# Impact of innovation on employment and skill upgrading[1]

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## Abstract

The paper investigates the dual effect of innovation on employment and skill upgrading in manufacturing and service industries. Based on the Harrison et al (2008) approach and using four waves of CIS data for the period 2004-2010 for 23 European countries, we find that product innovation has a consistent positive effect on employment growth. This effect is similar for manufacturing and service industries. Process innovations are found to exhibit labor displacement effects for manufacturing, but no negative effects for service industries, while organizational and marketing innovations reveal a consistent positive impact on employment. We also study the impact of innovation on skill upgrading and find that increasing the share of firms engaged in process innovation by 10 per cent will lead to an increase in share of high skilled labor by 2 per cent, while increasing the share of firms engaged in organizational and marketing innovation by 10 per cent will lead to an increase in share of high skilled labor by 4 per cent and an increase in share of scientific workers by 2 per cent. These effects of innovation on demand for skilled labor are, however, limited mainly to manufacturing sector, while in service industries these effects are lower by some 60 to 80 per cent. Finally, we also control for the impact of Chinese import penetration and find no significant impact on employment growth, but find a strong positive impact on skill upgrading. Our results indicate that increasing the share of Chinese imports in total imports by 10 per cent leads to an increase in share of high skilled labor by 2 per cent. These findings are consistent with the "trapped factor" model of innovation developed by Bloom et al (2011).

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# 1. Introduction

Economic theory suggests there is a dual effect of innovation on employment. Depending on innovation type, on overall it may lead to a reduction in employment due to destruction of existing jobs (displacement effect) or creation of new/additional jobs (compensation effect). The complexity of the relationship between successful innovation and employment growth is further enhanced by the existence of many transmission mechanisms, feedback loops and institutional factors, which play a role in the determination of the end effect on employment (Pianta, 2006; Vivarelli, 2011).

Theoretical contributions analyzing the effect of innovation on employment at the firm level stress the importance of a distinction between product and process innovations. For both types of innovation, the overall effects on the labor demand of a firm are not clear. Whereas the direct effect of product innovation could be increased turnover and a likely increase in employment, the indirect effect could lead to a reduction in employment if the innovation leads to a market monopoly or displaces older, more labor intensive products (Lachenmaier, Rottman 2011). Similarly, process innovation, while having a negative direct effect on employment as improved production processes reduce the need for labor, may ultimately lead to an increase in employment if lower production costs are passed through to consumers, which, in turn, increase their demand for the product (Garcia et al., 2004).

Empirical literature on the firm-level relationship between innovation and employment finds that whether the impact of innovation is positive or negative rests primarily on the type of innovation (Harrison, et al. 2008; Hall et al., 2008; Lachenmaier and Rottmann, 2011) and the sector in question (Greenhalgh, et al. 2001; Coad and Rao, 2011; Bogliacino et al., 2011). Lastly, at the sectoral level innovation can also trigger competitive redistributions of output and ultimately jobs from non-innovating to innovating firms, job losses due to firm exit and second order job creation from spin-off firms.

While the literature tends to focus almost exclusively on the link between innovation and employment in manufacturing sectors, the importance of innovation in services is widely acknowledged. Namely, tertiary sector innovation was found to be a key driver of firm performance and productivity growth (OECD, 2008; Cainelli et al., 2006; Lööf and Heshmati, 2006; van Leeuwen and Klomp, 2006; Abreu et al., 2008; Castellacci and Zheng, 2008; Abreu et al., 2010).

The rare studies that did focus on the service sector found that the effect of innovation in services is governed by a very similar dynamic as the manufacturing sector. As pointed out by Djellal and Gallouj (2008), the discussion on the relation between innovation and employment in the context of service economy needs to take account of both, innovation in services (be it technological or non-technological) and innovation by services, where services as inputs to other sectors may cause changes in employment.

Evangelista and Vezzani (2010) find that there are both similarities and differences between the manufacturing and service-sector innovations. The former have to do with the dominant role played by *complex* and *organizational* innovation modes as drivers of firms' performances. The differences, on the other hand, stem from the fact that product or process oriented innovation strategies exert a positive and significant impact on firms' economic performance only in the manufacturing sector. All in all, these findings suggest that different types of innovation strategies are feasible in both macro-sectors, services firms have "less strategic options" vis à vis manufacturing firms, if they want to get an economic return from innovation. The extent to which these increase firm-level performance (and in particular productivity growth) and generate new jobs (or are obtained through labor saving innovation) remains an aspect that has been largely neglected, especially in the case of services (Djellal et al., 2013).

Amongst notable exceptions, Evangelista and Savona (2003) using CIS II data for Italian firms find that the direct impact of innovation on employment varies with the type of innovation strategy perused by firms, across industries and firm skill intensity. The net effect of innovation on employment is found to be positive in small firms and firms with a strong scientific and technological base. On the contrary, large firms, capital-intensive industries and financial-services sectors experience a labor-saving effect of innovation. The authors attribute this to the impact of the widespread use of information and communication technologies, which have lead to an increase in labor productivity and the rationalization of employment.

Peters et al. (2013) use CIS survey data on 20 European countries to show that product innovations significantly stimulate employment in services sectors. The effects of process innovations on employment are found to be much weaker, while the impact of organizational innovation is found to be mixed for European firms. In fact, the majority of the change in employment can be explained by changes in output of existing and new products, process innovations have a negligible positive effect on employment, while organizational innovations is found to have a very weak negative effect. Compared to manufacturing sectors, product and process innovations are found to have a stronger positive effect, while the effect of organizational innovation is weakly negative in both segments with a slightly smaller magnitude in case of manufacturing.

Marketing innovation is also considered as an important element of non-technological innovation, the assessment of its impact on employment in services, however, is highly deficient. Empirical analysis of CIS 2008 data for sixteen European economies illustrates that those forms of non-technological innovation activities, which impact on external relations and sales channels, have a positive effect on the growth of firm sales in any sector (Som et al., 2012). Taking into account the results of the analysis by Evangelista and Vezzani (2012), we may infer that the sales growth may also result in employment increase, suggesting that marketing innovation may indirectly lead to job creation via growth of firms' sales. Nonetheless, the assumption deserves detailed empirical assessment and testing on the basis of longer data series to earn validity.

