in shrinking firms is notably larger—approximately twice the size—compared to those observed in growing firms. Furthermore, being simultaneously engaged in both product and process innovation activities does not exhibit a significantly different association with employment churning for shrinking firms. In contrast, R&D expenditures display a positive correlation with churning in both expanding and contracting firms, albeit with a more pronounced effect observed in shrinking firms. This evidence supports the notion of an asymmetric firm-level response in employment strategies, particularly emphasizing stronger workforce reshuffling in shrinking firms actively engaged in R&D investments compared to their expanding counterparts.

Table 5. Tobit - Churning for growing firms

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product & Process innovation	-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)
Internal R&D			-0.0167	-0.0191	-0.0189	-0.0134	-0.0167	-0.0174
			(0.22)	(0.25)	(0.25)	(0.18)	(0.23)	(0.22)
External R&D			-0.0271	-0.0369	-0.0419	-0.0381	-0.0356	-0.0347
			(0.27)	(0.35)	(0.40)	(0.40)	(0.36)	(0.32)
Both Internal & External R&D			-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

Notes: The dependent variable is the churning. ***, **, * 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. 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. Size, investments and time dummies included.

Table 6. Tobit - Churning for shrinking firms

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product & Process innovation	-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)
Internal R&D			0.179	0.181	0.18	0.181	0.182	0.176
			(1.48)	(1.53)	(1.57)	(1.44)	(1.56)	(1.45)
External R&D			0.248	0.225	0.228	0.229	0.233	0.234
			(1.45)	(1.32)	(1.35)	(1.39)	(1.39)	(1.31)
Both Internal & External R&D			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

Notes: The dependent variable is the churning. ***, **, * 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. 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. Size, investments and time dummies included.

Robustness

In this section, we present the Tobit estimation results obtained from various subsample analyses. These robustness checks are essential to ensure the stability and validity of our findings, addressing potential biases stemming from unobserved heterogeneity, temporal changes in economic conditions, and differences in firms' innovation commitment. First, we replicate the analysis by restricting the sample to the first two waves of the survey, followed by a separate analysis using only the last two waves, thereby testing the temporal stability of our findings. Second, we focus on firms that exhibited a consistent pattern of job creation or destruction compared to the previous year, which allows us to ascertain whether the observed effects are sensitive to firms' underlying employment dynamics and not driven by firms with volatile employment patterns. Additionally, we conduct separate estimations on SMEs and young firms to assess whether innovation effects vary by firm size and age, reflecting evidence in the literature that firm characteristics significantly moderate the relationship between innovation and employment dynamics (Vaona and Pianta, 2008; Brouwer et al., 1993). Finally, we re-estimate the models by interacting the innovation output measures with the lagged R&D dummy, enabling us to isolate the effects in firms with stronger innovation commitments, given that prior studies indicate heterogeneous employment effects contingent on R&D intensity (Falk, 2012; Calvino and Virgillito, 2018). Overall, the findings reported in Tables 7 and Table 8 remain largely consistent with previous estimates, both in terms of magnitude and statistical significance, strengthening the robustness of our conclusions.

6. Conclusions

This paper investigates the relationship between innovation activities and employment dynamics by analyzing the impact of product and process innovation, as well as R&D investment, on job creation, job destruction, and churning for a sample of Italian manufacturing firms between 1998 and 2006. Given the theoretical ambiguity surrounding the employment effects of innovation—where compensation mechanisms (e.g., increased demand, market expansion) can offset productivity-driven labor reductions (Harrison et al., 2014)—we examine whether the impacts of innovation differ asymmetrically for firms experiencing growth versus those facing contraction.

Our empirical findings indicate that product and process innovations amplify job creation and reduce job destruction. When pursued jointly, the positive impact on job creation remains prominent, but the link to job destruction becomes somewhat milder than in the process-only case. In contrast, R&D investment constrains job creation and amplifies destruction, suggesting that although R&D-active firms are less prone to large employment swings, they also incur higher worker replacement and retraining needs. Turning to churning, product and process innovations generally reduce excess worker flows—particularly in shrinking firms—while R&D activities tend to increase churning, with the effect most pronounced in contracting firms. These asymmetries underscore the importance of the interplay between innovation, workforce reallocation, and firms’ growth trajectories.

Our study has substantial implications for both managerial practices and public policies. Managers should acknowledge the diverse workforce management requirements driven by their innovation strategies and design talent-management systems that facilitate re-skilling and retention, especially in knowledge-intensive areas. Since churning is lower when product or process innovations are in play but higher under R&D-intensive regimes, mechanisms to absorb workers into new roles or functions—such as structured internal training and mobility pathways—can reduce excessive turnover costs. Public policy frequently views innovation through the lens of net job creation. However, our findings show that innovation strategies can modify both job creation and destruction and produce distinct effects on workforce turnover. Policy measures that look solely at net job gains may overlook significant worker flows and resulting adjustment costs. Also, policymakers should design targeted instruments—such as specialized training vouchers or tax credits—to reduce skill mismatches created by process innovations, and dedicated incentives to help R&D-intensive firms manage re-skilling more efficiently. In R&D-intensive settings, churning is substantial, indicating that frequent skill redeployment or staff reshuffling is common. Policymakers can facilitate this process by supporting transitional mechanisms (e.g., portable benefits, training subsidies, or wage insurance) that cushion workers shifting across roles or sectors. Indeed, from a policy perspective, the results highlight that innovation affects not only net employment but also excess worker turnover. This suggests that differentiated approaches—tailored to firms' innovation strategies and specific sectoral contexts—could better address reskilling needs and adjustment costs associated with labour reallocation.

Finally, several avenues for further investigation remain open. First, future research could delve deeper into how skill composition within firms mediates the impact of innovation on churning. Second, more granular data on worker flows—including detailed skill and occupational information—would help disentangle whether reskilling policies can offset the short-term job destruction linked to process innovations. Third, cross-country comparisons could shed light on institutional factors (e.g., labour market regulations or innovation policy regimes) that shape firm-level reallocation. Fourth, integrating firm entry and exit dynamics would clarify whether the observed effects generalize to new entrants or are primarily driven by incumbent firms. Addressing these lines of inquiry would further enrich our understanding of how innovation strategies shape the microfoundations of labour market adjustment.

Table 7. JCR and JDR – Robustness

Dependent variable	JCR	JDR	JCR	JDR	JCR	JDR	JCR	JDR	JCR	JDR	JCR	JDR	JCR	JDR
Variables	2000-2003		2003-2006		Path dep		SME		Large		Young		Old	
Product & Process innovation	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: Dependent variables: JCR / JDR. ***, **, * 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. 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. Churning for Growing and Shirking firms – Robustness

Dependent variable	Growing	Shirking	Growing	Shirking	Growing	Shirking	Growing	Shirking	Growing	Shirking	Growing	Shirking	Growing	Shirking
Variables	2000-2003		2003-2006		Path dep		SME		Large		Young		Old	
Product & Process innovation	-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 churning for growing and shirking firms. ***, **, * 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. 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.

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Appendix A

Table A1. Summary statistics

	Overall sample (N=2999)		Stable firms (N=813)		Growing firms (N=1389)		Shrinking firms (N=797)	
Variable	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 innovation	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