More and Better Jobs, But Not for Everyone: Effects of Innovation in French Firms

Richard Duhautois, Christine Erhel, Mathilde Guergoat-Larivière, Malo Mofakhami

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Richard Duhautois, Cnam, LIRSA, CEET

Christine Erhel, Cnam, LIRSA, CEET

Mathilde Guergoat-Larivière, Cnam, LIRSA, CEET

Malo Mofakhami, Cnam, CEET

Abstract

This article analyses the effect of technological innovation on employment and job quality using a difference-in-differences matching model and a unique matched dataset of French firms (the Community Innovation Survey with administrative and fiscal data). Overall, there is evidence that product innovation increases employment and some dimensions of job quality, such as the number of permanent contracts and working hours. However, this overall virtuous circle between innovation, employment and job quality should be nuanced: first, because not all social groups benefit from firm innovation, as lower-skilled workers are less positively affected in terms of employment and sometimes negatively affected in terms of wages; second, as the positive effects of innovation appear mainly in Manufacturing, and not in Services. Public policy should then pay attention to the consequences of innovation across individuals and sectors to ensure that innovation is beneficial to all.

Contacts:

Richard Duhautois,
CEET
29 Promenade Michel Simon
93166 Noisy-Le-Grand Cedex
France
richard.duhautois@lecnam.net

Christine Erhel,
CEET
29 Promenade Michel Simon
93166 Noisy-Le-Grand Cedex
France
christine.erhel@lecnam.net

Mathilde Guergoat-Larivière
Cnam, EPN 9 – CEET
40 rue des Jeûneurs
75002 Paris
mathilde.guergoat-lariviere@lecnam.net

Malo Mofakhami
CEET
29 Promenade Michel Simon
93166 Noisy-Le-Grand Cedex
France
malo.mofakhami@univ-paris1.fr

Innovation is considered a major determinant of employment changes in both empirical and theoretical economics. At the policy level, it is generally assumed that encouraging firm innovation will produce more and better jobs. This is at the heart of the Europe 2020 Strategy (and, before that, the Lisbon Strategy). From this perspective, there is a virtuous circle among innovation, employment and job quality: a growth strategy based on innovation would be a driver of more and better jobs in Europe (which, in turn, may favor the development of new innovations at the workplace). However, while empirical work generally reveals a positive impact of innovation on employment, there is little analogous evidence for job quality, so we are not able to fully assess whether there is a virtuous circle between innovation and better-quality jobs.

Innovation is also likely to have different effects on workers according to their individual characteristics. It may well produce unemployment, especially for those in low-skilled (following the hypothesis of skill-biased technological change) or 'routine' intermediate occupations according to the more recent polarization hypothesis (Autor *et al.*, 2003; Goos *et al.*, 2014). Similarly, while the current development of new technologies may improve job quality (wages, working conditions, etc.), recent work has shown rather flat job quality over time, with some evidence of decreasing job quality for specific social groups (low-skilled and, to a lesser extent, young workers) (Green *et al.*, 2013). The development of telework/ICT-mobile work has also been shown to have ambiguous effects on various dimensions of job quality (working time and work–life balance) as well as on health and well-being (Eurofound and ILO, 2017).

In this context, further research is needed to inform the policy debate about innovation and employment and job quality. Such research should take differences by types of innovation into account – introducing a new product may have more favorable effects on employment than implementing a new labor-saving production process – as well as differences in the effects by skill, which is a crucial issue with respect to the debate on employment polarization. It is also important for public policies to differentiate innovation effects by industry, when tertiary employment is increasing and when most developed countries are trying to support the manufacturing sector in a context of increased international competition.

In this article, we focus on the impact of technological innovation (product and process innovation) on job quality at the firm level. Following the recent socioeconomic literature, we adopt a multidimensional approach to job quality, including wages as well as some nonwage indicators (the type of employment contract and working hours). In addition to bringing some job-quality dimensions into the analysis of the labor-market effects of innovation, our main contributions are the following. First, we use a large and original panel database of French firms (including information on both innovation and employment) that was specifically collected for our analysis and which covers both manufacturing and services to analyze the effects by industry. Second, as we are able to follow firms over time, we use econometric techniques that go beyond simple correlation to better identify causal effects. Last, in addition to overall job-quality effects at the firm level, we also consider the distribution of jobs and job quality by occupation following innovation to see if innovation is beneficial to all or may lead to an increase in inequalities.

INNOVATION, EMPLOYMENT AND JOB QUALITY: POLICY ISSUES AND EXISTING LITERATURE

Innovation and employment

In standard economic theory, technological innovation has ambiguous employment effects at the firm level that will also depend on the type of innovation (product or process) (Van Reenen, 1997). Process innovation may decrease the level of employment through a direct labor-saving effect: the required level of employment for a given output decreases when a firm implements a new production process. However, compensation mechanisms might mitigate or even overcome that negative impact: such process innovations also reduce the effective cost of labor and may lead firms to increase output. Product innovation leads to the opening of new markets or to an increase in the range or quality of products or services, which should have a job creation effect. This effect should be stronger when the innovation is more radical, for instance, when the firm is the first to implement an innovation at the international or at the market level. However, even in the case of new products (goods or services), some contradictory mechanisms are at play: indeed, new products might displace the older ones, reducing the positive effect on employment. Much empirical literature (see Vivarelli, 2014, and Calvino and Virgilitto, 2018, for very detailed reviews) concludes somewhat positive employment effects of product innovation in various countries in recent years, especially when combined with patent applications and when the product innovation takes place in high-technology firms. Effects are mixed for process innovation: literature shows often insignificant effects and sometimes negative effects in line with the labor-saving hypothesis at the firm level (Calvino and Virgilitto, 2018). We herein follow this literature but also more specifically focus on two issues on which research has, to date, been more limited: the effects of innovation on some dimensions of job quality and the potential heterogeneity in the employment and job-quality effects, by both occupation and industry.

Innovation and job quality

Considering a multidimensional approach to job quality as in recent socioeconomic literature (Osterman, 2013, Green *et al.*, 2013, Muñoz de Bustillo *et al.*, 2011, Davoine *et al.*, 2008), we can make a number of different hypotheses about the general impact of innovation on job quality. First, technological change is a determinant of productivity, which is generally thought to be positively correlated with job quality. However, this effect depends on workers' bargaining power and their ability to capture the returns from higher productivity. Second, technological change can affect the structure of the workforce, leading to the creation and/or destruction of good/bad jobs and different aggregate job qualities (at the macro but also the firm level). Finally, the adoption of new technologies may have significant effects on the work environment, work organization, task division and working conditions (Muñoz de Bustillo *et al.*, 2016). We herein focus more specifically on employment-quality variables, namely, wages, employment contracts and working hours, and identify the precise channels through which innovation affects workers. These variables do not reflect the whole set of dimensions that may be included in a job quality concept (for instance, Gallie, 2007; Green *et al.*, 2013), but their importance for workers is confirmed by empirical analyses focusing on the determinants of job satisfaction. Indeed, the literature on job satisfaction has shown that earnings, job security and working hours matter for job satisfaction (see, for instance, Clark, 2005, or Sousa-Poza and Sousa-Poza, 2000 on International Social Survey Programme data). In the French case, higher wages and higher working hours increase job satisfaction, and temporary contracts tend to decrease job satisfaction (Davoine, 2007).

From a theoretical point of view, the effects of innovation on wages are ambiguous (Calvino and Virgilitto, 2018). In the neoclassic approach, workforce displacement after innovation leads to a greater labor supply followed by a decrease in wages that produces the labor demand required to put the labor market back in equilibrium. However, in a Keynesian-Schumpeterian perspective, higher productivity following innovation can produce an increase in wages if workers are able to appropriate some of the productivity gains. More generally, the bargaining power of workers may affect the relationship between innovation and the different dimensions of job quality.

Considering the type of employment contract, the effect of innovation—which is generally found to be positive on firm-level employment—is expected to favor permanent employment if the firm expects the innovation to have durable positive consequences on its activity and has a long-run strategy (labor-force hoarding and investment in human capital and specific skills). In contrast, innovation can encourage temporary contracts if it is, instead, considered to be more transitory, in depressed economic conditions (Malgarini *et al.*, 2013) and again depending on the firm's strategy (Antonucci and Pianta, 2002).

Last, the effect of technological change and especially digitization on the number of hours worked is also ambiguous. Productivity may increase and lead to a decrease in working hours, as has been seen in developed countries over the last century. Conversely, from a frictional labor-market perspective (with a scarcity of specific skills), innovation may increase working hours for some categories of workers. Digitization can also bring greater potential to work longer hours away from the workplace/from home. In terms of job quality, longer working hours can be considered as an improvement for some workers (e.g., involuntary part-timers) but can also mean excessive working hours for full-timers.

Only a few empirical economic analyses have considered the effects of innovation on job quality. When they have done so, they mostly focus on wages and investigate the impact of innovation on the *relative* dynamics of wages and not on the *absolute* levels of wages. At the firm level, only a few studies exist (mainly on the UK or the US) and show contrasting effects of innovation on wages, either insignificant or positive (Doms *et al.*, 1997, Van Reenen, 1996, Aghion *et al.*, 2017). Even less literature has also looked at the relationship between the type of employment contract and innovation, mostly from the point of view of the effect of the former on the latter, and not the potential effect of innovation on the development of permanent and/or temporary jobs. Using data from various countries, most of these conclude a negative relationship between the use of flexible contracts and innovation: firms with greater shares of temporary workers have fewer patents (Franceschi and Mariani, 2016), lower sales of innovative new products (Zhou *et al.*, 2011) and lower R&D investment (Kleinknecht *et al.*, 2014). Only Giulodori and Stucchi (2012) conclude that product and process innovation favored both temporary and permanent employment following the decrease in employment protection legislation in Spain in 1997 (while beforehand, they only increased temporary employment).

