Research Policy 47 (2018) 1762–1776

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms

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ARTICLE INFO

JEL classification:
O31
O33

Keywords:
Technological change
Innovation
Patents
Employment
GMM-SYS

ABSTRACT

This paper explores the possible job creation effect of innovation activity. We analyze a unique panel dataset covering almost 20,000 patenting firms from Europe over the period 2003–2012. The main outcome from the proposed GMM-SYS estimations is the labor-friendly nature of innovation, which we measure in terms of forward-citation weighted patents. However, this positive impact of innovation is statistically significant only for firms in the high-tech manufacturing sectors, while not significant in low-tech manufacturing and services.

1. Introduction and motivation

In the past decades, the emergence and widespread diffusion of a new paradigm based on ICT and automation has led to a dramatic adjustment of the employment levels and structure in all the industrialized economies, triggering intense debates and capturing news headlines (see Brynjolfsson and McAfee, 2012, 2014; Crespi and Tacsir, 2012; OECD, 2016; UNIDO, 2013; World Bank, 2016).

Indeed, the relationship between innovation and employment is a ‘classical’ controversy, where a clash between two views can be singled out. One states that labor-saving innovations create technological unemployment, as a direct effect. The other view argues that product innovations and indirect (income and price) effects can counterbalance the direct effect of job destruction brought about by the process innovations incorporated in new machineries and equipment (for fully articulated surveys, see Calvino and Virgillito, 2018; Petit, 1995; Pianta, 2005; Spiezia and Vivarelli, 2002; Ugur et al., 2018; Vivarelli, 2013, 2014).

In particular, the so-called “compensation theory” – which traces back its origins to classical economists such as Say (1964), Ricardo (1951) and Marx (1961) – puts forward the view that process innovations lead to more efficient production and thus, assuming competitive markets, increasing demand and hence employment (for modelling based on the same hypotheses, see Neary, 1981; Sinclair, 1981; Waterson and Stoneman, 1985). Alternatively – in case of imperfect competition where prices decline with some attrition and lags – innovative firms distribute the benefits associated with the new technologies in the form of extra profits and wages. In turn, these additional incomes can create jobs either through increased investment, or through increased demand due to higher consumption expenditures (see Boyer, 1988; Pasinetti, 1981; Vivarelli, 1995). However, these compensation mechanisms can be seriously dampened in case of monopolistic markets where prices do not decrease due to lack of competition, in case the demand elasticity is low, or when investment and consumption decisions are limited by different factors such as pessimistic expectations or credit rationing (for analyses focusing on these critical aspects, see Freeman and Soete, 1987; Pianta, 2005; Vivarelli, 1995, 2014).

While these controversies center on the overall employment effect of process innovations, there is less debate about the positive employment effect of product innovations. These are generally understood to lead to the opening of new markets, or to an increased variety within the existing ones (see Antonucci and Pianta, 2002; Bogliacino and Pianta, 2010; Ciriaci et al., 2016; Edquist et al., 2001; Falk and Hagsten, 2018; Freeman and Soete, 1987; Katsoulacos, 1984; Vivarelli, 1995).

However, even the labor-friendly impact of product innovation may

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https://doi.org/10.1016/j.respol.2018.06.008
Received 23 January 2017; Received in revised form 14 June 2018; Accepted 14 June 2018
Available online 14 July 2018

vary extensively. The so-called "welfare effect" (the creation of new goods) should be compared with the "substitution effect", *i.e.* the displacement of mature products by the new ones (see Katsoulacos, 1984, 1986): think, for instance, of MP3 format replacing music CDs in turn replacing vinyl.

As it should be obvious even from the brief summary discussed above, theoretical models cannot claim to have a clear answer in terms of the final employment impact of process and product innovation. Price and income mechanisms do have the possibility to compensate the direct labor-saving effect of process innovation, but their actual effectiveness is unsteady and depends on key parameters such as the degree of competition, the demand elasticity, the consumers' and entrepreneurs' expectations. On the one hand, depending on the different institutional and economic contexts, compensation can be more or less effective and technological unemployment only partially reabsorbed (Amendola et al., 2001; Feldmann, 2013). On the other hand, labor-friendly products may overcome the possible labor displacement brought about by process innovation and so foster job creation.

Since economic theory does not have a clear-cut answer about the employment effect of innovation, there is a strong need for empirical analyses able to test the final employment impact of technological change.[1] In particular, a recent strand of literature – based on micro-econometric studies – has the great advantage to allow a direct and precise firm-level mapping of innovation variables and their effect on employment.

This paper aims to provide further and novel empirical evidence within this strand of literature (surveyed in Section 2). In more detail, the novelties of this study are the following.