Finally, technological and organizational changes have been shown to lead to a change in the composition of the workforce as well. Information-based technologies for instance that substitute workers in routine tasks and complement workers in analytical and interactive tasks (Autor, Levy and Murnane, 2003; Spitz-Oener, 2006). This has increased the demand for skilled workers on the labor market, generating in turn a rise in the relative wage of highly educated workers despite the rising skill supply (see Chennells and Van Reenen (2002) for a review). The adoption of innovative workplace practices induced by the development of new technologies had very similar effects and further increased the relative demand for skilled labor (see Caroli and Van Reenen, 2001 and Walkowiak, 2006). Behagel et al. (2008), for instance, using a sample of 1000 French plants, show that skill upgrading consistently follows technological and organizational changes with one third of the employment changes coming from the external labor market (hiring and firing), while the remaining two thirds coming from in-house promotions.

In this paper we investigate the dual effect of innovation on employment and skill upgrading. Based on the Harrison et al (2008) approach we first study which of the effects – displacement vs. compensation effect – prevails in the impact of innovation on employment growth. In doing so, we distinguish between technological (product and process) and non-technological innovation (organizational and marketing). We make use of four waves of CIS data for the period 2004-2010 for 23 EU countries and estimate the empirical models using country-industry data.

We find that product innovation, as reflected in differential output growth of the new products, has a consistent positive effect on employment growth. This effect is similar for manufacturing industries. Process innovations are found to exhibit no labor-displacement effects neither in manufacturing nor in service industries. On the other hand, organizational and marketing innovations reveal a consistent positive impact on employment.

We also find that product, process, organizational and marketing innovation have substantial positive impacts on skill demand in manufacturing sector. For instance, we find that increasing the share of firms engaged in process innovation by 10 per cent will lead to an increase in share of high skilled labor by 2 per cent, while increasing the share of firms engaged in organizational and marketing innovation by 10 per cent will lead to an increase in share of high skilled labor by 4 per cent and an increase in share of scientific workers by 2 per cent. These effects of innovation on demand for skilled labor are, however, limited mainly to manufacturing sector. We find that in service industries, these effects are lower by some 60 to 80 per cent.

Finally, when studying both issues we also control for the impact of Chinese import penetration. While no significant impact of Chinese import competition on employment growth is found in manufacturing industries, a strong positive impact on skill upgrading is revealed. Our results indicate that increasing the share of Chinese imports in total imports by 10 per cent leads to an increase in share of high skilled labor by 2 per cent. These findings are consistent with the "trapped factor" model of innovation developed by Bloom et al (2011).

The outline of the paper is as follows. Next section discusses the empirical approach, section 3 describes the data, while section 4 presents the results. Last section concludes.

## 2. Empirical approach

We account for the impact of innovation on employment growth and skill upgrading by using the approach developed by Harrison et al. (2008) and further amended by Peters et al. (2013). We first briefly outline the general empirical approach and then present an extension of the model that allows to account for effects additional to firm's innovation.

### 2.1. General empirical approach

The model employs a simple multi-product approach that allows accounting for employment effects of different types of innovation. In its original form, most of the employment effects of product innovation are captured by the differential growth of sales due to new products, while the remaining part of employment growth is due to the efficiency gains stemming from process innovation. It is simple to extend the model in order to allow the remaining efficiency gains to capture the effects of other innovation types, such as organizational and marketing innovation.

Each firm is assumed to be able to produce two products[5] – the "existing product" and a "new product". As a firm is observed in two periods ($t$ = 1,2), output in the first period $y_{1t}$ will simply equal the sum of revenues from existing products in period $t$ = 1), while output in the second period $y_{2t}$ will be either zero (if firm has not introduced new products) or equal to a sum of revenues of new or

[5] The term product is used generically to label either products or services produced by firms.

significantly improved products in period $t = 2$. Note that the new product can either (partially or totally) replace the existing products if products are substitutes or enhance demand for new products if they are complements.

Production technology for each product $i$ in period $t$ is approximated by following the constant returns to scale production function:

$$Y_{it} = \theta_{it} F\left(K_{it}, L_{it}, M_{it}\right) e^{\eta + \omega_{it}} \quad (1)$$

where $K$, $L$ and $M$ are the usual inputs capital, labor and intermediate consumption, respectively, and $\theta_{it}$ are different Hicks-neutral technology parameters that capture product specific efficiencies. $\eta$ is firm-specific fixed effect and $\omega_{it}$ is time-specific productivity shocks with $E(\omega_{it}) = 0$.

Firm invests in R&D to be able to generate product and process innovations. New products can be produced with higher or lower efficiency than existing products, whereby a firm can affect the efficiency of producing existing or new products by engaging in process (and organizational) innovations. The efficiency gains in producing existing products can be measured by the ratio $\theta_{12}/\theta_{11}$, while efficiency differences in producing new versus old products can be captured by the relative efficiency $\theta_{22}/\theta_{11}$.

Employment effects of firm's innovation activities can be derived from the conditional labor demand functions for each product and can be written in the form of the following regression model of the overall employment growth (see Harrison et al. (2008) for full details):

$$l = \alpha + y_1 + \beta y_2 + u \quad (2)$$

where $l$ is employment growth, $y_1$ and $y_2$ are real outputs of old and new products, while $\alpha$ is efficiency gain in the production of old products and $u$ is a random error term. In this model, employment growth is affected by three different sources:

(i) from efficiency gain $\alpha$ in the production of old products that has a negative impact on labor demand;

(ii) from the growth rate of the existing products $y_1$, which can be a result of firm's non-product innovations, but also of number of other factors, such as indirect effect (positive or negative) of own new products and new products introduced by rivals and changes in demand affected by in changes in consumer preferences and business cycles, etc.; and

(iii) from introducing new products $y_2$, which positively affects employment, whereby the employment effect depends on the relative efficiency ratio of both technologies ($\beta = \theta_{22}/\theta_{11}$) and output growth of new products $y_2$.

As noted above, efficiency gains in the production of both types of products can be a result of process or organizational innovation, but can arise also due to better use of human capital, improved skill structure, firm's learning effects and of various spillover effects. The latter typically stem from increased competition in the industry (domestic or foreign). Following Peters et al (2013), the empirical model of employment growth capturing both process and organizational innovation can be written as:

$$l = \alpha_0 + \alpha_1 pc + \alpha_2 org + y_1 + \beta y_2 + u \tag{3}$$

where $\alpha_0$ accounts for efficiency gains of firms without process and organizational innovation, while $\alpha_1$ and $\alpha_2$ capture improvements in efficiency of producing existing products by firm's deliberate process and organizational innovation, respectively.