Heterogeneous effects of innovation by occupation and industry

Another question we raise here refers to the potentially heterogeneous effects of innovation by occupation. In the economic literature, under skill-biased technological change, innovation favors higher-skilled employment and destroys low-skilled jobs. There is by now considerable empirical support for this hypothesis using national, sectoral and firm-level data (Autor *et al.*, 1998, Machin and Van Reenen, 1998). However, more recently, the job-polarization hypothesis has appeared in both the economic literature and political debate, with a number of empirical contributions (Autor, 2015, Goos *et al.*, 2014, Eurofound, 2015). This hypothesis describes the process by which low- and high-skilled jobs are simultaneously created in most economies, while middle-skilled jobs disappear. While the level of analysis in the empirical polarization literature (the aggregate employment level) differs from that mentioned previously (firm-level data), it does seem crucial to evaluate the effect of technological innovation separately for different groups of workers, especially by skill level. We thus consider potentially different effects by occupation, which has rarely been the case at the firm level (Calvino and Virgilitto, 2018).

We also carry out estimations by industry to see if the effects differ in manufacturing and services. The existing results for the employment effects of innovation generally come from the manufacturing sector. Very few studies have focused on the effect of technological innovation in services, while services account for more than 75% of private employment in France (and in many developed countries). The scarcity of analyses on innovation in services is because technological innovation is historically associated with manufacturing. Different types of approaches coexist about how technological innovation should be understood and analyzed in services: assimilation (or technologist) approaches argue that theories and concepts developed for manufacturing apply in services; demarcation approaches stand that specific theories and tools are required to analyze innovation in services; and synthesis approaches try to think about a comprehensive framework that would borrow from each approach to analyze innovation across the economy (Gallouj and Savona, 2010, Coombs and Miles, 2000). The few existing quantitative analyses of innovation in services usually adopt the first perspective using the same tools and hypotheses for services as for manufacturing. However, some characteristics of services must be underlined, which question the transposability of hypotheses on employment effects of innovation from manufacturing to services. First, the degree of competition is generally expected to be lower in services than in manufacturing. While in manufacturing, product innovation is a way to challenge competitors, it may be less the case in services due to lower competition. Second, some authors also point out the ‘intangibility’ of the service product, which makes it difficult to convince consumers about the superiority of innovative services (Miles, 2010) and could lead to lower effects of product innovation on sales and employment in services. Combined with the hypothesis on the lower level of competition, even when sales increase, this may not lead to higher employment if it only increases the profit margin. Third, the diversity of firms in services is even stronger than in manufacturing. Services include very diverse activities from microbusinesses in family shops, consultants, accountants, etc. to very large organizations in finance or insurance so that the overall effect of innovation in services may be a sum of diverse and heterogeneous effects. In empirical quantitative approaches, services are usually analyzed as a whole and the effects of technological innovation on employment are found to be lower than in manufacturing (Ugur *et al.*, 2017).

DATA AND EMPIRICAL STRATEGY

A firm-level database linking innovation and employment outcomes

We use three different databases at the firm level: the Community Innovation Survey (CIS), administrative data on employment, and fiscal data.

The CIS was designed at the European level to collect data on innovation activities in firms following the Oslo Manual definitions of innovation (see Box 1). In France, the sample is 18,109 firms in the market sector (once nonresponse and unusable questionnaires are dropped)[1]. The French survey data are considered to be of good quality, with an unweighted nonresponse rate of 25%, which is far below the nonresponse rates observed in many other European countries (for instance, 49% in Germany and 35% in Italy)[2]. The database only includes firms with 10 or more employees and is exhaustive for firms with over 250 employees. It covers most market activities (NACE B to N) including the following industries: mining, manufacturing, electricity, water supply, construction, retail, transport, hotels and restaurants, information and communication, financial and insurance services, real estate, technical, scientific activities and administrative services. The industries excluded are agriculture, public services, education, health, arts and entertainment, extraterritorial activities and private household employment (such as babysitting and cleaning).

The DADS (*Déclarations Annuelles de Données Sociales)* are administrative data on employment collected every year on the basis of establishments' compulsory declarations. These include information collected at the establishment level in the private sector on

[1] Source: the quality report for the CIS carried out by the French Statistical Institute INSEE (*fiche qualité - fiche descriptive de l'enquête*), available online: https://www.insee.fr/fr/metadonnees/source/operation/s1199/gestion-qualite.

[2] Source: Eurostat Community Innovation Survey 2014, synthesis quality report, available online: http://ec.europa.eu/eurostat/cache/metadata/Annexes/inn_cis9_esms_an6.pdf.

employment, as well as contract type (fixed-term or permanent), annual working hours and wages. While employment, working hours and wages can be disaggregated by occupation, contract types (fixed-term vs permanent) cannot. These administrative data are of very good quality, with their main limitation only being the small number of variables that are collected (in particular, they contain no information on the work environment). We aggregate this establishment-level data up to the firm level to match them with the other datasets.

Our fiscal data (FARE-FICUS) include the standard accounting data used by the government to collect taxes on benefits, etc. These databases provide information on productivity and labor costs[3].

We construct our database by merging CIS, DADS and FARE-FICUS at the firm level, which yields a sample of 14,491 firms. The coverage of the merged dataset is the same as CIS coverage in terms of firm size and industry (firms with 10 or more employees and exhaustive for firms with over 250 employees, covering the NACE B to N sectors). The final sample represents 17% of total employment in France in 2011 and 28% of the total value added.[4]

Box 1: Innovation in the Community Innovation Survey 2014

Innovation is broadly defined in CIS 2014 as "*the introduction of a new or significantly improved product, process, organizational method, or marketing method by your enterprise*". This is in line with the so-called Oslo Manual on measures of innovation published by the OECD that defines four types of innovation: product innovation, process innovation, marketing innovation and organizational innovation (OECD, 2005).

[3] Productivity is measured as the ratio of value added to the number of full-time equivalent jobs, and labor cost as the ratio of the total wage bill plus employers' social security contributions to the total number of hours.
[4] These shares are calculated by comparing total employment in DADS to total value added in FARE-FICUS.

In the 2014 CIS survey, firms are asked about innovations that took place during the two years preceding the survey (2012 to 2014). We here consider four innovation variables, based on four questions of the survey:

Product innovation (goods or services) – Question 2.1: "*Did your enterprise introduce new or significantly improved goods (exclude the simple resale of new goods and changes of a solely aesthetic nature) or new or significantly improved services?*"

New-to-the-market product innovation – Question 2.3: "*Did your enterprise introduce a new or significantly improved product onto your market before your competitors?*"

Product innovation and application for a patent – Question 2.1 (see above) and Question 11.1: "*Did your enterprise apply for a patent?*"

Process innovation – Question 3.1: "*Did your enterprise introduce new or significantly improved methods of manufacturing for producing goods or services, new or significantly improved logistics, delivery or distribution methods for your inputs, goods or services, or new or significantly improved supporting activities for your processes, such as maintenance systems or operations for purchasing, accounting, or computing?*"

Firms were then asked whether the innovation was subsequently abandoned (over the same period). All of our empirical analyses will only refer to ongoing (nonabandoned) innovation.

Source: CIS questionnaire, 2014, available online: http://ec.europa.eu/eurostat/fr/web/microdata/community-innovation-survey.

The merged database includes three sets of variables. The first concerns technological innovation behavior (as declared by firms in the 2012-2014 CIS data), separated into product and process innovation in accordance with the Oslo Manual typology and the CIS questionnaire (see Box 1). We capture the intensity of product innovation by two complementary measures of innovation: product innovation that is "new to the market" and product innovation that is accompanied by a patent application. Although organizational innovation is also identified in the CIS, we do not consider it here, as it may reflect heterogeneous management choices of which the potential job-quality effects are not straightforward (Rubery and Grimshaw, 2001, Lam, 2004).

The second set of variables covers the employment and job-quality outcomes in firms (available every year). This includes the total number of firm employees, the number of employees decomposed by occupation, and three dimensions of job quality: hourly wages, average annual number of hours worked per employee and type of employment contract (permanent vs. fixed-term). In comparison to the job-quality literature, our approach focuses on employment quality and does not include the work environment or working conditions, for which there is no comprehensive database that could be matched to our data in France. We interpret higher wages and more permanent contracts as reflecting greater job quality (in accordance with job satisfaction analyses mentioned above). The interpretation for working hours is less straightforward, as we cannot disentangle voluntary from involuntary increases in hours worked. However, in the French context, there is considerable involuntary part-time employment and overtime is quite heavily regulated, suggesting a positive relationship between hours of work and job quality. The third set of variables (available every year) relates to firms' structural characteristics and economic performances (industry, size, age, productivity, labor costs, etc.). We use two sectoral classifications: the usual one distinguishing among manufacturing, construction, retail and services (based on NACE codes) and another developed by Eurostat to better characterize firms by their levels of technology and knowledge intensity (distinguishing among high-tech, medium high-tech, medium low-tech and low-tech manufacturing, and between knowledge-intensive and less knowledge-intensive services)[5].

[5] Source: Eurostat indicators on the high-tech industry and knowledge-intensive services, Annex 3 – High-tech aggregation by NACE Rev.2, see http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf. Here retail appears in less knowledge-intensive services, while construction is in low-tech manufacturing.

This merged database then tells us whether the firm innovated between 2012 and 2014 and provides information on firm employment, job quality and characteristics in 2011 and 2015. We can thus carry out a difference-in-differences analysis combined with a matching model to evaluate the impact of different types of innovation on employment and job quality. Given our methodological framework, our analysis is limited to the short-term effects of innovation. However, we will provide an alternative specification in the robustness checks that controls for repeated innovation in a longer period.

Empirical strategy: A difference-in-differences matching model

As the firms that innovate have different characteristics from firms that do not, a simple variation of firms' employment or job quality outcomes does not correspond to the proper effect of innovation: employment or job quality trends are also influenced by many other factors, of which some may be observed (firm size, technological level …), and others remain unobservable in the data. In addition, we also have to disentangle between the effect innovation has on job quality and the effect job quality may exert on innovation: for instance, workforce qualification level may favor firms' innovations.

We use an empirical method that takes observable differences among firms into account (through propensity score matching) and corrects for unobserved characteristics (through difference-in-differences). The aim is to better approximate a causal effect of innovation, i.e., the effect innovation has on employment and job quality, independently of firms' characteristics (whether they are observable or not). This method proceeds in two steps. First, we use the firms' characteristics, such as sector, size, age, and level of technology to predict whether firms will introduce innovations and to identify the characteristics of innovating firms. Among firms with these characteristics, some innovated and some did not innovate over the period considered for our empirical analysis. In the second step, we match firms that innovated with their "twins" that did not innovate and compare changes in job quality between the two groups of firms (that did or did not introduce innovations).