- We use a unique, longitudinal database of approximately 20,000 patenting firms from 22 European countries, over the period 2003–2012.[2] In comparison with the extant literature which is mainly focusing on single countries, to our knowledge this is the first study characterized by such a comprehensive European coverage and such a large microdata sample[3].
- We proxy innovation with a non-dummy indicator of innovation output (patents), while most of the previous literature (see next Section) use either innovation input indicators (such as R&D) or output indicators imperfectly measured by dummies (such as the dummies for process and product innovation extracted by the Community Innovation Surveys – CIS)[4].

  However, as it is well known in the field of innovation studies, different "innovation proxies" have their *pros* and *cons* (for an assessment on how innovation can be measured, see Smith, 2005): using the number of granted patents, we enrich the extant literature on the employment impact of innovation since we move to a continuous indicator of innovation output; nevertheless, counting patents is not immune from limitations (see next point).

- Indeed, simple patent counting can be seen as a preliminary (and somehow rough) proxy of a firm's innovation effort. As a matter of fact, patents may reflect different firm's strategies (such as deterrence, see Cohen et al., 2000); they are more effective in protecting product *vs* process innovation and therefore more frequently used in some economic sectors rather than in others (see Levin et al., 1987)[5]; moreover, not all patents have the same importance in terms of the nature, pervasiveness and economic potentialities of the related innovations. Indeed, patents vary enormously in their technological importance and economic value, and therefore simple patent counting is not fully informative about the relevance of a given innovation output (see Trajtenberg, 1990).

  Therefore, we measure the impact of innovation also from a "quality" perspective, in order to take into account the relative importance of a given innovation: since patens may refer to innovations that have very different value/quality (and so very different potentialities in terms of their employment impact), we weight them using citations, as common in the reference literature. In particular, we rely on forward-citation weighted patent counts that reflect both the technological novelty of patents (Trajtenberg, 1990) and their economic value (see Gambardella et al., 2008; Harhoff et al., 1999, showing the revealed positive correlation between forward citations and the economic value of a given patent).[6] Although there is a large extant literature – investigating different topics – weighting patents through forward citations, as far as we know this is the first study able to distinguish the relevance of different innovations in assessing their possibly diverse impacts on employment. Our hypothesis being that high-quality innovations might have a larger effect on employment, since their overall impact should be deeper, pervasive and anticipated by the innovative firm

[1] The investigation of the impact of innovation over skills and tasks is out of the scope of the present study; however, the issue is crucial and the extant literature vast. In a nutshell, the relevant debate started in the '90s focusing on the so called "Skill-Biased Technological Change" (SBTC) and pointing to the fact that "technological unemployment" was far more likely for the low skilled and less educated workers (see Acemoglu and Autor, 2011; Berman et al., 1994; Bogliacino and Lucchese, 2016; Machin and Van Reenen, 1998; Piva et al., 2005). More recently, the debate has shifted the focus on the difference between routine-based and non-routine-based tasks, with the former at risk of cancellation (see, among others, Autor and Dorn, 2009; Cirillo, 2017a; Frey and Osborne, 2017; Goos and Manning, 2007; Michaels et al., 2014). In this context, not only low-skilled agricultural and manufacturing jobs appear at risk, but "white collars" in manufacturing and services – including cognitive skills – are no longer protected: see for instance how IBM Watson may displace the majority of legal advices, how Uber is crowding out taxi companies and how Airbnb is becoming the biggest "hotel company" in the world. Frey and Osborne (2017) – using a Gaussian process classifier applied to data from the US Department of Labor – predict that 47% of the occupational categories are at high risk of being automated, including a wide range of service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing. It this context, it has to be recognized that – dealing with the aggregate employment impact of innovation – this paper is unable to disentangle the intrinsic heterogeneity within the labor force, in terms of skills and tasks differently affected by technological transformations.

[2] By construction, the database used in this study only consider firms identified by the EPO/OHIM study (2013) as having filed at least one patent over the period 2004–2008 (see the following Section 3.1). In doing so, and differently from other innovation studies based for instance on CIS surveys, we do not investigate whether and why a firm is innovative, but rather limit the analysis to only innovative firms. However, this is consistent with the purpose of this paper where the research question is whether actual innovation at the firm level (measured on a continuous scale) has a positive or negative impact on employment.

[3] Few previous studies are characterized by a multiple-country dimension: among them, Harrison et al. (2014) covering 4 European countries and Bogliacino et al. (2012), covering 18 European countries (see next section).

[4] The only exceptions being Van Reenen (1997) using the number of relevant innovations in the UK; and Buerger et al. (2010) and Coad and Rao (2011) both using composite innovativeness indexes including patents (see Section 2).