By substituting unobserved real output growth by observed nominal output growth and by rearranging model (3) can be written as:

$$l - (g_1 - \tilde{\pi}) = \alpha_0 + \alpha_1 pc + \alpha_2 org + \beta g_2 + v \tag{4}$$

where $g_1$ and $g_2$ are nominal output growth rates for old and new products, respectively.

Using the CIS data, one can calculate $g_2$ as an increase in output due to introduction of new products, while $g_1$ is accordingly calculated by the total sales growth rate minus the growth rate due to new products. When using sector level data, the price effects are captured by deflating nominal growth rates of output with industry-specific producer price indices (PPI).

## 2.2. Empirical model of employment effects

In our empirical estimations, we further augment the model (4) in order to allow for additional forms of innovation and to account for the effects that may, in addition to firm's innovation, impact its technical efficiency and hence its employment.

First, in addition to process and organizational innovation, we also take marketing innovation into account. As shown by Som et al., (2012) and Evangelista and Vezzani (2012) marketing innovations affect sales growth, which may in turn induce employment growth, suggesting that marketing innovation may indirectly lead to job creation. A more practical reason for including marketing innovation into the empirical model is that in the CIS surveys organizational and marketing innovation are highly correlated. This suggests that, though theoretically working in opposite directions in terms of employment effects, both types of innovation go hand in hand or at least they are reported by firms as such.

Second, we extend the model by controlling for the quality of human capital. We introduce variables on shares of high-skilled human resources and shares of science and technology workers in total employment. Here, we use Eurostat data from the Human Resources in Science and Technology (HRST) database, which provides information on the number and share of human resources and science and technology workers in total number of employees.

Third, we control for the effect of increased foreign competition in the industry. We follow the idea of Bloom et al. (2011), who demonstrated that Chinese import competition after 2000 had substantial effects on innovation activities and employment of European firms. On the one hand, it led to increases in R&D, patenting, IT and TFP growth within firms, while on the other hand Chinese import competition promoted employment reallocation between firms towards more innovative and technologically advanced firms. Bloom et al. (2011) show that these within and between effects (both equal in magnitude) are responsible for about 15% of European technology upgrading between 2000-2007. Furthermore, increased Chinese import competition also had a negative effect on employment, profits, prices and the skill share, while import competition from developed countries had no effect on innovation. To account for the spillover effect of Chinese import competition, we introduce the share of Chinese imports in total industry imports in individual country.

And finally, while most of the papers study employment effects of innovation in manufacturing sectors only, we are interested studying the differential effects of innovation on employment growth in services and manufacturing industries. In order to do so, we introduce interaction terms with service industry dummies for all explanatory variables.

Based on the above considerations, our final empirical model is specified as:

$$\tilde{l}_{jkt} = \alpha_0 + \alpha_0 * S + \alpha_1 pc_{jkt} + \alpha_2 pc_{jkt} * S + \alpha_3 org_{jkt} + \alpha_4 org_{jkt} * S + \beta_1 g^n_{jkt} + \beta_2 g^n_{jkt} * S + \tag{5}$$

$$+ \beta_3 h_{jkt} + \beta_4 h_{jkt} * S + \beta_5 st_{jkt} + \beta_6 st_{jkt} * S + \beta_7 Ch_{jkt} + \beta_8 Ch_{jkt} * S + \eta_j + \eta_k + \eta_t + u_{jkt}$$

where dependent variable $\tilde{l}_{jkt}$ $(= l_{jkt} - g^o_{jkt})$ is the "corrected" employment growth of industry *j* in country *k* and year *t* defined as total employment growth rate minus the output growth rate due to old products. *pc*, *org* and *g* are process, organizational and marketing innovation and output growth due to introduction of new products, respectively. Among the additional variables, *h* and *st* denote shares of high-skilled human resource and science and technology workers in total employees, respectively. To control for differential employment effects in service industries, all explanatory variables are interacted with the service industry dummy variable assuming 1 for all service industries and zero otherwise. $Ch_{jkt}$ is a share of Chinese imports in industry *j*'s imports in individual country *k*. Finally, $\eta_j$, $\eta_k$ and $\eta_t$ are industry, country and year fixed effects, respectively, while $u_{jkt}$ is the remaining i.i.d. error term.

### 2.3. Empirical model of skill upgrading

As noted above, technological and organizational changes are shown to lead to a change in the composition of the workforce by increasing the demand for skilled workers (Chennells and Van Reenen, 2002; Caroli and Van Reenen, 2001; Walkowiak, 2006). Furthermore, Behagel et al. (2008) show that skill upgrading consistently follows technological and organizational changes.

It is therefore reasonable to extend our empirical exercise from overall employment effects to the importance of innovation for skill upgrading as well. In order to do so, we estimate the following empirical model:

$$h_{jkt} = \alpha_0 + \alpha_0 * S + \alpha_1 pc_{jkt} + \alpha_2 pc_{jkt} * S + \alpha_3 org_{jkt} + \alpha_4 org_{jkt} * S + \beta_1 g^n_{jkt} + \beta_2 g^n_{jkt} * S + \tag{6}$$

$$+ \beta_3 l_{jkt} + \beta_4 l_{jkt} * S + \beta_5 Ch_{jkt} + \beta_6 Ch_{jkt} * S + \eta_j + \eta_k + \eta_t + u_{jkt}$$

where $h_{jkt}$ is a generic dependent variable that stands for shares of high-skilled human resource and science and technology workers of industry *j* in country *k* and year *t* in total number of employees. As a dependent variable we use interchangeably either the overall share of HR employees in total employment or shares of HR professionals by education, by occupation and by core HR professions or, in addition, share of scientists and engineers in the population of employees is used as a robustness check. We also control for the overall employment growth (*l*) and for employment and demand-for-skill effects stemming from output growth due to introduction of new products (*g*). Similarly to model (5), in order to control for differential skill upgrading effects in service industries, we interact all explanatory variables with the service industry dummy variable. The rest of the variables in the model (6) are specified in the same way as in the model (5).

As demand for skilled labor may be jointly determined with firm's innovation efforts, we also estimate a version of the model (6) with lagged innovation variables.