In technical terms, this method combines difference-in-differences with propensity score matching (PSM). To compare job-quality outcomes in similar firms, we use a propensity score matching model initially developed by Rosenbaum & Rubin (1983) to assess the effects of medical treatments. This consists of considering innovation (I) as a treatment and constructing, for each firm that innovated between 2012 and 2014, a similar counterfactual firm that did not innovate.

The effect of innovation is measured by the outcome variable (here, different measures of employment and job quality). Each firm thus has two potential outcomes: y_0 if I=0 and y_1 if I=1. However, the effect of innovation on job quality at the firm level is never observed, as y_0 and y_1 are never seen simultaneously: we only see the actual outcome.

Let Y_i be the vector of result variables. For each firm, only the couple (Y, I) is observed. Nevertheless, if the latent outcome variables are independent of assignation to the treatment ($(y_0, y_1) \perp I$)—i.e., if the treatment is randomly assigned—then the average effect on the treated firms (i.e., innovative firms) can be identified: $E[(y_0, y_1)/I = 1]$. However, this independence property is unlikely to hold. One solution is to construct a control group so that the distribution of a set of observable characteristics (a set of control variables, denoted by *X*) is identical to that of innovating firms. This helps us to reduce the selection bias, as the identification condition becomes less restrictive, and the independence property should be checked ($(y_0, y_1) \perp I / X$). When there are many control variables, it can be difficult to find a counterfactual for each treated firm. According to Rosenbaum & Rubin (1983), conditional independence to the set of control variables implies independence relative to the propensity score, $P(X)$, which is a one-dimensional summary of the matching variables that estimates the probability of being assigned to the treatment conditional on these variables: $(y_0, y_1) \perp I / X$. To be valid, this method requires that there are observations in both groups with similar propensity scores (a common support, which makes matching feasible) and that similar propensity scores are based on similar observed characteristics/covariates.

In practice, there are many propensity score matching methods in the literature. For instance, Caliendo & Kopeining (2005) recommend using a number of estimators. We here use radius matching with a caliper of 0.00001, which is small and implies a precise matching between the treated and control firms. Indeed, as mentioned above, one of our main contributions is to capture as much as possible a causal effect of innovation on job quality, which requires comparing very similar firms. There is, however, a trade-off between the size of the matching group and the reduction of the bias between the treated and untreated firms. A small caliper value implies that more firms drop out of the support as they are too particular for counterfactuals to be found. In our case, the share of innovating firms dropping out of the support is between 12.6% and 18.8% depending on the innovation variable we analyze, which seems reasonable. Figure 1 (in the appendix) depicts the share of treated, untreated and off-support firms by the predicted propensity score. Off-support firms do indeed have high propensity scores but no comparison firms. We test different methods and parameters in the robustness checks (kernel matching and radius matching with different calipers, see final section).

We evaluate the matching robustness via a balancing test (see Appendix Table A1) that analyzes the standardized differences. This compares the mean of the control variables for the treated and untreated firms, and thus the reduction in the selection bias before and after matching. The results show that after matching, there are no average differences in the control variables between the treated (innovating firms) and control (non-innovating firms) groups. The selection model then reduces the bias between treated and untreated firms (see the appendix). Our choice of a small caliper value explains the considerable similarity between the two groups of firms, although it does exclude some very particular firms. Table A2 reports the characteristics of off-support firms compared to on-support firms in the case of product innovation[6]: off-support firms appear larger and belong more often to the high-technology sector. Choosing a very small caliper leads to dropping these big innovating firms and to focusing only on comparable firms to measure as much as possible a causal effect. It may of course change some of the effects usually found when big innovating firms are kept in the sample but gives a better measure of the proper effect of innovation.

A last condition for PSM validity is that there should be no systematic differences between the treated and control groups in terms of unobserved characteristics that may influence the outcomes. This hypothesis may well not hold, as there are likely important unobserved factors influencing innovation behavior at the firm level: we therefore introduce differences in differences using the time dimension of our data to correct for unobserved heterogeneity. This consists of calculating the change in the outcome variable between two dates (the first difference) and comparing this change between the treated and untreated firms (the second difference). The formula for the treatment effect on the treated firms is as follows:

$$\Delta = \frac{1}{N_1} \sum_{i \in I_1} \left\{ \left(Y_{t,i} - Y_{t',i} \right) - \sum_{j \in I_0} M^i \left[\frac{\left[\left(P\left(X_j\right) - P\left(X_i\right) \right) \right]}{\sum_{i \in I_0} \left[\left(P\left(X_j\right) - P\left(X_i\right) \right) \right]} \right] \left(Y_{t,j} - Y_{t',j} \right) \right\}$$

6 Statistics on other types of innovation display the same differences. They are available on request.

where N_1 is the number of firms that innovate; I_1, the sample of innovating firms; I_0, those that do not innovate; P(X), the estimated propensity score; and Y, the outcome variable of employment or job quality. Last, $M_i[]$ is the average value of the outcome variable for the population of firms *j* that belong to the control group selected from firms *i*, and *t* and *t'* are the periods before (2011) and after (2015) treatment, respectively. This estimator is supposed to satisfy the common-trend assumption so that the trend in the outcome variables before innovation was the same in the treated and control firms. We check this assumption in our data for employment, hourly wages and working hours from 2006 to 2015[7]. The common trend holds for employment, working hours and the hourly wage (see Figures 2 and 3 in the appendix for product and process innovation). However, testing this assumption is not obvious in our case as innovation can be repeated and the two groups of firms may have already innovated before our observation period. To overcome this limitation, we also run regressions on a more limited subsample of firms from 2009 to 2015 for which we have information about repeated innovation (see the robustness checks).

Our empirical strategy consists of two steps. In the first, we estimate a logit model to produce the propensity score. We here consider various determinants of innovation: firm size and age, industry, whether the firm is part of a business group, labor costs and labor productivity. All of these variables are measured in 2011, i.e., before the firms decide whether to innovate. For age, productivity and labor costs, we calculate quartiles over the sample as explanatory variables. In the second step, we estimate the average effect of the treatment (ATT)—the treatment here

7 We cannot do so for contract type, as this variable was not available from 2006 to 2008. The DADS (administrative data on employment we used) are not available after 2015 due to changes in data collection procedure. We can thus only compare the evolution of employment variables between innovating and not innovating firms one year after treatment (in 2015).

being innovation—on the difference in employment and job-quality changes for the treated and control groups using the radius-matching estimator.

Descriptive statistics

In our database, we identify the firms that innovated between 2012 and 2014 (Table 1): 27.6% of the firms declared to have introduced a new or significantly improved product, and 27.5% introduced a new or significantly improved process[8]. 18.9% of the firms developed product innovations that they declared to be "new to the market", which we consider as an indicator of the novelty or intensity of innovation. Far fewer firms (7.3%) declared both product innovation and patent application, which also indicates more intensive innovation activity.

[Insert table 1 here]

The innovating firms have particular characteristics. They are overrepresented in manufacturing but underrepresented in retail and construction. 47.0% of product innovators and 44.9% of process innovators are in manufacturing, and this figure is higher for the more intensive types of innovation (50.5% of new-to-the-market product innovators, 70.8% of product innovation and patenting firms). The share of innovating firms in services is slightly below their sample share, but the difference is small. Decomposing by technology, the innovating firms are overrepresented in all groups except less knowledge-intensive services (LKIS). Larger firms (over 50 employees) are overrepresented among innovators (57.1% of product innovators and 53.4% of process innovators have over 50 employees, vs. 37% in the whole sample), as well as members of a business group (65.2% of product innovators and 60.9% of process innovators). Innovating firms are older on average and have higher average labor costs and productivity[9].

[8] 18.4% introduced both types of technological innovation over the period.
[9] Detailed statistics on the characteristics of innovating and non-innovating firms are available on request.

We can use our matched sample of firms to compare a number of indicators of employment and job quality in innovating and non-innovating firms. Some of the main indicators are summarized in Table 2 for 2011.

In Table 2, the shares of open-ended and temporary contracts are similar in the subsamples of innovating and non-innovating firms, for product and process innovation. However, in the case of more intensive product innovation (new to the market or patent), the share of permanent contracts appears higher in innovating firms. Average annual hours worked per employee are close in innovating and non-innovating firms. Hourly wages are systematically higher in innovating firms, with the gap being higher for more intensive innovators (product new to the market, and especially product and patenting). Innovating firms also have different workforce skill structures[10]: they have smaller shares of manual and clerical workers but more managers and professionals as well as technicians and associate professionals.

[Insert table 2 here]

ECONOMETRIC RESULTS: THE IMPACT OF INNOVATION AT THE FIRM LEVEL

As set out in the methods section, we apply a two-step strategy to estimate the impact of innovation on job quality: we first use a matching model to match innovating firms to similar firms that did not innovate, and second, compare the differences in the changes in job quality and employment between innovating and non-innovating firms. We estimate four models for the different types of technological innovation: product innovation, product innovation "new to

[10] The French occupational classification (PCS) is not always easily comparable to that in other countries. We here use the following terms: 'managers and professionals' for French *cadres*, which corresponds to ISCO 1-2, 'technicians and associate professionals' for French *professions intermédiaires* (ISCO 3-4) and 'manual and clerical workers' for French *ouvriers et employés* (ISCO 4-9).

the market", product innovation in patenting firms, and process innovation. The outcome variables include employment (decomposed by occupation), employment by contract type (permanent vs. temporary) and wages and working hours (also decomposed by occupation). The presentation of the results proceeds as follows: we first analyze the determinants of innovation in the matching model; second, we analyze the impact of innovation on employment and job quality for the whole sample and by occupation; third, we consider industry-level heterogeneity by running separate analyses for manufacturing and services. Last, we present the sensitivity analysis and robustness checks.