[5] This a general limitation of this study, also recalled in the conclusive remarks in Section 6. In addition, not all the innovations are patentable or immediately patented and this is also a shortcoming of this particular proxy of innovation.

[6] Although being the most popular indicator in the extant literature, forward-citation counting is not the only way to measure the economic value of a given innovation (see Squicciarini et al., 2013 for a detailed discussion of the different available indicators). For instance, Verhoeven et al. (2016) have proposed a multifaceted way to measure the novelty of innovations; although their measures cannot be applied here for data limitations, it has to be noticed that they have been found to be positively correlated with forward-citations (see Verhoeven et al., 2016, pp. 718 and ff.).

as conducive of larger implications in terms of demand evolution and market share appropriability (see Hall et al., 2005; Harhoff et al., 2003).

- We present evidence separately for manufacturing and services and for high-tech *versus* low-tech manufacturing sectors and so we are able to disentangle the possible emergence of job-creating/job-displacing effects across the different economic sectors[7].

The remainder of the paper is organised as follows: Section 2 provides an overview of previous empirical literature on the relationship between innovation and employment at the firm level; Section 3 presents the dataset and the variables; Sections 4 and 5 describe the econometric model and discuss the results. We conclude in Section 6, also providing some policy implications.

2. Previous empirical literature

Since this study uses microdata at the firm level, this section will be limited to discuss the extant microeconometric literature devoted to investigate the link between innovation and employment at the company's level. The interested reader can refer to Sinclair (1981), Layard and Nickell (1985), Vivarelli (1995) and Simonetti et al. (2000) as far as the macro level is concerned, and to Vivarelli et al. (1996), Evangelista and Savona (2002), Antonucci and Pianta (2002), Bogliacino and Pianta (2010), Bogliacino and Vivarelli (2012) and Cirillo (2017b) with regard to the sectoral level.[8]

However – starting in the '90s – the bulk of the econometric literature devoted to investigate the link between technological change and employment has focused on the micro level. Early studies, although interesting, were based on cross-section analyses, unable to control for firms' unobserved heterogeneity and affected by – possibly serious – endogeneity problems (for instance, Entorf and Pohlmeier (1990), finding a positive impact on employment by product innovation; Brouwer et al. (1993), Klette and Førre (1998) and Zimmermann (1991), all finding a prevailing negative employment impact of innovation, with particular reference to process innovation).

More recent studies have fully taken the advantage of new available longitudinal datasets and have applied panel data econometric methodologies that jointly take into account the time dimension and individual variability and so can effectively deal with the unobserved heterogeneity and the endogeneity issues recalled above.

For example, Van Reenen (1997) matched the London Stock Exchange database of manufacturing firms with the SPRU (Science Policy Research Unit at the University of Sussex) innovation database and obtained a panel of 598 British firms over the period 1976–1982. The author found a positive employment impact of innovation (especially when product innovation is isolated) and this result turned out to be robust after controlling for fixed effects, dynamics and endogeneity.[9]

Using a dynamic specification similar to the one tested by Van Reenen (1997) and Piva and Vivarelli (2004, 2005) found evidence in favor of a positive effect – although small in magnitude – of innovation on employment in 575 Italian manufacturing firms observed over the period 1992–1997.

A number of recent studies further explored the displacement or compensation mechanisms due to different types of innovation. Peters (2004) and Harrison et al. (2014) – using the 3rd Community Innovation Surveys (CIS) from France, Germany, UK and Spain – concluded (in accordance with the theoretical literature, see Section 1) that process innovation tends to displace employment, while product innovation is basically labor friendly. Compensation mechanisms were found to be particularly effective in the service sectors through increased demand for new products (see also Evangelista and Savona, 2003; Evangelista and Vezzani, 2012).[10]

Interestingly, Lachenmaier and Rottmann (2011) are somewhat in contrast with the former findings. The authors applied a dynamic employment equation (GMM-SYS) on a very comprehensive dataset of German manufacturing firms over the period 1982–2002: their estimates show a positive, significant impact of different innovation measures on employment, with the positive impact of process innovations even higher than that of product innovations.

Moving to even more recent contributions, Pantea et al. (2017) investigate the employment impact of ICT using firm-level EUROSTAT data; running first difference OLS, the authors found that different proxies of ICT use have a statistically insignificant labor-saving effect across countries and sectors.[11]

Finally, Dachs et al. (2017) applied the model developed by Harrison et al. (2014) to investigate the employment impact of innovation over the different phases of the business cycle. Using firm-level pooled data from five CIS waves in 26 European countries over the period 1998–2010 (EUROSTAT data) and running IV regressions, they found that product innovations were labor friendly in all the phases of the business cycle, while process innovation and organizational change exhibited a labor-displacing nature during both upturn and downturn periods.