## 3. Data

### 3.1. Data sources

We estimate empirical models (5) and (6) by using industry level data for 28 EU countries. The dataset in use for the analysis is constructed from three separate datasets collected and maintained by Eurostat. The primary source of data are the four waves of Community Innovation Survey (CIS) conducted biannually since 2004 (2004-2010). The survey, harmonized across the participating countries, is designed to provide information on the innovation activities of companies by type of enterprises (size, sector), on different types of innovation and on various aspects of the development of an innovation. The latter involves the objectives, the sources of information and the private and public funding of research and development activities.

The four waves of CIS employed here (CIS 4, CIS 2006, CIS 2008 and CIS 2010) differ somewhat in scope and coverage.[6] In addition to changes in participating countries, the differences also stem from changes in the questionnaire itself. The most pronounced changes were implemented in CIS 2008 to reflect the suggestions of the third revision of the Oslo manual (2005), such as differentiation between technological and non-technological innovation. The second reason for the changes in CIS 2008 was also the implementation of NACE Rev. 2, whereas the previous waves are based on NACE Rev. 1. In addition to the industries, which were considered core and were included mandatorily,[7] other industries were added to individual waves based on a voluntary basis.

In addition to covering a broad sample of EU countries, the survey also includes Norway, Iceland, Bulgaria, Romania and Croatia, which were not EU member states in all (or none as the case may be) of the survey waves. The survey is conducted on enterprises with at least 10 employees and the respondents provide information on innovation activity for a reference period of the past three years. The data available from Eurostat is aggregated across countries, industries, size classes, types of innovation activity and firm type with respect to internationalization. The additional issue with the data is that Eurostat provides innovation information for a breakdown of firms according to whether they are

[6] The structure of the survey changed substantially between CIS III and CIS 4. Given the breaks in both the country coverage, structure of the questionnaire and the timing of the survey, we only include surveys from 2004 onwards.

[7] Core (mandatory) coverage of CIS prior to CIS 2008 includes following NACE Rev.1 sectors: mining and quarrying (C10-C14), manufacturing (D15-D37), electricity, gas and water supply (E40-E41), wholesale trade and commission trade, except of motor vehicles and motorcycles (G51), transport, storage and communication (I60-I64), financial intermediation (J65-J67), computer and related activities (K72), architectural and engineering activities (K74.2), technical testing and analysis (K74.3).

Since 2008, the core industries are defined in terms of NACE Rev.2 sectors, i.e.: mining and quarrying (B05-B09), manufacturing (C10-C33), electricity, gas steam and air conditioning supply (D35), water supply; sewerage, waste management and remediation activities (E36-E39), wholesale trade, except of motor vehicles and motorcycles (G46), transportation and storage (H49-H53), publishing activities (J58); telecommunications (J61); computer programming, consultancy and related activities (J62), information services activities (J63), financial and insurance activities (K64-K66), and architectural and engineering activities; technical testing and analysis (M71).

foreign owned or part of a firm group as well as where their primary markets are (local, regional, national, etc.). Given that data for all firms are not provided separately, we use the average of all firm types for our analysis.

Given the available aggregated data, we have constructed a CIS database at the industry level. The database provides information on numbers of innovating firms by country, industry, size class and type of innovation (such as technological (product and process) and non-technological (organizational and marketing) innovation). We provide greater detail on types of firms according to their innovative activity in Appendix A. We also collect information on the average employment, average total sales and average turnover from newly introduced products (services). We use the combination of three variables to construct the corrected employment growth variable ($l$) and output growth due to introduction of new products ($g$) for two-year intervals.

We merge the CIS dataset with Eurostat's data on Human Resources in Science and Technology (HRST), which provide information on the number and share of human resource and science and technology workers in total number of employees. By definition of the Canberra manual (OECD, 1995) human resources are considered to be those employees that have either successfully completed tertiary education or not formally qualified as above but employed in a science and technology occupation where the above qualifications are normally required. Eurostat does not include managers (ISCO 1) in the HRST population and we choose to focus only on the subset of population ages 25-64 years. We use the share of HR employees in total employment and information on the shares of HR professionals by education, by occupation and by core HR professions. Finally, we also employ data on the share of scientists and engineers in the population of employees.

The data is, again, aggregated by country, year and industry.[8] The data is only available for broad categories of NACE at the 1-letter level. This impacts the analysis and regression results at the latter stages.

The final dataset employed in the analysis is the Eurostat's Comext data on internal and external bilateral trade of EU countries. Here we utilize information on the value of imports from China to any of the EU countries as well as data on imports to the reference country from the remaining EU 27 countries. We construct the share of Chinese imports in EU-28 imports by industry to measure the impact of Chinese competition in a given country-sector-year combination. All data are provided at the HS 2-digit level and we employ the appropriate concordance tables to the NACE Rev.2 1-letter classification in order to merge the dataset to both innovation and HRST databases.

[8] Note that the HRST data does not include information separated by size classes.

Note that data before 2008 was collected according to the NACE Rev. 1 classification, while after 2008 data is available according to the NACE Rev. 2 classification. The data before and after 2008 was matched, where possible, at NACE 2-digit code using the concordance table between NACE Rev.1 and NACE Rev.2 classifications.[9]

Finally, we combined all three datasets using the NACE Rev.2 1-letter code. The complete dataset provides us with information on 28 EU countries (the number varies somewhat due to changes in EU membership) disaggregated by NACE Rev.2 1-letter classification of industries. Table 1 presents the sample breakdown in terms of number of observations for the whole period 2004-2010.

**Table 1:** Data sample breakdown: number of observations for the period 2004-2010

| | | NACE Rev.2 codes | | | | |
|---|---|---|---|---|---|---|
| | Variable | **A-B** | **C** | **D-F** | **G-N** | **Total** |
| 2004 | Innovation share | 145 | 310 | 160 | 270 | 885 |
| | Employment | 87 | 176 | 94 | 135 | 492 |
| | High Skilled share | 360 | 405 | 810 | 405 | 1,980 |
| | Chinese Import share | 405 | 405 | 0 | 0 | 810 |
| 2006 | Innovation share | 120 | 315 | 195 | 285 | 915 |
| | Employment | 95 | 225 | 146 | 176 | 642 |
| | High Skilled share | 390 | 420 | 840 | 420 | 2,070 |
| | Chinese Import share | 405 | 405 | 0 | 0 | 810 |
| 2008 | Innovation share | 110 | 320 | 290 | 265 | 985 |
| | Employment | 194 | 354 | 518 | 270 | 1,336 |
| | High Skilled share | 546 | 318 | 954 | 318 | 2,136 |
| | Chinese Import share | 756 | 378 | 0 | 0 | 1,134 |
| 2010 | Innovation share | 123 | 360 | 382 | 312 | 1,177 |
| | Employment | 217 | 423 | 587 | 336 | 1,563 |
| | High Skilled share | 0 | 457 | 1,128 | 420 | 2,005 |
| | Chinese Import share | 658 | 451 | 0 | 0 | 1,109 |

*Notes*: A-B – Agriculture, forestry and fishing and Mining and quarrying, C – Manufacturing, D-F – Energy supply, Water supply, waste management and Construction, G-N – Business services.