The determinants of innovation at the firm level

The logit regressions (for the four innovation types defined above) include some structural firm characteristics that are correlated with innovation, such as industry decomposed by level of technology, firm size and age, and whether the firm belongs to a business group. Productivity is also introduced as an economic performance indicator, as well as labor costs that are usually considered as a factor determining innovation capacity. We introduce the corresponding quartiles for the continuous variables (age, productivity and labor costs). Table 3 shows the results for product innovation (the results for the other innovation variables appear in table A3 in the appendix).

As in the descriptive analysis, all types of innovations occur more in larger firms, which can be explained by large fixed innovation costs and there being more employees dedicated to innovative work. Being in a group also increases the probability of innovation. Compared to less knowledge-intensive services (the reference category), innovation is more likely in all other industries. Innovation increases with the technological level and is higher in manufacturing (compared to services). The effect of age differs from that in the descriptive statistics: once we control for other firm characteristics, older firms are less innovative. This may reflect a

Schumpeterian effect: new firms compete with older firms by introducing new products or processes. High productivity (the fourth quartile of *ex ante* 2011 productivity) increases product innovation. Higher labor costs also increase innovation. In a given institutional context (French firms generally face the same law in terms of minimum wage and social contributions[11]), higher labor costs are actually a sign of a more educated workforce that drives more innovation from a human capital perspective.

These results for the factors explaining innovation are very similar to those for new-to-the-market product innovation and process innovation (see Appendix Table A3) [12].

[Insert table 3 here]

A fairly positive impact of innovation on employment and some dimensions of job quality but strong differences by occupation

The second step compares the 2011-2015 changes in employment and job quality between innovating (treated) and non-innovating (control) firms. We also decompose the employment and job-quality effects (and in particular, wages) of innovation by occupation.

We first find a positive and significant impact of product innovation on firm employment, which also appears when firms have applied for a patent (see Table 4 below). More precisely, that positive impact corresponds to a positive difference in employment variations between innovating and non-innovating firms. In the case of process innovation, the impact on employment is negative (i.e. the difference in employment variations between innovating and

11 There might be some temporary exceptions, for instance for very small firms in the context of the 2008 recession, for which the Government created a temporary exemption of social contributions. However, such very small firms are not included in our sample.

12 There are some particularities for product innovation in patenting firms, which may indicate that this type of innovation (which is the least frequent in our sample) is determined differently and for different types of firms: firm age is insignificant, and the effect of productivity is no longer significant for the top quartile.

non-innovating firms is negative). These results appear to be consistent with the existing theoretical and empirical literature that generally finds a more positive effect of product innovation at the firm level, whereas the results are more mixed for process innovation. The average size of the results is rather small but grows with the intensity of innovation: the workforce increases amount to 5.7 employees for product innovation and 14.4 employees for product innovation in patenting firms[13].

[Insert table 4 here]

When decomposing employment by type of labor contract (permanent vs. temporary), there is a positive effect of innovation on permanent-contract employees both for product innovation and combined with patent application, whereas that for temporary-contract employees is either insignificant (for product innovation) or negative (for process innovation). Concerning permanent contracts, the effects are stronger than in the case of total employment: product innovations increase the number of permanent employees by 8.2 and 19.8 in the case of patenting firms. The negative effect of process innovation on fixed-term contracts is more limited (-3 employees). Technological innovation (product as well as process) then favors stable employment (at least in terms of labor contracts). Innovative firms appear to invest in their human capital rather than increase labor flexibility.

In terms of working hours, there is a positive impact of total product innovation on annual hours, which remains relatively small (+12.7 hours on average, to be compared with the 1826.7 hours worked annually in sample firms). The effect is insignificant for process innovation as

[13] The average number of employees for firms in our sample is 235.1 (see Table 2) while the median number is 33 (reflecting the “Pareto” distribution of firm size). Median numbers of employee by groups of innovating firms are the following: 86 employees in firms doing product innovation; 67 employees in firms doing process innovation; 114 employees in firms doing new to the market innovation; 359 employees in firms doing both product innovation and patenting.

well as for more intensive forms of product innovation. This positive effect for product innovation may reflect a number of phenomena that we cannot disentangle: an increase in the share of full-time workers or more hours being worked by part-time and/or full-time workers.

Last, the impact of product and process innovation on hourly wages is insignificant: in our sample, innovation activities thus do not seem to produce any rent-sharing with workers. This insignificant result is not surprising since theoretical literature indicates ambiguous effects of innovation on wages (Calvino and Virgilitto, 2018). As mentioned before, an increase in wages can appear if workers are able to appropriate some of the productivity gains. It will thus depend on their bargaining power. In our case, the relatively short time horizon of our study does not necessarily enable workers to exert their bargaining power and negotiate higher wages especially in the aftermath of the 2008 crisis. In addition, an increase in the workforce may hide some flows in and out of the firm so that we cannot measure the impact on the wages of employees who are staying (and should be able to capture part of the productivity gains).

To sum up, the empirical results underline ambiguous effects of technological innovation on employment, somehow positive in the case of product innovation but negative for process innovation. They also show a fairly positive impact of both product and process innovation on the stability of employment contracts, which are an important component of job quality. However, there is no effect on wages and a limited positive effect on working hours, so job quality effects appear limited (although rather positive). In the case of product innovation only, these results tend to confirm the hypothesis that innovation could produce a virtuous circle at the firm level, favoring both the quantity and quality (especially here, stability) of jobs. This interpretation is, of course, speculative, as the definition of job quality is restricted to only a few dimensions and does not include important components such as working conditions. We, in addition, do not know whether temporary contracts and low working hours are voluntary or involuntary. However, given the importance of job security for French workers and the very protective legislation in France regarding working hours, these features do seem central to worker well-being.

The overall employment and job-quality effects of innovation may also differ according to skill level. Apart from contract type, we can decompose these effects by occupation.

For employment (Table 5), there are notable differences by occupational group. First, all types of product innovation increase the number of managers and professionals as well as intermediate occupations[14], compared to non-innovating firms, whereas this is not the case for manual and clerical workers (the effect is insignificant). Second, process innovation significantly decreases the number of manual and clerical workers, whereas its effects on other occupational categories are insignificant. There is thus a skill-biased pattern in the employment effects of firm-level innovation: product and process innovations are associated with skill upgrading and benefit higher-skilled workers. According to the estimations, the growth in the number of managers and professionals is stronger for patenting firms (+15 managers and professionals compared to +5.6 for total product innovation). Given the positive impact on the employment of intermediate occupations obtained for product innovation (in general or combined with patent application), our results do not correspond to the hypothesis of skill polarization from innovation but are rather in line with skill-biased technological change.

[Insert table 5 here]

Regarding wages and working time, most effects by occupational group are insignificant, but product innovation leads to slightly lower wages[15] for manual and clerical workers (see Table A4). This can also be read as skill bias in the effects of innovation that reduces wages for less-

14 Except in the case of product new to the market for which the effect on intermediate occupations is nonsignificant.
15 The effect seems very small: the hourly wage decreases by 0.17 euros.

qualified workers. However, this effect is only found for total product innovation and disappears for the more intensive forms of innovation (new to the market and patenting firms). Working time also increases for lower skilled occupations following product innovation, indicating that firms tend to prefer longer hours for these categories of workers rather than hiring new employees or increasing wages.

Heterogeneity in job-quality outcomes by industry

The general results above may conceal considerable industry-level heterogeneity: we thus re-estimate our innovation regressions by industry[16]. The results appear in Tables 6 and 7 below.

The results for manufacturing are similar to those in the whole sample but display stronger and more significant effects on employment. Product innovation increases total and permanent employment but reduces fixed-term employment. The positive effects on employment are larger than those observed for the whole sample (+15.7 employees and +16.9 permanent contracts in the case of product innovation, +22.7 employees and +25.1 permanent contracts in the case of product innovation in patenting firms). The negative impact of process innovation on total employment becomes nonsignificant when focusing on manufacturing, but the negative effect on fixed-term contracts is confirmed. There are only few significant estimated coefficients in the service sector, and these confirm general results for process innovation (negative effect on total employment, which appears stronger than for the whole sample, and negative effect on fixed-term contracts), but often differ from those in manufacturing: in particular, the new-to-the-market product innovation positively affects fixed-term contracts.

[16] We do not run the analysis separately for retail and construction as the number of observations is too small. The results presented here are based on the traditional decomposition between manufacturing and services, but there is also heterogeneity by the technological intensity proposed by Eurostat.

The results for other job quality variables are less clear-cut. Considering working hours, the only significant effect is an increase in the case of total product innovation in manufacturing (as in the general results). As far as wages are concerned, a slightly negative effect on wages appears for product innovation in manufacturing (only in the general case, not for the more intensive forms of innovation), whereas for services, we find a positive effect for product innovation in patenting firms. Although both effects are very small (-0.2 euros per hour for the first one, and +0.6 euros for the second one), they suggest that wage effects of innovation are not homogeneous across industries.

Although the literature on innovation effects by industry is limited, the differences between manufacturing and services may be interpreted with regard to some hypotheses mentioned before. In particular, the insignificant effect of product innovation in services may be related to lower competition compared to manufacturing. However, services remain a very broad category and this result could also hide different effects in subcategories of services. When we run regressions only in high-tech or low-tech services[17], it appears that the increase in fixed-term contracts and the slight increase in wages is concentrated in low-tech services, while in high-tech services, the results are slightly closer to manufacturing (with a positive effect of product innovation on employment). These results on low- and high-tech services are in line with the rare previous studies analyzing the effect of innovation distinguishing by technology level of services using CIS (Evangelista and Savona, 2002). These results also show that the labor-saving hypothesis on process innovation seems to hold for services and is concentrated in low-tech services.

Comparing the results between manufacturing and services suggests different human resources strategies coexist regarding innovation: in manufacturing, firms increase the workforce

[17] These regressions are available on request.

(number of employees and working hours) and invest in employment stability, whereas in services (especially in low-tech services), they develop rather flexible jobs and slightly increase wages. Wages and employment flexibility can be related both directly and indirectly: in accordance with French labor law, fixed-term contracts come with a flexible wage premium, and more generally, wages may be a way of compensating for greater job flexibility.

[Insert table 6 here]

[Insert table 7 here]

DISCUSSION AND ROBUSTNESS CHECKS

We have considered a number of alternative models to check the validity and stability of our empirical results[18].