Since in this contribution we will split our micro analysis according to sectoral belonging, it is useful to look at prior literature to investigate whether some previous studies have singled out sectoral specificities in the relationship between innovation and employment.

Indeed, a handful of microeconometric studies found important differences in the employment job creation effect of innovation across different industry groups. For instance, Buerger et al. (2010) – using data concerning four manufacturing sectors across German regions over the period 1999–2005 – have studied the co-evolution of R&D expenditures, patents and employment through a VAR methodology. Their main result is that patents and employment turned out to be positively and significantly correlated in two high-tech sectors (medical and optical equipment and electrics and electronics), while not significant in the other two more traditional sectors (chemicals and transport equipment).

A positive relationship between innovation and jobs is also found by Coad and Rao (2011) who limit their focus on U.S. high-tech manufacturing industries over the period 1963–2002 and investigate the

[7] As detailed in Section 2, few previous studies have compared the employment impact of innovation across different sectors.

[8] Still at the industry level of analysis, a very recent debate has emerged about the sectoral employment impact of artificial intelligence and robots, opposing scholars confident in the complementarity between these new technologies and humans (Autor, 2015) and those predicting mass unemployment across a wide range of jobs and tasks (Frey and Osborne, 2017). Among the few empirical studies on the issue, Graetz and Michaels (2015) – running OLS and 2SLS estimates in long differences using industry-country data on robot intensity across 17 countries over the 1993–2007 period – found no evidence of any impact of robot densification over the aggregate hours worked; in contrast, Acemoglu and Restrepo (2017) – running cross-sectional estimates in long differences using data about the sectoral exposure to robots in US local labor markets over the period 1990–2007 – found a negative impact on employment.

[9] Using the SPRU database, the author only considers "commercially successful" innovations; in this respect, this is the only previous contribution

(*footnote continued)*
taking into account the "quality" of innovation, an aspect that is central to our study. However, in this paper we introduce a measurement of quality (see Section 3.2) and we can distinguish different degrees of innovation quality.

[10] Using a model similar to Harrison et al. (2014) and Hall et al. (2008) found a positive effect on employment of product innovation and no evidence of employment displacement due to process innovation using a panel of Italian manufacturing firms over the period 1995–2003.

[11] In contrast, Kılıçaslan and Töngür (2017) – running GMM estimates using an unbalanced panel of 43,567 Turkish manufacturing firms over the 2003-2013 period – found an employment-enhancing impact of ICT technologies, in particular tangible ICT capital (office and computing equipment and communication equipment).

impact of a composite innovativeness index on employment. The main outcome of their quantile regressions is that innovation and employment are positively linked, and that innovation has a stronger impact for those firms that reveal the fastest employment growth.

By the same token, Bogliacino et al. (2012) – using a panel database covering 677 European manufacturing and service firms over 19 years (1990–2008) – found that a positive and significant employment impact of R&D expenditures is clearly detectable only in services and high-tech manufacturing but not in the more traditional manufacturing sectors, where the employment effect of technological change is not significant (see also Bogliacino and Vivarelli, 2012).

Finally, Kancs and Siliverstovs (2017) put forward an original econometric approach where R&D expenditures were considered the "treatment effect" in a Generalised Propensity Score (GPS) model. Using JRC-IPTS Scoreboard microdata, the authors focused on 483 companies in the high-tech sectors in the year 2007. Their results showed a non-linear employment impact of R&D expenditures with a positive and significant impact detectable only at the medium and medium-high innovation intensity levels.

On the whole, recent microeconometric studies offer a detailed mapping of the job-creating impact of innovation which generally turns out to overcome its possible job displacement effects. However, the (few) studies investigating the sectoral dimension reveal that this labor-friendly impact is generally limited to the high-tech sectors, characterized by a higher R&D intensity and by the prevalence of product innovation.

3. Data and variables

3.1. Data

Our original dataset is based on a panel of European patenting firms. We make use of a joint statistical effort made by the European Patent Office (EPO) and the Office for Harmonization in the Internal Market (OHIM). In particular, we matched company accounting data originating from ORBIS[12] with patent and patent quality information from the OECD PATSTAT dataset using firm-patent concordance tables developed by EPO and OHIM (2013). This allowed us to assign a quality measure – based on forward citations – to patents and to control for differences across patent classes.