*Innovation share* represents the share of respondent firms that declared themselves as innovators (either product, process, organizational or marketing); *Employment* is total employment; *High skilled* measures the share of university graduates and people employed in positions that would otherwise require a degree in total employment; and *Chinese import share* is measured as value of total sector imports from China relative to imports of the sector from the rest of the EU-28.

[9] Note that HRST data is available only at NACE 1-letter code, which required a lot of sacrifices in terms of number observations.

Since data in different sources has incomplete coverage across countries and industries, we are left with diverging sizes of samples for different variables. Unfortunately, when matching the datasets we are restricted to the smallest size sample, which is usually the innovation data or employment data. Hence, in 2004 our sample comprises 492 datapoints, increasing to 1,177 datapoints in 2010. The sample size is further reduced when we calculate growth rates for employment and sales and when accounting for lagged variables.

## 3.2. Summary statistics

We present a brief summary of some key variables in Table 2, which features country-industry average values of share of innovators by type of innovation, share of high skilled labor and share of scientists and engineers in the population of employees.

**Table 2:** Summary of key variables: shares of innovative firms by type of innovation and share of skilled and scientific workers in total employment, period 2004-2010

| | | **A-B** | **C** | **D-F** | **G-N** | **Total** |
|---|---|---|---|---|---|---|
| 2004 | Any innovation | 0.327 | 0.558 | 0.311 | 0.465 | 0.476 |
| | Prod. & Proc. Innov. | | | | | |
| | Org. & Mark. Innov. | | | | | |
| | High Skilled | 0.129 | 0.265 | 0.201 | 0.474 | 0.292 |
| | Scient. & Prof. | 0.021 | 0.046 | 0.039 | 0.059 | 0.037 |
| 2006 | Any innovation | 0.353 | 0.566 | 0.410 | 0.455 | 0.480 |
| | Prod. & Proc. Innov. | | | | | |
| | Org. & Mark. Innov. | | | | | |
| | High Skilled | 0.134 | 0.271 | 0.203 | 0.483 | 0.297 |
| | Scient. & Prof. | 0.022 | 0.048 | 0.042 | 0.061 | 0.040 |
| 2008 | Any innovation | 0.460 | 0.666 | 0.559 | 0.587 | 0.588 |
| | Prod. & Proc. Innov. | 0.186 | 0.213 | 0.161 | 0.142 | 0.157 |
| | Org. & Mark. Innov. | 0.289 | 0.440 | 0.377 | 0.435 | 0.420 |
| | High Skilled | 0.155 | 0.155 | 0.239 | 0.495 | 0.256 |
| | Scient. & Prof. | 0.022 | 0.022 | 0.047 | 0.061 | 0.064 |
| 2010 | Any innovation | 0.435 | 0.650 | 0.607 | 0.597 | 0.591 |
| | Prod. & Proc. Innov. | 0.158 | 0.190 | 0.160 | 0.136 | 0.148 |
| | Org. & Mark. Innov. | 0.246 | 0.444 | 0.413 | 0.450 | 0.430 |
| | High Skilled | 0.145 | 0.292 | 0.232 | 0.508 | 0.365 |
| | Scient. & Prof. | 0.022 | 0.053 | 0.044 | 0.063 | 0.047 |

*Notes*: A-B – Agriculture, forestry and fishing and Mining and quarrying, C – Manufacturing, D-F – Energy supply, Water supply, waste management and Construction, G-N – Business services.

*Any innovation* represents the share of respondent firms that declared themselves as innovators (either product, process, organizational or marketing), *Prod. & Proc. Innov.* and *Org. & Mark. Innov.* represents shares of firms engaging in product and process or organizational and marketing innovation, respectively. *High skilled* measures the share of university graduates and people employed in positions that would otherwise require a degree in total employment, and *Scient. & Prof.* represents the share of scientific and professional workers in total employment.

Prior to CIS 2008, information on innovation was available only for two types of technological (process and product) innovation, while CIS 2008 and later includes also information on non-technological (organizational and marketing) innovation. Table 2 reveals that, on average across countries, the largest share of innovative firms are in the manufacturing sector, followed by business services and energy and water supply, waste management and construction, while the lowest shares are recorded in the agriculture, forestry and fishing and mining and quarrying. On the other hand, business services have the largest shares of skilled workers and of scientific and professional workers in total employment, followed by energy and water supply, waste management and construction industries.

What we are interested in, however, is the dynamics of innovation, employment and skill upgrading over time. Table 3 presents changes of main variables over the sample period, indicating that between 2004 and 2010 the overall share of innovative firms has increased by almost 12 percentage points. The largest innovation gains were recorded in energy and water supply, waste management and construction, followed by business services. The former industries also recorded the highest increases in employment. All sectors also engaged in skill upgrading by increasing shares of skilled workers on average by 7 percentage points and the shares of scientific and professional workers by 1 percentage point.

**Table 3:** Changes of main variables over the sample period between 2004 and 2010

| | A-B | C | D-F | G-N | Total |
|---|---|---|---|---|---|
| Share of innov. firms* | 10.8 | 9.2 | 29.6 | 13.2 | 11.5 |
| Employment# | 3.1 | 33.9 | 157.6 | 29.5 | 31.9 |
| Share of High Skilled* | 1.6 | 2.7 | 3.0 | 3.4 | 7.3 |
| Share of Scient. & Prof.* | 0.0 | 0.7 | 0.5 | 0.5 | 1.0 |

*Note*: * in per cent; # in percentage points.

Table 4 shows that employment growth is correlated with innovation, whereby product and process innovation seem to positively affect employment growth, while organizational and marketing innovation exhibit a negative impact. Employment growth does not seem to be significantly associated with skill upgrading, but the latter seems to be positively associated with all types of innovation. Finally, Chinese import penetration seems to positively affect employment and sales growth, but has a mixed effect on innovation and a negative effect on skill upgrading.