First, we consider different types of matching. We have re-estimated all our models with radius matching and a caliper of 0.001 and estimated kernel-matching models. Overall, our results change little by matching type and parameters. Effects on total employment tend to be smaller, but polarization by occupation is stronger when we increase caliper. Indeed, this leads to reintroduce in the analysis some firms that were off-support in our baseline estimations. As mentioned in the methods section, our off-support firms are larger and concentrated in the high-technology sector, and their global employment variations are quite specific, which can explain such variations in the size of the effects. However, this reduces the precision of the matching

[18] All these estimations are available on request; the appendix reports the most important results.

and, therefore, the ability to capture causal effects of innovation, which leads us to maintain the 0.00001 caliper.

Second, our baseline models were tested on the previous wave of CIS (2012) matched with data from DADS and FARE-FICUS from 2009 to 2013. Here, innovation took place between 2010 and 2012, while the employment and job-quality changes were measured between 2009 and 2013[19]. All results continue to hold over time for product innovation, in particular, the skill-biased effects (differences between managers and professionals on the one hand and manual and clerical workers on the other hand). The results for process innovation are different in the sense that the effect on employment variables is positive. The interpretation here is not straightforward as both periods cover booms and busts in France (the global financial crisis followed by the sovereign-debt crisis in Europe), but this result is, however, not surprising considering the heterogeneity of the empirical results concerning the effects of process innovation in the literature (Calvino and Virgilitto, 2018).

Last, we used the two CIS waves (2012 and 2014) to construct a database that includes firms that were present in both waves. The sample is, of course, much smaller (2,977 firms), but we can now look at innovation over a longer period of time. Based on this sample, we run a model using data from CIS 2014, looking at changes in employment and job quality between 2011 and 2015, introducing as a control a dummy for innovation in the previous 2010-2012 period. This model is a way to control for repeated innovation and thus overcomes the limits of the parallel-trend assumption. The main results of this model (see Table A5) are in line with those from the baseline: they display positive effects of product innovation on employment and on permanent contracts. Effects on managers and professionals as well as on intermediate occupations are

[19] We could not compare the effect of innovation on employment decomposed by type of contract because of the high proportion of missing values in the 2009-2013 dataset.

also much stronger, while they become insignificant (instead of negative) for manual and clerical workers. Product innovation (in general and in patenting firms) also increases the number of hours worked. All estimated effects are clearly stronger than in the general sample (+37.2 employees and +39.3 permanent contracts for product innovation, and up to +59.8 employees and +61.1 permanent contracts for product innovation in patenting firms)[20]. Although the sample size may limit the general validity of these results, it clearly indicates that innovation persistence increases the size of its positive effects on employment and job quality even though inequalities among occupations persist. In contrast, in the case of process innovation, effects become nonsignificant in this panel perspective, which corresponds to the idea developed in the literature that some positive compensation effects may appear over time following a labor-saving process innovation.

All of these robustness checks help ensure the validity and stability of our results. In addition to the global positive effects of product innovation, on employment level as well as on employment stability, they confirm the differences by occupations and the skilled-biased effects of innovation at the firm level. They also recall the higher volatility of the empirical results concerning process innovation as pointed out in recent empirical literature. However, it is useful to note the main limitations of our study, which are mainly related to the level of analysis and the collection and timing of the data.

A first limit applies to all firm-level analyses of the effects of innovation. As underlined by Vivarelli (2014), microeconomic approaches do not account for so-called business stealing effects and more aggregate innovation dynamics. Firm-level analysis may, thus, overestimate the positive effects of innovation. We find that innovating firms have somehow better

[20] See Table 4 for the baseline results. The increase in average annual hours worked per employee is also stronger in this new model: +25.9 for product innovation and +36.7 for product innovation in patenting firms (this last effect was nonsignificant in the baseline model).

employment and job-quality outcomes but do not consider the effect on rivals. However, firm-level analyses do allow a better grasp of the nature of firms' innovations, while more aggregate analyses (macro or sectoral) generally struggle to find good proxies for innovation and disentangle their effects on employment from institutional and macroeconomic factors.

A second limitation is that we rely on innovation measures declared by firms, which are liable to the usual biases related to surveys: in particular, firms may overestimate their innovation behaviors. However, the innovation indicators from the Oslo Manual are often considered to be better innovation proxies than the traditional measures of R&D expenditures or patenting behavior (Kleinknecht *et al.*, 2002).

CONCLUSION

This article has explored how different types of innovation may not only affect employment but also its qualitative dimensions (wages, contract stability and working hours). In that sense, this paper asks whether there is a virtuous circle among innovation, employment and job quality, as stated in the Europe 2020 strategy. The answer is mixed, as the analyses show differentiated employment effects for product and process innovation (positive for product and mixed for process). Innovation also has a positive effect on employment stability, but other job quality effects (wages, working hours, …) are generally not significant, except for the number of working hours that increase in firms with product innovations. The methodology of this article also helps to catch the effect of innovation in similar firms and avoids this effect to be "pulled" by very large innovating firms.

In addition, decomposition by occupation and industry clearly shows that the hypothesis of a virtuous circle among innovation, employment and job quality should be nuanced. First, not all social groups benefit from firm innovation, as lower-skilled workers are less positively affected in terms of employment and wages. This confirms the hypothesis of a skill-biased technological change and calls for public policies that ensure lower-skilled workers can access training throughout the life cycle to participate in and to benefit from technological change. Second, the positive effects of innovation on employment level and employment stability appear mainly in manufacturing, while innovation in services, especially low-tech services can lead to more flexible employment. This heterogeneity is rarely highlighted in the literature, which generally focuses on the aggregate effects of firm innovation or on manufacturing only. Considering that services are the main provider of employment in all developed countries, more research is certainly needed on that industry. Analyses of innovation in different subsections of services are promising avenues for research. The measurement of innovation in services should also be questioned: if Community Innovation Surveys already represent a step towards better measurement of innovation focusing not only on R&D expenditure and patents, the questionnaire could be better adapted to firms in services. Our results in services also emphasize that effects of innovation are mediated by the institutional context. The increase in flexible employment following product innovation in services raises the question of how public policies can set a framework that ensures innovation is beneficial to all and does not develop more precarious forms of employment, especially in services. While innovation brings more and better jobs in some cases, public policy should focus on the consequences of innovation for the individuals and in sectors where its effects are notably less positive.

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TABLES AND FIGURES

Table 1- Share of innovating firms by type of innovation and across industries (between 2012 and 2014)

Type of innovation	Total	Manufacturing	Services
Product innovation	27.6%	42.1%	26.2%
Product innovation new to the market	18.9%	31%	16.8%
Product and patenting firms	7.3%	16.8%	3.6%
Process innovation	27.5%	40%	24.7%

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, authors' calculations, 14,491 firms.

Table 2- Job quality and employment by firm innovation status

	Total	Product innovation		Process innovation		Product innovation new to the market		Product innovation + patent	
		NO	YES	NO	YES	NO	YES	NO	YES
Total Workforce (number of employees)	235.1	152.0	453.1	160.2	432.6	166.2	531.4	188.9	821.6
Permanent contracts (share)	94%	94%	95%	94%	95%	94%	96%	94%	97%
Temporary contracts (share)	6%	6%	5%	6%	5%	6%	4%	6%	3%
Managers and professionals (share)	17%	13%	25%	15%	22%	14%	28%	16%	29%
Technicians and associate profs (share)	17%	16%	21%	16%	20%	16%	22%	17%	24%
Manual workers (share)	65%	70%	53%	68%	58%	69%	49%	67%	47%
Number of hours (annual)	1826.7	1825.6	1829.8	1827.1	1825.9	1826.0	1830.0	1826.2	1834.0
Hourly gross wage (in euros)	19.2	18.3	21.7	18.6	20.8	18.5	22.6	18.8	24.6

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, authors' calculations, 14,491 firms.

Table 3- The determinants of firm product innovation

Dependent variable	**Product innovation**
Size (ref. 10-19 employees)	
20 to 49	0.25 (0.06)***
50 to 499	0.93 (0.06)***
500 to 999	1.35 (0.09)***
>1000	1.82 (0.10)***
Member of a business group *(ref. No)*	
Yes	0.33 (0.05)***
Sector by level of technology (ref. Less knowledge-intensive Services)	
High-tech (Manufacturing)	2.04 (0.15)***
Medium high-tech (Manufacturing)	1.79 (0.08)***
Medium low-tech (Manufacturing)	0.82 (0.07)***
Low-tech (Manufacturing)	0.44 (0.06)***
Knowledge-intensive Services	0.79 (0.06)***
Age (ref. lowest quartile)	
2nd quartile	-0.08 (0.06)
3rd quartile	-0.12 (0.06)**
Top quartile	-0.12 (0.06)**
Productivity (ref. lowest quartile)	
2nd quartile	0.05 (0.07)
3rd quartile	0.15 (0.07)**
Top quartile	0.30 (0.08)***
Labor cost (ref. lowest quartile)	
2nd quartile	0.09 (0.07)
3rd quartile	0.22 (0.08)***

Top quartile	0.38 (0.09)***
Intercept	-2.45 (0.07)***
Number of observations	14 491
LR $\chi_2(18)$	2369.02
Prob> χ_2	0.0000
Pseudo R_2	0.1388
Log likelihood	-7350.23

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 4- The impact of innovation on employment and job quality

Dependent variables	**Product**	**Process**	**Product new to the market**	**Product patenting firms**
Total workforce	5.7 (3.0)*	-5.6 (2.8)**	3.2 (4.0)	14.4 (8.1)*
Open-ended (permanent) contract employees	8.2 (3,0)***	-2.9 (2.7)	5.7 (4.0)	19.8 (7.8)**
Fixed-term contract employees	-1.7 (1,1)	-3.0 (1.1)***	-1.1 (1.2)	-2.0 (2.0)
Average annual hours worked per employee	12.7 (6.8)*	0.4 (7.0)	8.6 (7.3)	10.9 (10.0)
Hourly wages (gross)	-0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.2 (0.1)

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations. The first three variables represent the variations in the number of employees. The fourth variable shows the difference in hours (per employee) and the last one represents the difference in euros (per employee).
These results are from difference in differences models, psmatch 2; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 5- The impact of innovation on employment by occupations