The matched dataset covers 63,561 EU-based, patenting firms from 27 EU Member States for the years 2003–2012 and belonging to manufacturing and service sectors. This unique database provides information on firms' legal aspects and location, industrial activity (NACE sector) and fundamental economic information (including employment, sales, value added, capital formation, and cost of labor).

We then cleaned our dataset following a methodology similar to that applied by Hall and Mairesse (1995); in particular: (1) we excluded firms for which either sectoral belonging, employment, value added, fixed assets or cost of labor were missing or not positive; (2) we dropped outliers in both levels and growth rates.[13] A more detailed discussion of the data sources and the cleaning process can be found in the Appendix A. Here it is enough to notice that the economic data provided by ORBIS are rather patchy and their quality is heterogeneous across countries. Across the 27 EU countries, almost 60% of firms were dropped in what was described above as step (1), and about 4% in step (2). As a consequence, countries with relatively better data quality and a larger number of available observations – mostly Italy – are overrepresented in the cleaned sample, while others – most notably the UK – are underrepresented (see Table A5 in the Appendix A).[14] Obviously, the fact that our resulting dataset is unbalanced in terms of country coverage might imply a possible bias due to structural and institutional factors[15] that can play a role in the investigated relationship between innovation and employment.[16]

Eventually, our final sample comprises 23,111 firms, further reduced to 19,978 companies (resulting in 104,074 observations) for computational reasons concerning our estimation procedure (see Section 4). The resulting sample covers 56% of the granted patents in the sample countries in the relevant period.

3.2. Variables and descriptive statistics

Our dependent variable is denoted by the natural logarithm of the number of employees within the firm. Explanatory variables of the models are derived from a standard labor demand function (see Section 4) and include firm output, gross investment and labor cost. In particular, we measure firm output through the natural logarithm of value added and gross investment through the annual rate of growth in fixed assets; finally, labor cost is measured as the natural logarithm of the gross wage per employee. Value added, fixed capital investment and labor cost were deflated using industry-specific deflators.[17] While we expect a negative impact of the labor cost on labor demand, the other two variables are expected to contribute with a positive sign.

Prior studies assessed the impact of innovation on labor demand by using input measures of innovation such as R&D expenditures, or discrete output measures such as innovation dummies (see Section 2). However, these indicators are not without drawbacks; indeed, the link between R&D expenditures and successful innovative outcomes involves lags, uncertainty and superadditive effects (Amoroso, 2017; Dosi, 1988; Dosi and Nelson, 2013; Nelson and Winter, 1982), while innovation dummies do not capture differences of magnitude and quality in innovation outcomes.

To overcome these disadvantages, we use the natural logarithm of citation-weighted patents in our model. As already discussed in Section 1, the selected key impact variable is characterized by some advantages and some limitations. In particular, patents better proxy product innovation rather than process innovation for which other appropriability instruments are preferred (see Levin et al., 1987; Lissoni et al., 2013). Indeed, while new products are patented to prevent imitation and reverse engineering, process innovations are often embodied in new machineries provided by supplier companies. Hence, process innovations can be kept secret more easily and therefore are more rarely patented, so accounting for only about 20/30% of total patents (Arundel

[12] ORBIS is a commercial database of Bureau van Dijk which provides legal and financial information on companies worldwide. Data originates from company reports collected by different providers specific to each country.

[13] This was carried out by allocating firms to four groups based on size in which we allowed smaller firms to grow more than larger ones (see Appendix A).

[14] At least part of this country unbalances can be attributed to the fact that companies below a certain threshold in terms of employment and value added are allowed to file abbreviated financial accounts in many countries in our sample.

[15] Examples of national/institutional factors that may have an impact on the relationship between innovation and employment at the firm level and that are not explicitly considered in this study are the following: the particular structure of a given workforce in terms of gender, age and skills (see also footnote [1]); the degree of flexibility of the labor market in terms of wages and labor mobility (Gomez-Salvador et al., 2006; Grimalda, 2016); the union coverage, since unionized workers can appropriate the rents associated to technological progress and so involving a disincentive to invest in innovation, although other theoretical arguments may contradict this conclusion (see, for example, Grout, 1984; Ulph and Ulph, 1994); the nature of the industrial relations, whether centralized or decentralized.

[16] While this data limitation has to be explicitly admitted, any possible institutional bias should have been mitigated by the insertion of country dummies in all the performed regressions (see below). In addition, in Table B4 in the Appendix B, we provide estimations excluding the over-represented Italian firms; as can be seen, results remain virtually unchanged.