In the next section we present more thorough empirical results on how different types of innovation contributed to employment growth and skill upgrading.

**Table 4:** Correlation matrix for main variables, complete sample in 2004-2010

| | Δ Empl. | Δ Sales | All innov. | Prod. & Proc. | Org & Mark. | High Skilled | Scient. & Prof. | Chin. imports share |
|---|---|---|---|---|---|---|---|---|
| Δ Empl. | 1 | | | | | | | |
| Δ Sales | 0.87* | 1 | | | | | | |
| All innov. | -0.13* | -0.13* | 1 | | | | | |
| Prod. & Proc. | 0.09* | 0.14* | 0.28* | 1 | | | | |
| Org. & Mark. | -0.08* | -0.10* | 0.73* | -0.05* | 1 | | | |
| High Skilled | -0.01 | -0.04* | 0.25* | 0.08* | 0.33* | 1 | | |
| Scient. & Prof. | 0.01 | 0.01 | 0.13* | 0.18* | 0.15* | 0.69* | 1 | |
| Chinese imp. share | 0.03* | 0.05* | 0.04* | 0.10* | -0.06* | -0.30* | -0.31* | 1 |

*Note*: * Significantly different from zero at 10 per cent.

# 4. Results

This section presents empirical results on impact of innovation on employment growth and skill upgrading by using the approach presented in section 3. We first present results of impact of innovation on employment growth and then proceed with the results for skill upgrading.

## 4.1. Impact of innovation on employment growth

We estimate empirical model (5) to infer about the impact of innovation on employment growth. As explained above, the model is estimated using industry level data for a panel of four CIS waves for 28 EU countries. The model includes industry, country and year fixed effects, which makes fixed effects regression model the obvious choice. In all subsequent estimations, we use AREG specification[10] with industry-country-year fixed effects. All estimations include robust standard errors.

Base results are presented in Table 5. Results indicate that product innovation, as reflected in differential output growth of the new products, has a consistent positive effect on employment growth. The effect is similar for manufacturing and service industries. Process innovation, on average, does not have any impact

[10] AREG is another form of fixed effects (FE) regression analysis producing equivalent results. In contrast to the FE regression, AREG does not transform the variables using time-demeaning transformation, but instead creates a full set of specific fixed effects of choice (in our case, industry-country-year fixed effects).

on employment growth implying that there are no displacement effects of process innovation neither in manufacturing nor in service industries.

**Table 5**: Impact of innovation on employment growth, base results with process innovation only, period 2004-2010 [dependent variable: employment growth]

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Sales | | 0.591*** | 0.591*** | 0.601*** |
| | | (26.42) | (26.17) | (14.14) |
| Δ Sales *Service | | | | -0.014 |
| | | | | (-0.29) |
| Process innov. | 0.002 | -0.026 | -0.041 | -0.126 |
| | (0.03) | (-0.37) | (-0.58) | (-1.13) |
| Process innov.*Service | | | | 0.138 |
| | | | | (1.17) |
| High skilled | -0.426*** | -0.432*** | | -0.316*** |
| | (-3.99) | (-4.68) | | (-2.73) |
| High-skilled *Service | | | | 0.066 |
| | | | | (0.52) |
| Scient. & Prof. | 0.119* | 0.092* | -0.024 | -0.139* |
| | (1.93) | (1.77) | (-0.51) | (-1.79) |
| Scient.&Prof.*Service | | | | 0.311*** |
| | | | | (4.13) |
| Chinese imp.share | -0.017 | -0.040 | -0.043 | -0.026 |
| | (-0.58) | (-1.38) | (-1.48) | (-0.91) |
| Constant | 11.189*** | 11.190*** | 9.731*** | 10.730*** |
| | (25.16) | (27.82) | (40.51) | (25.32) |
| Observations | 762 | 737 | 737 | 737 |
| R-squared | 0.873 | 0.907 | 0.907 | 0.915 |

*Notes*: Dependent variable is employment growth. Fixed effects estimations with industry-country-year fixed effects. Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Increases in shares of high skilled workers and shares of scientific and professional workers have opposite effects on employment growth – the former has a negative effect, while the latter positively contributes to employment growth. Both effects, however, are driven by the services industries. Finally, Chinese import penetration has a negative, but marginally insignificant effect on employment growth. This implies that, in general, Chinese import competition has not significantly contributed to lower employment growth in manufacturing.[11]

In Table 6, we further differentiate between different types of innovation. Process innovation, on average, still does not have any impact on employment growth. However, when interacting process innovation with the service industry dummy

[11] Note that we only dispose with data on goods trade, which can be attributed to manufacturing industries only and hence cannot test this effect for service industries.

we find a negative significant impact on employment growth in manufacturing, but a positive impact on employment in service industries. As a matter of fact, both effects are similar in magnitude but of opposite signs, so they cancel each other out.

**Table 6**: Impact of innovation on employment growth, results with different types of innovation, period 2008-2010

| | (1) | (2) | (3) |
|---|---|---|---|
| Δ Sales | | 0.676*** | 0.684*** |
| | | (32.93) | (22.44) |
| Δ Sales *Service | | | -0.011 |
| | | | (-0.27) |
| Process innov. | 0.028 | -0.001 | -0.130* |
| | (0.59) | (-0.02) | (-1.69) |
| Process innov.*Service | | | 0.139* |
| | | | (1.66) |
| Org. & Mark. innov. | 0.351*** | 0.307*** | 0.452*** |
| | (3.36) | (3.69) | (3.90) |
| Org. & Mark.*Service | | | -0.179 |
| | | | (-1.46) |
| High skilled | -0.459*** | -0.378*** | -0.310*** |
| | (-3.27) | (-3.68) | (-2.61) |
| High-skilled *Service | | | 0.118 |
| | | | (0.92) |
| Scient. & Prof. | 0.090 | 0.039 | -0.132* |
| | (1.09) | (0.68) | (-1.82) |
| Scient.&Prof.*Service | | | 0.222*** |
| | | | (3.28) |
| Chinese imp.share | 0.029 | -0.015 | -0.008 |
| | (0.60) | (-0.32) | (-0.18) |
| Constant | 11.893*** | 11.486*** | 10.883*** |
| | (18.74) | (21.69) | (19.27) |
| Observations | 399 | 387 | 387 |
| R-squared | 0.908 | 0.947 | 0.957 |

*Notes*: Dependent variable is employment growth. Fixed effects estimations with industry-country-year fixed effects. Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

On the other hand, organizational and marketing innovations reveal a consistent positive impact on employment. On average, increasing the share of firms engaged in organizational and marketing innovation by 10 per cent would lead to an increase of employment by 3 to 4.5 per cent. This implies that, after controlling for product and process innovation, organizational and marketing innovations have an important positive impact on efficiency gains, which does not hurt employment. This is true both for manufacturing and service industries, whereby the effects for the latter might be a bit smaller in magnitude (though the coefficient on interaction term is marginally insignificant).