Dependent variables	**Product**	**Process**	**Product new to the market**	**Product patenting firms**
Number of managers and professionals	5.6 (1.6)***	0.4 (1.6)	6.5 (2.5)***	15.0 (5.9)**
Number of intermediate occupations	2.8 (1.1)**	-0.2 (1.0)	1.3 (1.5)	6.6 (3.3)**

Number of manual and clerical workers	-2.8 (2.9)	-5.8 (2.7)**	-4.5 (3.8)	-7.1 (8.4)

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations. These results are from difference in differences models, psmatch 2; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 6- The impact of innovation on employment and job quality: Manufacturing

Dependent variables	Product	Process	Product new to the market	Product patenting firms
Total workforce	15.7 (3.2)***	-1.8 (3.1)	9.4 (4.5)**	22.7 (7.6)***
Open-ended (permanent) contract employees	16.9 (3.2)***	-5.2 (3.0)	11.3 (4.4)**	25.1 (7.4)***
Fixed-term contract employees	-2.8 (0.9)***	-2.0 (0.9)**	-4.0 (1.2)***	-3.9 (2.1)*
Average annual hours worked per employee	25.6 (10.0)**	-5.3 (8.6)	16.2 (9.9)	5.0 (11.3)
Hourly wage (gross)	-0.2 (0.09)*	0.1 (0.1)	-0.1 (0.1)	0.1 (0.1)

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 5,058 observations, authors' calculations. The first three variables represent the variations in the number of employees. The fourth variable shows the difference in hours (per employee) and the last one represents the difference in euros (per employee).
These results are from difference in differences models, psmatch 2.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 7- The impact of innovation on employment and job quality: Services

Dependent variables	Product	Process	Product new to the market	Product patenting firms
Total workforce	-1.3 (5.4)	-15.4 (5.5)***	-4.1 (7.8)	4.6 (23.4)
Open-ended (permanent) contract employees	2.4 (5.4)	-8.4 (5.4)	-0.4 (8.1)	18.0 (22.4)
Fixed-term contract employees	0.1 (2.5)	-5.2 (2.7)*	4.0 (2.2)*	4.0 (3.4)
Average annual hours worked per employee	8.7 (12.3)	0.6 (15.9)	4.7 (13.4)	13.0 (21.4)
Hourly wage (gross)	-0.0 (0.1)	-0.04 (0.1)	0.1 (0.1)	0.6 (0.4)*

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, 4,462 observations, matched data, authors' calculations. The first three variables represent the variations in the number of employees. The fourth variable shows the difference in hours (per employee) and the last one represents the difference in euros (per employee).
These results are from difference in differences models, psmatch 2.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

APPENDIX

Figure 1- The matching share by propensity score (radius method, caliper 0.00001, product innovation).

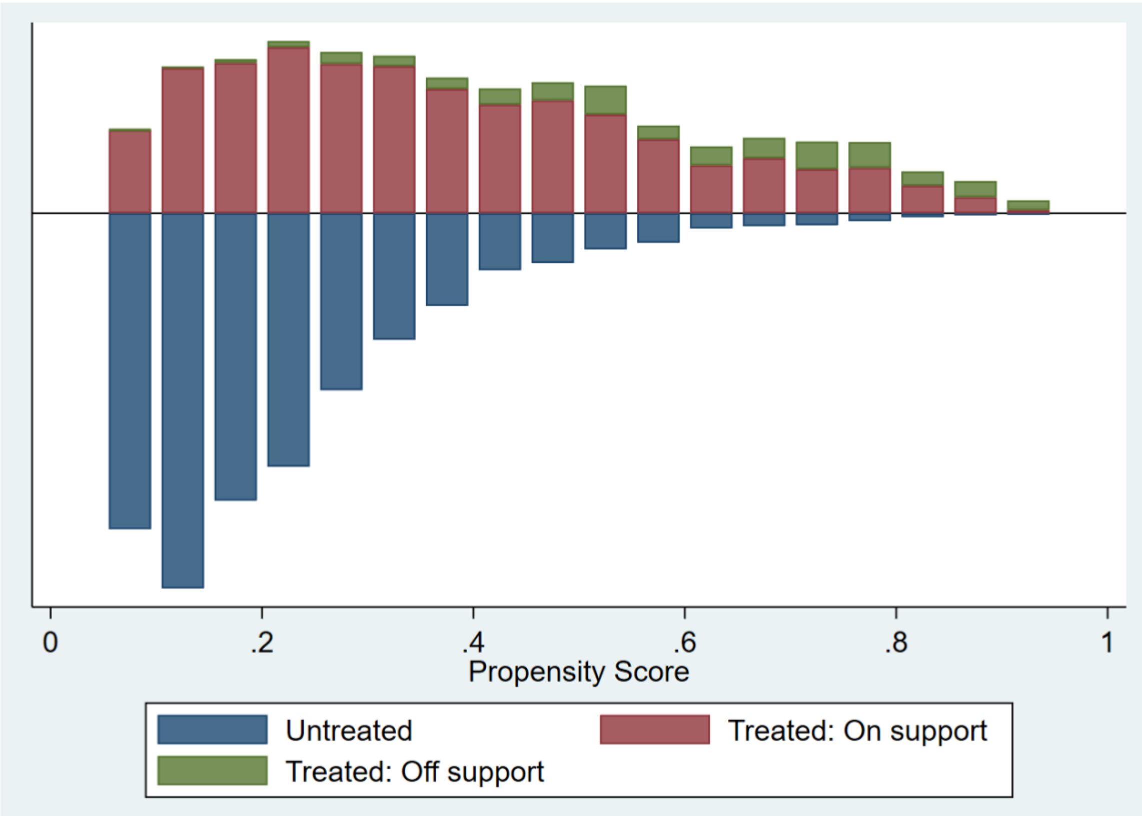
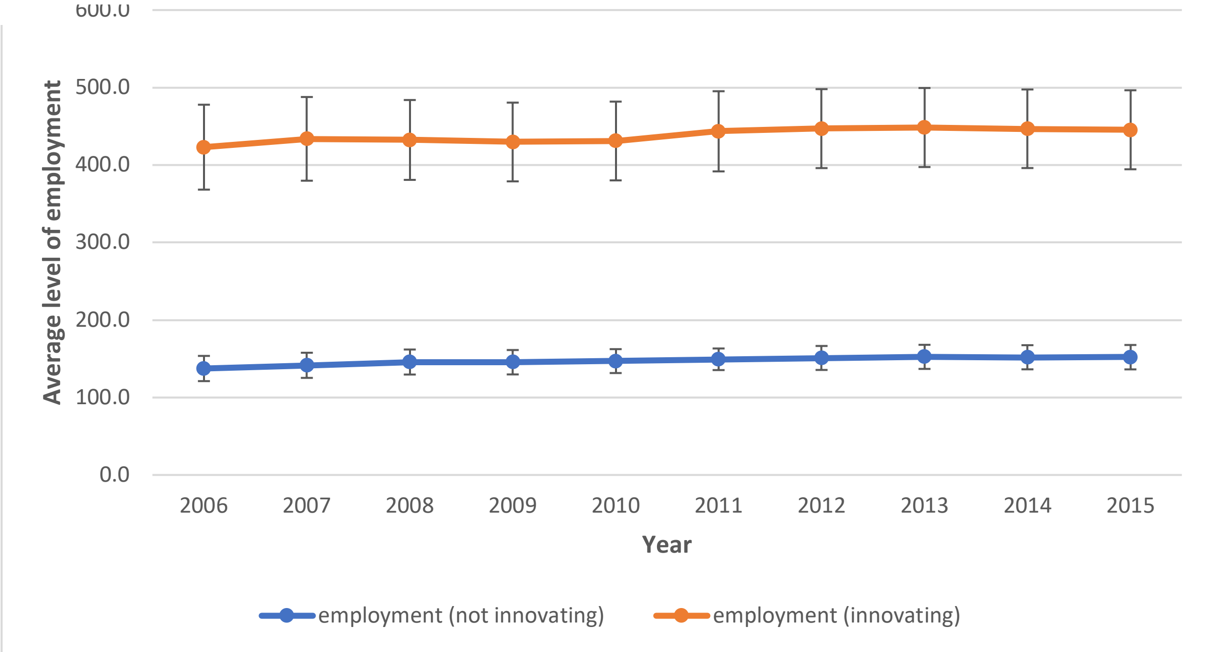
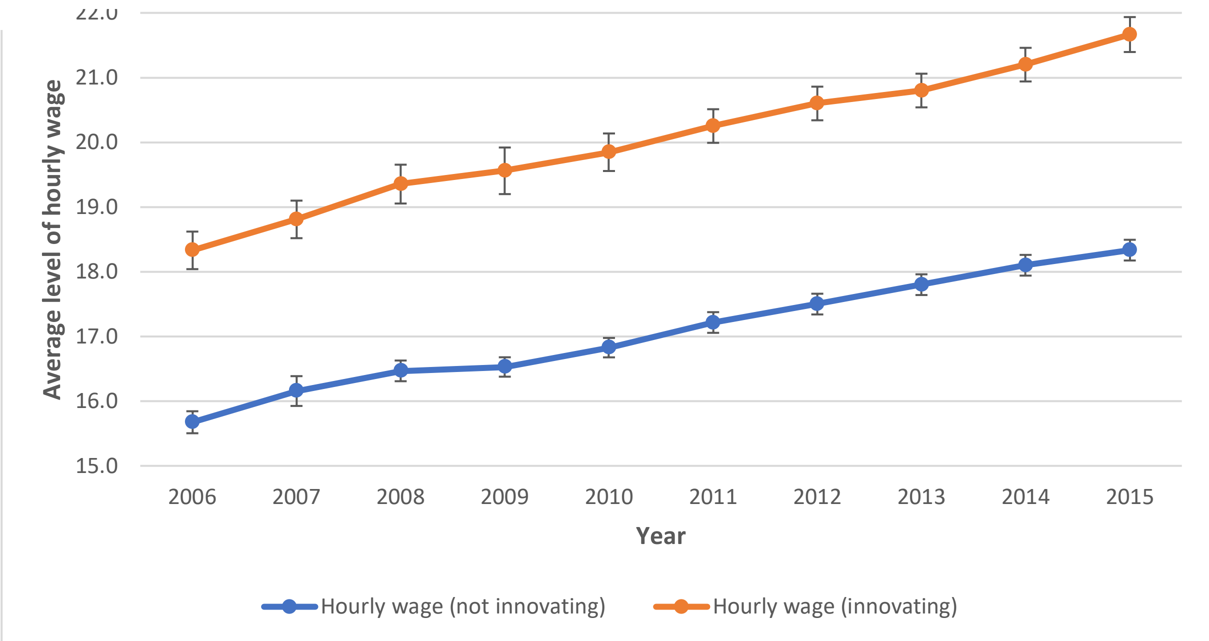