[17] In more detail, financial information provided in current prices in the ORBIS database were converted into constant prices by using sectoral GDP deflators (source: Eurostat National Accounts) centered on the year 2005.

and Kabla, 1998; Conte and Vivarelli, 2014). Since product innovations tend to be more labor-friendly than process innovation (see Sections 1 and 2), this bias in our key impact variable will have to be taken into account in interpreting our results (see Section 6).[18]

The patent quality indicator we use for the regression estimations is denoted as follows:

$$Weighted\quad patents_{i,t} = \sum_{p=1\,\in i,t}^{n} \frac{1 + Forward\quad citations_{p,\,t,f}}{Max.\quad Forward\quad citations_{t,f}} \tag{1}$$

This indicator is obtained by augmenting a simple patent count by the number of subsequent citations that a patent p receives, with forward citations counted over a period of three years after the patent's publication date.[19] The weighted patent indicator is normalized by technology field f and filing year t in order to account for the differences in citation patterns across technology fields and over time (*i.e.* we control for the well-known circumstance that patents are more cited in certain technology fields and years, while less in others). This is implemented by dividing the forward citations received from each patent p by the maximum number of forward citations in the same technology field and filing year, prior to summing up all patents issued by firm i in the year t.[20]

Finally, we lag our patent indicator by 3 years, to take into account the potential delay in the possible impact of innovation on employment.[21]

In addition to the specifications with the preferred patent quality indicator, we also run the regressions using a simple normalized patent count indicator.

To control for industry, year and country-specific differences in labor demand dynamics, we include 22 industry-, 9 year- and 22 country-dummies in the model.

Table 1
Description of variables used.

Variable name	Variable definition
Employment	Natural logarithm of the number of employees in period t
Employment $_{t-1}$	Natural logarithm of the number of employees in period t-1
Value added	Natural logarithm of gross value added
Weighted patents	Natural logarithm of patents weighted by forward citations (3-year window)
Patents	Natural logarithm of patent count
Gross investment	Growth in fixed assets
Labor cost per employee	Natural logarithm of labor cost per employee

Note: The data source of the firm-level financial and employment data is ORBIS, patents and patent citation data were obtained from the OECD PATSTAT database.

Table 1 offers a description of the variables used, while Table 2 reports the summary statistics of the dependent and explanatory variables used in the estimations. It presents scores for the full sample as well as for subsamples of firms with main activity in manufacturing and service sectors. Moreover, we split manufacturing into high and low-tech sectors, according to the Eurostat classification (European Commission, 2016; Hatzichronoglou, 1997). About 73% of the firms in the total sample are active in manufacturing, 53% of which are in high-tech sectors. Service firms are rather heterogeneous, reporting the lowest average logarithmic values of employment, value added, but highest wage levels, while high-tech manufacturing firms have on average the highest logarithmic levels of employment, value added, weighted patents, patents and investment growth. Low-tech manufacturing firms are outperformed by high-tech manufacturing firms in all measures, considering mean logarithmic scores for the variables, and are at par with service sector firms in terms of weighted patents and investments.

Table 2
Summary statistics of the dependent and explanatory variables.

Variable name	Mean	Min.	Max.	SD	SD between	SD within
Full Sample (N = 104,074)						
Employment	4.65	0.69	11.23	1.75	1.77	0.18
Value added	4.21	0.00	12.17	1.83	1.84	0.26
Weighted patents	0.05	0.00	4.43	0.20	0.17	0.08
Patents	0.02	0.00	3.12	0.09	0.08	0.03
Gross investment	0.03	−2.92	5.43	0.28	0.18	0.25
Labor cost per employee	0.37	0.00	1.17	0.11	0.11	0.04
Manufacturing firms (N = 75,546)						
Employment	4.73	0.69	11.23	1.58	1.59	0.17
Value Added	4.26	0.01	12.17	1.66	1.66	0.26
Weighted Patents	0.06	0.00	4.43	0.20	0.17	0.08
Patents	0.02	0.00	3.12	0.10	0.08	0.03
Gross investment	0.03	−2.92	5.42	0.28	0.17	0.25
Labor cost per employee	0.36	0.00	1.09	0.10	0.10	0.04
High-tech manufacturing firms (N = 40,059)						
Employment	4.75	0.69	11.21	1.58	1.60	0.17
Value Added	4.32	0.01	12.17	1.67	1.68	0.26
Weighted Patents	0.07	0.00	4.43	0.24	0.20	0.09
Patents	0.03	0.00	3.12	0.12	0.10	0.04
Gross investment	0.04	−2.92	5.42	0.30	0.18	0.26
Labor cost per employee	0.38	0.00	1.09	0.11	0.10	0.04
Low-tech manufacturing firms (N = 35,487)						
Employment	4.70	0.69	11.23	1.57	1.57	0.17
Value Added	4.18	0.04	11.56	1.65	1.65	0.25
Weighted Patents	0.04	0.00	3.09	0.15	0.13	0.07
Patents	0.01	0.00	1.69	0.06	0.05	0.03
Gross investment	0.03	−2.51	4.48	0.26	0.15	0.23
Labor cost per employee	0.34	0.00	1.09	0.09	0.09	0.04
Services firms (N = 28,528)						
Employment	4.45	0.69	11.17	2.13	2.09	0.21
Value Added	4.09	0.00	11.91	2.21	2.16	0.27
Weighted Patents	0.04	0.00	4.18	0.18	0.16	0.07
Patents	0.02	0.00	2.95	0.09	0.07	0.03
Gross investment	0.03	−2.84	5.43	0.29	0.20	0.25
Labor cost per employee	0.39	0.00	1.17	0.14	0.14	0.05