Above finding is consistent with previous empirical studies showing that in manufacturing industries process innovation may lead to labor displacement effects, which are more than balanced by the compensation effects stemming from product innovation and organizational and marketing innovation. In service industries, however, process innovation does not seem to have any displacement effects.

Results for the impact of high skilled labor and scientific workers on employment growth remain unaltered. Chinese import penetration is still shown to have no impact on employment growth in manufacturing. This is in contrast to the findings by Bloom et al (2011), who find a negative impact of Chinese import competition on employment in six EU countries. However, as Bloom et al (2011) use firm-level data while we use country-industry-level data, one can argue that these negative effects that may arise at the firm level might cancel each other out once being aggregated to the industry level.

## 4.2. Impact of innovation on skill upgrading

In this section we present results on the impact of innovation on skill upgrading by estimating the model (6). As above, the model was estimated using AREG specification with industry-country-year fixed effects.

Table 7 presents results with lagged innovation variables and lagged variable on Chinese import penetration as explanatory variables. This specification was chosen to mitigate the issue of potential simultaneity as the demand for skilled labor may be jointly determined with firm's innovation efforts. As organizational and marketing innovation are observed in CIS 2008 and CIS 2010 only, using this specification means that the model is effectively estimated for the period captured by the CIS 2010 (i.e. for 2009-2010). The drawback of this specification is that results might capture mainly the effect of the economic crisis 2009-2010 on skill upgrading. To minimize this adverse effect, we control for the overall changes in employment and overall turnover.

Our prior is that innovation of any type is positively correlated to increased demand for skilled workers. Table 7 essentially confirms this by demonstrating a positive impact of product innovation (as reflected in increased turnover), process innovation and of organizational and marketing innovation on skill upgrading. On average, increasing the turnover of newly introduced products by 10 per cent leads to an increase in share of high skilled labor by about 0.5 per cent. On the other hand, increasing the share of firms engaged in process innovation by 10 per cent leads to an increase in share of high skilled labor by 2 per cent and an increase in share of scientific workers by 1 per cent. Moreover, increasing the share of firms engaged in organizational and marketing innovation by 10 per cent leads to an increase in share of high skilled labor by 4 per cent and an increase in share of scientific workers by 2 per cent.

**Table 7**: Impact of innovation on skill upgrading, results with different types of innovation, period 2008-2010

| | (1) All high skilled | (2) high skilled by education | (3) high skilled by occupation | (4) Scientific & prof. workers |
|---|---|---|---|---|
| Δ Employment | -0.094*** | -0.094*** | -0.096*** | -0.077** |
| | (-3.26) | (-2.67) | (-2.73) | (-2.33) |
| Δ Employ. *Service | 0.103*** | 0.079** | 0.122*** | 0.059 |
| | (3.27) | (2.04) | (3.14) | (1.44) |
| Δ Sales | 0.056* | 0.048 | 0.056 | 0.057* |
| | (1.93) | (1.41) | (1.57) | (1.73) |
| Δ Sales *Service | -0.070** | -0.041 | -0.083** | -0.029 |
| | (-2.27) | (-1.11) | (-2.17) | (-0.78) |
| Process innov. (t-2) | 0.178*** | 0.187*** | 0.219*** | 0.100** |
| | (4.36) | (3.66) | (4.42) | (2.02) |
| Process innov.*Service (t-2) | -0.131*** | -0.161*** | -0.139*** | -0.087 |
| | (-3.10) | (-3.06) | (-2.68) | (-1.60) |
| Org. & Mark. innov. (t-2) | 0.358*** | 0.364*** | 0.439*** | 0.193*** |
| | (7.24) | (6.07) | (6.99) | (2.82) |
| Org. & Mark.*Service (t-2) | -0.266*** | -0.316*** | -0.275*** | -0.163** |
| | (-5.10) | (-5.00) | (-4.24) | (-2.02) |
| Chinese imp.share (t-2) | 0.222*** | 0.175*** | 0.268*** | 0.059 |
| | (5.00) | (3.03) | (5.84) | (1.01) |
| Constant | 5.344*** | 4.127*** | 5.596*** | 1.722*** |
| | (15.88) | (9.53) | (16.13) | (3.98) |
| Observations | 307 | 307 | 307 | 301 |
| R-squared | 0.950 | 0.952 | 0.963 | 0.889 |

*Notes*: Dependent variable indicated in the header of each column. Variables process, organizational and marketing innovation and Chinese import share are lagged by t-2. Fixed effects estimations with industry-country-year fixed effects. Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

These effects of innovation on demand for skilled labor are quite strong. They are, however, confined mainly to manufacturing sector. In service industries, the effects of innovation on skill upgrading are much lower - for process innovation they are lower by some 80 per cent as compared to manufacturing, while for organizational and marketing innovation these skill-upgrading effects are lower by some 60 per cent. This implies that in service industries skill upgrading due to innovation activities of firms is by far more difficult than in manufacturing.[12]

Table 7 also shows that Chinese import penetration has a consistently positive impact on skill upgrading in manufacturing industries, with the exception of scientific workers where the effect is insignificant. Our results indicate that

[12] As a robustness check, we also estimate model (6) using contemporaneous variables on innovation, but the results are qualitatively unaltered. See Appendix B for these results.

increasing the share of Chinese imports in total imports by 10 per cent leads to an increase in share of high skilled labor by 2 per cent.