Figure 2a-Evolution of employment before and during treatment in innovating and non-innovating firms (product innovation)



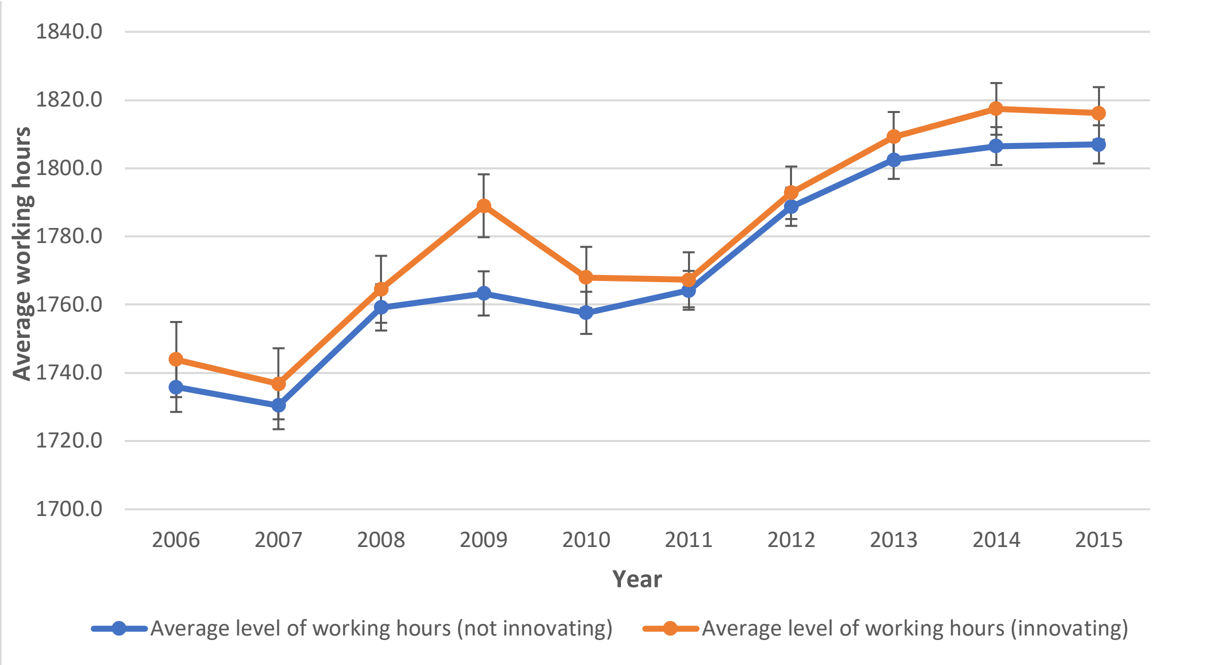
Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Figure 2b-Evolution of wages before and during treatment in innovating and non-innovating firms (product innovation)



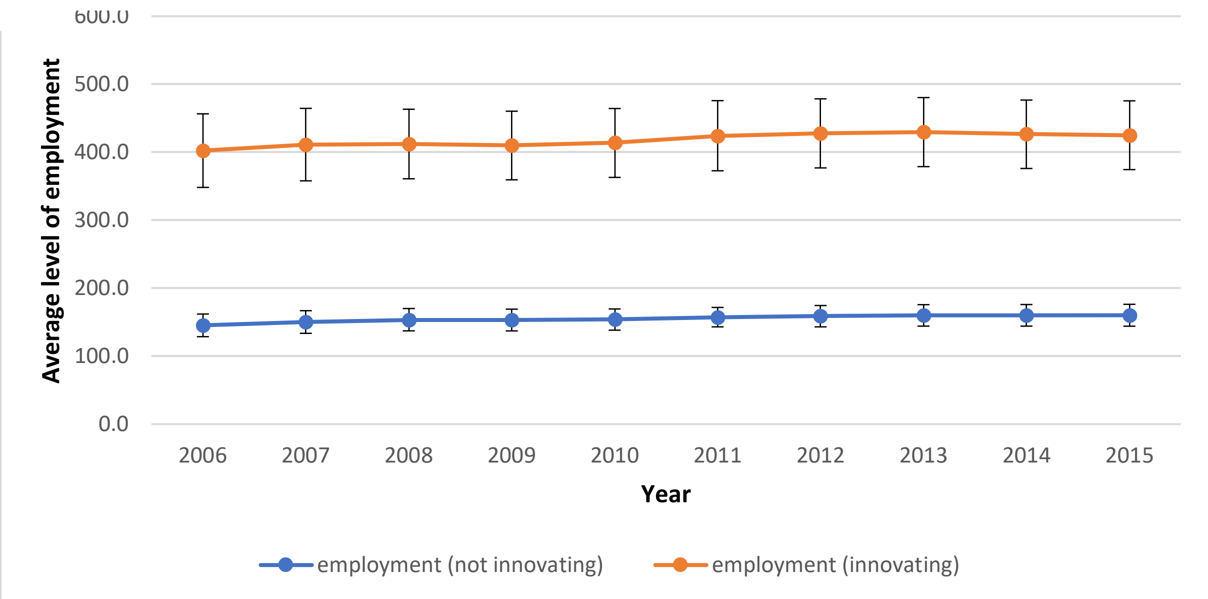
Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Figure 2c-Evolution of working hours before and during treatment in innovating and non-innovating firms (product innovation)



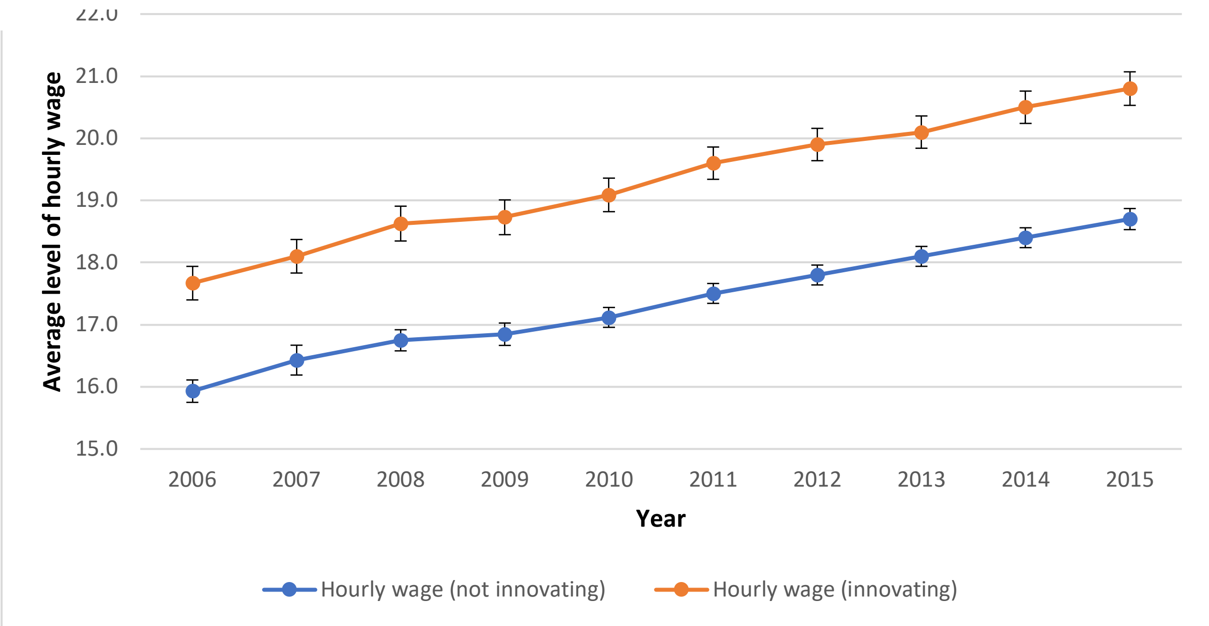
Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Figure 3a-Evolution of employment before and during treatment in innovating and non-innovating firms (process innovation)



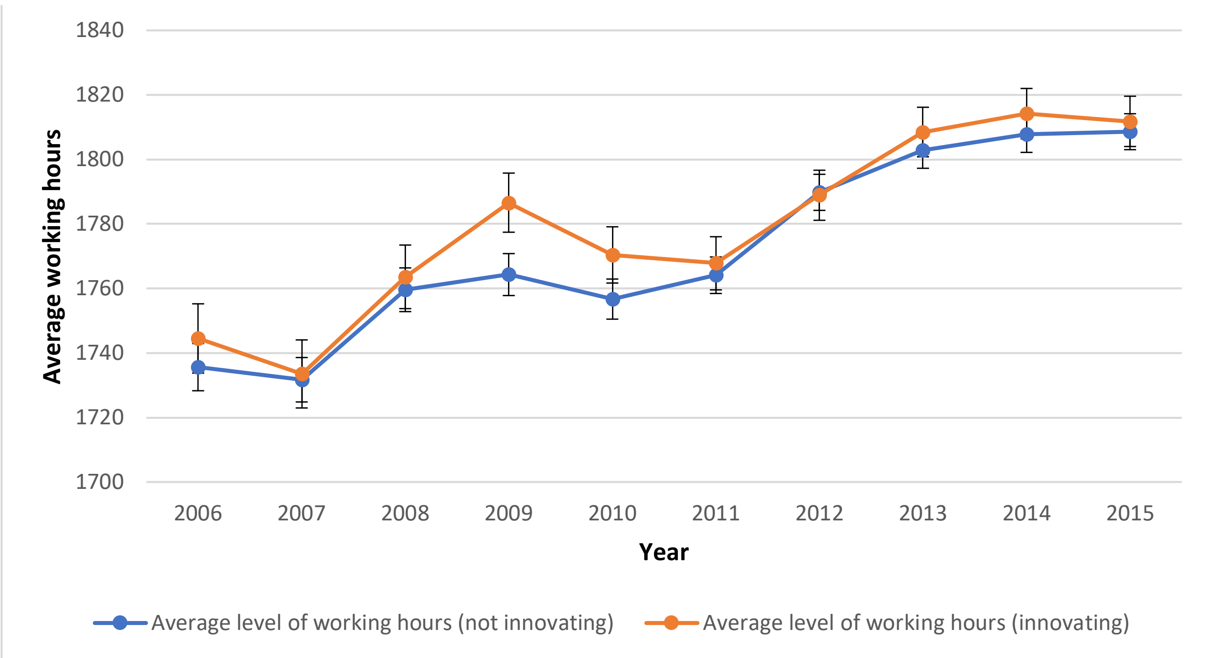
Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Figure 3b-Evolution of wages before and during treatment in innovating and non-innovating firms (process innovation)



Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Figure 3c-Evolution of working hours before and during treatment in innovating and non-innovating firms (process innovation)



Source: CIS 2014-DADS 2006 to 2015, matched data, 14,491 firms, authors' calculations. Note: confidence interval at 95% level.