Notes: Employment, Value added, patents, weighted patents and labor costs are expressed as natural logarithms, while gross investments denote percentage growth.

Correlations among the log-normal variables are presented in Table 3 for the full sample. We note the positive Pearson correlation between the two patent measures and the employment as well as the value added scores.

[18] Moreover, this bias might be more pronounced in the service sectors where patenting is less common (see the limitations of this study listed at the end of Section 6).

[19] The percentage of patents from our firm sample that do not get cited in subsequent patents within a 3-year window equals to 75.64. While this can be considered a limitation of our dataset, it is worthwhile to notice that the limited number of forward-citations makes it less (and not more) likely to find significant results using the weighted patent variable.

[20] Since many patents do not receive any forward citation (see previous footnote), the numerator is increased by 1 in order to keep these patents. Although our normalization procedure is related to technology fields (as standard in the literature) it also takes indirectly into account the differences in patent propensity across industries and according to firm's size; in fact, technological fields (think for instance to drugs) are highly correlated with sectoral belonging and firm's average size (in the cited example large firms in pharmaceutical sector). We refer to Dernis et al. (2015) for stylized facts on the differences in patent propensity of top R&D spenders across high- and low-tech sectors.

[21] Model estimations have also been run with a 2-year lagged patent indicator and yielded similar results (available upon request).

Table 3
Correlation matrix.

	Variables	1	2	3	4	5	6	7
1	Employment	1.000						
2	Employment $_{t-1}$	0.994	1.000					
3	Value added	0.960	0.955	1.000				
4	Weighted patents	0.312	0.310	0.326	1.000			
5	Patents	0.278	0.277	0.290	0.925	1.000		
6	Gross investment	−0.002	−0.019	0.011	0.004	0.004	1.000	
7	Labor cost per employee	0.125	0.136	0.306	0.138	0.116	−0.002	1.000

Notes: N = 104,074 observations; Values expressed as natural logs, apart from gross investments growth. Industry, country and year dummies are omitted due to space limitation.

4. The model

The stochastic version of a standard labor demand augmented by including innovation (see Bogliacino et al., 2012; Lachenmaier and Rottmann, 2011; Van Reenen, 1997 for similar specifications) for a panel of firms *i* over time *t* is:

$$l_{i,t} = \alpha y_{i,t} + \beta\, w_{i,t} + \gamma\; invest_{i,t} + \delta\; innov_{i,t-3} + (\varepsilon_i + \nu_{i,t}) \quad i = 1, .., n;\; t = 1, .., T \tag{2}$$

where small letters denote natural logarithms, *l* is labor, *y* output (in our setting proxied by value added), *w* wages, *invest* is gross investments, *innov* denotes – in our setting – either normalized patent counts or citation-weighted patent counts, ε is the idiosyncratic individual and time-invariant firm's fixed effect and ν the usual error term.

In order to take into account viscosity in the labor demand (as common in the literature, see Arellano and Bond, 1991; Van Reenen, 1997), we move from the static expression (2) to the following proper dynamic specification:

$$l_{i,t} = \chi\; l_{i,t-1} + \alpha y_{i,t} + \beta w_{i,t} + \gamma\; invest_{i,t} + \delta\; innov_{i,t-3} + (\varepsilon_i + \nu_{i,t}) \tag{3}$$

To solve the obvious endogeneity problem in the model (see Section 2), we estimate Eq. (3) using the system GMM approach developed by (Blundell and Bond, 1998).[22] Hence, estimates are obtained by running a system of equations in first differences and in levels, which are run simultaneously (with the level equations also including a set of industry, year and country dummies as controls).

By construction, our dynamic equation suffers from endogeneity due to the presence of the lagged dependent variable in the model. However, endogeneity problems may also arise from other covariates in the model (for instance, it may well be the case that wage and employment decisions are jointly and simultaneously adopted, as well as the output and investment decisions can be jointly affected by a temporary shock). Hence, all the explanatory variables have been cautiously considered as potentially endogenous to labor demand and instrumented in all models, using up to thrice lagged instruments.