**Table 8**: Impact of innovation on skill upgrading, results with process innovation only, period 2004-2010

| | (1) All high skilled | (2) high skilled by education | (3) high skilled by occupation | (4) Scientific & prof. workers |
|---|---|---|---|---|
| Δ Employment | 0.003 | -0.002 | 0.033 | -0.038 |
| | (0.11) | (-0.05) | (0.95) | (-1.11) |
| Δ Employ. *Service | -0.002 | -0.007 | -0.033 | 0.021 |
| | (-0.06) | (-0.21) | (-0.91) | (0.56) |
| Δ Sales | -0.007 | -0.004 | -0.029 | 0.027 |
| | (-0.25) | (-0.15) | (-0.75) | (0.81) |
| Δ Sales *Service | 0.013 | 0.018 | 0.043 | -0.005 |
| | (0.45) | (0.59) | (1.08) | (-0.15) |
| Process innov. | 0.131*** | 0.145*** | 0.259*** | 0.077 |
| | (2.75) | (3.00) | (4.35) | (1.45) |
| Process innov.*Service | -0.096** | -0.143*** | -0.184*** | -0.151*** |
| | (-2.17) | (-3.17) | (-3.10) | (-2.99) |
| Chinese imp.share | 0.259*** | 0.239*** | 0.268*** | 0.223*** |
| | (7.85) | (7.43) | (6.85) | (6.96) |
| Constant | 5.357*** | 4.430*** | 5.205*** | 2.745*** |
| | (22.00) | (18.61) | (18.11) | (11.61) |
| Observations | 996 | 978 | 979 | 887 |
| R-squared | 0.903 | 0.926 | 0.897 | 0.892 |

*Notes*: Dependent variable indicated in the header of each column. Fixed effects estimations with industry-country-year fixed effects. Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

As noted in the previous section, this effect might be driven by the period under investigation. Table 7 captures results for period 2008-2010 only, whereby due to the lags imposed on innovation and Chinese import penetration the results mainly reflect the impact of innovation and Chinese import competition for skill upgrading in the panel of CIS 2010 only. To get a broader picture for the whole period, we estimate the model (6) for the panel data of 2004-2010 using contemporaneous variables on innovation and Chinese import penetration (see Table 8). The sacrifice here is to rely on information for process innovation only, while the effect of product innovation remains to be captured by the overall turnover growth.

Results in Table 8, considering the data for the whole period 2004-2010, however, confirm completely the results obtained using a shorter period. Process innovation is shown to drive the demand for skilled labor, whereby in service industries these skill-upgrading effects are again found to be lower by some 60 per cent.

Similarly, Chinese import competition is confirmed to be another driver of skill upgrading with the order of magnitude similar to the one found for the shorter period. Chinese import competition has therefore positively affected skill upgrading in EU-28 countries over the last decade. This is consistent with the "trapped factor" model of innovation developed by Bloom et al (2011), who show that Chinese trade may lead firms to switch from producing older low-tech goods to the design and manufacture of new goods, which in turn is likely to increase the demand for skilled workers. While the above model explains the within-firm efficiency improvements due to increased product competition, an important part of the overall skill-upgrading effect found at the industry level, however, is also due to the between firms reallocation. Increased product competition form China crowds out a number of less efficient domestic firms with below average skill structure leading to the overall improvement of aggregate industry skill structure.

# 5. Conclusions

The paper investigates the dual effect of innovation on employment and skill upgrading. Based on the Harrison et al (2008) approach and using four waves of CIS data for 23 EU countries we first study, depending on innovation type, which of the effects – displacement vs. compensation effect – prevails in the impact of innovation on employment growth. We find that product innovation, as reflected in differential output growth of the new products, has a consistent positive effect on employment growth. This effect is similar for manufacturing industries. Process innovations are found to exhibit no labor-displacement effects neither in manufacturing nor in service industries. On the other hand, organizational and marketing innovations reveal a consistent positive impact on employment. On average, increasing the share of firms engaged in organizational and marketing innovation by 10 per cent leads to an increase in overall employment by 3 to 4.5 per cent.

In addition, we also study the impact of innovation on skill upgrading. We find that product, process, organizational and marketing innovation have substantial positive impacts on skill demand in manufacturing sector. We find that increasing the share of firms engaged in process innovation by 10 per cent will lead to an increase in share of high skilled labor by 2 per cent, while increasing the share of firms engaged in organizational and marketing innovation by 10 per cent will lead to an increase in share of high skilled labor by 4 per cent and an increase in share of scientific workers by 2 per cent. These effects of innovation on demand for skilled labor are, however, limited mainly to manufacturing sector. We find that in service industries, these effects are lower by some 60 to 80 per cent.

Finally, when studying both issues we also control for the impact of Chinese import penetration. We find no significant impact of Chinese import competition on employment growth in manufacturing industries, but find a strong positive impact on skill upgrading. Our results indicate that increasing the share of Chinese imports in total imports by 10 per cent leads to an increase in share of high skilled labor by 2 per cent. These findings are consistent with the "trapped factor" model of innovation developed by Bloom et al (2011).

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## Appendix A:

Firm type according to innovation (definitions)

**Product innovative enterprises** are those who introduced, during the period under review, new and significantly improved goods and/or services with respect to their fundamental characteristics, technical specifications, incorporated software or other immaterial components, intended uses, or user friendliness. Changes of a solely aesthetic nature and the simple resale of new goods and services purchased from other enterprises are not considered as innovation.

**Process innovative enterprises** implemented new and significantly improved production technologies or new and significantly improved methods of supplying services and delivering products during the period under review. The outcome of such innovations should be significant with respect to the level of output, quality of products (goods or services) or costs of production and distribution. Purely organisational or managerial changes are not included.

**Organisational innovative enterprises** implemented a new organisational method in the enterprise's business practices, workplace organisation or external relations.

**Marketing innovative enterprises** implemented a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing.

**Innovative enterprises** had innovation activities during the period under review, including enterprises with on-going and abandoned activities. In other words, enterprises that had innovation activities during the period under review, regardless of whether the activity resulted in the implementation of an innovation, are innovation-active.

During a given period, innovation activities can be of three kinds:

● successful, in having resulted in the implementation of an innovation (although the innovation need not have been commercially successful);

● on-going, with work in progress that has not yet resulted in the implementation of an innovation.

● abandoned before the implementation of an innovation.

**Non-innovative enterprises** had no innovation activity whatsoever during the reference period. These enterprises answered only a limited set of questions from the survey in relation to the absence of innovation activity, factors hampering innovation, patents and other protection methods, etc. The CIS 2008 and CIS 2010 modules (on eco-innovation and on creativity and skills, respectively) targeted enterprises both with and without innovation activity.