Table A1- The balancing test after matching (radius method, caliper 0.00001, product innovation).

	Mean	*Mean*		*t-test*	
Variables	**Treated**	**Control**	**% bias**	**T**	**p>t**
Sector by technology (ref. less knowledge-intensive services)					
High-tech manufacturing	0.02	0.02	0.1	0.04	0.97
Medium high-tech manufacturing	0.12	0.12	-0.1	-0.05	0.96
Medium low-tech manufacturing	0.14	0.14	-0.1	-0.02	0.98
Low-tech manufacturing	0.19	0.19	0.0	0.02	0.99
Knowledge-intensive services	0.26	0.26	-0.0	-0.01	0.99
Size (ref. 10-19 employees)					
20 to 49	0.22	0.23	-0.2	-0.09	0.93
50 to 499	0.40	0.40	0.4	0.14	0.89
500 to 999	0.08	0.08	-0.3	-0.12	0.90
>1000	0.06	0.06	0.2	0.09	0.93
Age (ref. lowest quartile)					
2nd quartile	0.23	0.23	0.3	0.13	0.90
3rd quartile	0.25	0.25	0.3	0.11	0.91
Top quartile	0.28	0.28	-0.0	-0.01	0.99
Productivity (ref. lowest quartile)					
2nd quartile	0.21	0.20	0.3	0.14	0.89
3rd quartile	0.27	0.27	-0.4	-0.15	0.88
Top quartile	0.36	0.36	0.2	0.07	0.94
Labor cost (ref. lowest quartile)					
2nd quartile	0.20	0.20	0.5	0.24	0.81
3rd quartile	0.28	0.28	-0.3	-0.11	0.90
Top quartile	0.38	0.38	-0.1	-0.03	0.98
Member of a business group (ref. no)					
Yes	0.64	0.64	-0.1	-0.06	0.95

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations.

Table A2- Characteristics of firms doing product innovation on-support and off-support (PSM matched data)

	Treated on-support	Treated off-support
Characteristics		
High-tech (manufacturing)	2,2%	20,0%
Medium high-tech (manufacturing)	12,2%	30,3%
Medium low-tech (manufacturing)	14,1%	15,9%
Low-tech (manufacturing)	19,0%	14,4%
Knowledge-intensive services	26,0%	11,5%
Less-knowledge intensive services	26,6%	7,9%
10-19 employees	23,3%	11,1%
20 to 49 employees	22,4%	13,3%
50 to 499 employees	39,9%	27,9%
500 to 999 employees	8,4%	19,0%
>1000 employees	6,0%	28,7%
Age 1st quartile	23,8%	23,1%
Age 2nd quartile	23,0%	24,2%
Age 3rd quartile	24,7%	26,4%
Age Top quartile	28,5%	26,2%
Productivity 1st quartile	16,8%	20,5%
Productivity 2nd quartile	20,6%	21,4%
Productivity 3rd quartile	26,8%	30,9%
Productivity Top quartile	35,9%	27,2%
Labor cost 1st quartile	14,6%	11,1%
Labor cost 2nd quartile	20,1%	20,5%
Labor cost 3rd quartile	27,7%	34,0%
Labor cost Top quartile	37,6%	34,4%
Member of a business group: yes	63,9%	73,0%
Member of a business group: no	36,1%	27,0%
N on- and off-support	3456	541
Total N of treated	3997	

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 3,997 observations (firms doing product innovation), authors' calculations.

Table A3- The determinants of innovation (process, product new to the market, product innovation + patenting)

	Process	Product new to the market	Product and patenting firms
Size (ref. 10-19 employees)			
20 to 49	0.29 (0.05)***	0.23 (0.07)***	0.72 (0.16)***
50 to 499	0.82 (0.06)***	0.89 (0.07)***	1.82 (0.15)***
500 to 999	1.24 (0.09)***	1.36 (0.10)***	2.34 (0.17)***
>1000	1.77 (0.10)***	1.87 (0.11)***	3.16 (0.18)***
Member of a business group (ref. No)			
Yes	0.16 (0.05)***	0.29 (0.06)***	0.26 (0.10)***
Sector by technology (ref. Less knowledge-intensive Services)			
High-tech Manufacturing	1.46 (0.14)***	2.10 (0.14)***	2.61 (0.18)***
Medium high-tech Manufacturing	1.03 (0.08)***	1.85 (0.09)***	2.66 (0.13)***
Medium low-tech Manufacturing	0.85 (0.06)***	0.92 (0.08)***	1.83 (0.13)***
Low-tech Manufacturing	0.47 (0.06)***	0.68 (0.07)***	0.88 (0.14)***
Knowledge-intensive Services	0.45 (0.06)***	0.93 (0.07)***	0.72 (0.14)***
Age (ref. lowest quartile)			
2nd quartile	-0.00 (0.06)	-0.11 (0.07)	0.03 (0.12)
3rd quartile	-0.06 (0.06)	-0.18 (0.07)***	-0.10 (0.11)
Top quartile	-0.16 (0.06)***	-0.14 (0.07)**	0.10 (0.11)
Productivity (ref. lowest quartile)			
2nd quartile	0.11 (0.06)*	-0.04 (0.08)	-0.33 (0.14)**
3rd quartile	0.17 (0.07)**	0.09 (0.08)	-0.23 (0.14)
Top quartile	0.30 (0.08)***	0.26 (0.09)***	-0.01 (0.14)
Labor cost (ref. lowest quartile)			
2nd quartile	0.07 (0.07)	0.19 (0.09)**	0.77 (0.20)***

3rd quartile	0.12 (0.07)*	0.42 (0.09)***	1.34 (0.20)***
Top quartile	0.20 (0.08)**	0.64 (0.10)***	1.73 (0.21)***
Intercept	-2.15 (0.07)***	-3.21 (0.09)***	-6.33 (0.23)***
Number of observations	14 491	14 491	14 491
LR $\chi^2(18)$	1422.57	2172.31	2326.95
Prob> χ^2	0.00	0.00	0.00
Pseudo R^2	0.08	0.15	0.31
Log likelihood	-7806.67	-5927.27	-2616.24

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table A4- The impact of innovation on wages and annual working time by occupation

Dependent variables	**Product**	**Process**	**Product new to the market**	**Product patenting firms**
Hourly wage: managers and professionals	-0.10 (0.20)	-0.27 (0.18)	-0.09 (0.2)	-0.00 (0.28)
Hourly wage: intermediate occupations	0.02 (0.38)	0.27 (0.32)	-0.37 (0.37)	-0.53 (0.69)
Hourly wage: manual and clerical workers	-0.17 (0.09)*	-0.07 (0.08)	-0.04 (0.10)	-0.06 (0.17)
Working time: managers and professionals	2.9 (11.7)	-14.6 (10.3)	1.2 (11.9)	10.0 (14.7)
Working time: intermediate occupations	15.5 (13.8)	-0.6 (12.6)	4.6 (14.9)	16.3 (20.1)
Working time: manual and clerical workers	19.6 (10.3)*	2.4 (7.6)	16.3 (11.4)	17.2 (15.9)

Source: CIS 2014-FARE 2011 2015-DADS 2011 2015, matched data, 14,491 observations, authors' calculations.
These results are from difference in differences models, psmatch 2.
Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table A5- The impact of innovation on employment and job quality in 2014, with a control for innovation in 2012

Dependent variables	Product	Process	Product new to the market	Product patenting firms
Total workforce	37.2 (10.0)***	2.3 (9.2)	35.2 (11.7)**	59.8 (18.5)***
Open-ended (permanent) contract employees	39.3 (9.6)***	4.0 (9.2)	37.7 (11.3)**	61.1 (17.7)***
Fixed-term contract employees	1.4 (3.3)	-2.3 (2.2)	1.3 (3.1)	0.8 (4.9)
Average annual hours worked per employee	25.9 (14.1)*	-1.9 (12.76)	14.7 (14.3)	36.7 (14.4)**
Hourly wage (gross)	0.2 (0.2)	0.1 (0.2)	0.3 (0.2)	-0.1 (0.2)
Number of managers and professionals	21.2 (7.7)***	9.4 (7.5)	23.2 (8.8)***	35.3 (13.7)***
Number of intermediate occupations	13.4 (8.3)*	5.4 (3.9)	12.5 (5)***	23.8 (12.3)*
Number of manual and clerical workers	2.2 (14.3)	-12.9 (10.9)	-0.6 (12.1)	0.4 (22.4)

Source: CIS 2014-2012-FARE 2011 2015-DADS 2011 2015, matched data, authors' calculations, 2,977 observations.

The first three variables represent the variations in the number of employees. The fourth variable shows the difference in hours (per employee) and the last one represents the difference in euros (per employee).

These results are from difference in differences models, psmatch 2.

Note: *** p-value<0.01, ** p-value<0.05, * p-value<0.1.