Indeed, our choice of instruments was as parsimonious as possible (see Roodman, 2009a,b), once taken into account the outcomes of the autocorrelation tests AR (1), AR (2) and – when necessary – AR (3). In more detail, as instruments for the level equations we used the differenced values of the independent variables, *i.e.* thrice lagged differences in employment, value added, gross investments, wage cost per employee and forward citation-weighted patents. The level equations also include a set of industry, year and country dummies as controls. For the equations in differences we used thrice-lagged values of the above-mentioned explanatory variables as instruments for most of the models, in order to reject the null hypothesis of no autocorrelation (see the AR (1), AR (2) and AR (3) tests reported in the following tables).[23]

5. Econometric results

The results from the GMM-SYS estimation of Eq. (3) using the full sample – 104,074 observations originating from 19,978 European firms – are presented in Table 4. Overall, the model performs well and reveals highly significant coefficients with the expected signs. The positive and highly significant value of the lagged dependent variable confirms path-dependency and persistence in labor demand. The magnitude of this coefficient (0.67)[24] as well as the estimates of the other standard determinants of labor demand, *i.e.* value added (0.30) and gross investments (0.13) are in line with prior studies (see Section 2). Taking into account that process innovation can also be incorporated in new investments, in this first aggregate estimation no evidence of any labor-saving embodied technological change emerges since the expansionary component of capital formation seems to be dominant. Finally, the estimated effect of the labor cost per employee on labor demand is negative as expected.

Turning our attention to the main variable of interest, the estimate shows a positive but not significant effect of simple normalized patent counts over employment. Interestingly enough, moving to our more reliable indicator, the coefficient of citation-weighted patent counts becomes significant at a 95% level. This effect is far from being negligible: if a firm increases its innovative effort and doubles its number of patents (weighted by forward citations), the expected increase in employment amounts to 5%.[25]

As far as the diagnostic tests are concerned, both the Wald test on the overall significance of the regression and the LM tests on the AR(1), AR(2) and AR(3) dynamics are fully reassuring. Instead, the null of adequate instruments is rejected by the Hansen test. However, since it has been shown that the Hansen test over-rejects the null in case of very

[22] An alternative approach for estimating dynamic panel models is the difference GMM, developed by Arellano and Bond (1991). We favor the system GMM estimator since the difference GMM estimator has been proved to be strictly dominated by GMM-SYS when (1) there is strong persistence in the time series (as in our case, with a $\rho = 0.994$, see Table 3) and/or (2) the time dimension and time variability of the panel is small compared with its cross-section dimension and variability, as it is the case in our database (see Bond et al., 2001).

[23] Twice lagged instruments were sufficient to reject auto-correlation for the estimations on high-tech and low-tech manufacturing (see Table 6) as well as for the estimations without Italy (see Appendix B, Table B4).

[24] Table B1 in the Appendix B reports the Pooled Ordinary Least Squared (POLS) and Fixed Effects (FE) estimations of the baseline specification, as robustness checks. However, POLS estimates provide very preliminary and approximate results, since they do not control for unobserved individual effects and for the endogeneity of (at least) the lagged dependent variable, the corresponding coefficient being over-estimated. On the other hand, FE estimates control for individual unobservables but are still affected by the endogeneity of (at least) the lagged dependent variable, the corresponding coefficient turning out to be under-estimated. Indeed, it can be noticed that the GMM coefficients of the lagged dependent variable reported in Table 4 are correctly situated within the corresponding FE (lower bound) and OLS coefficients (upper bound) reported in Table B2.

[25] As discussed in Section 3.2, forward-citations normalized by technological field are considered the standard way to measure patent quality (Hall et al., 2005; Harhoff et al., 2003; Trajtenberg, 1990). However, as an alternative to the forward-citations-based measure of patent quality, we have also considered to use patent scope, defined as the number of distinct IPC classes associated to a given patent, a measure that can also be associated to the technological and economic value of patents (Squicciarini et al., 2013). At any rate, caution is advised when using this index, since the re-classification of patents from the 7th to the 8th edition of IPC results in an overestimation of values prior to 2006 (Squicciarini et al., 2013, p. 10). When we tested our modified baseline regression by using the patent scope variable, we obtained highly similar results, although the coefficient of the patent scope variable turned out to be somewhat smaller (see the robustness check reported in the Appendix B, Table B3).

large samples (Blundell and Bond, 2000; Roodman, 2009a), the same model was run and the Hansen test performed on different random subsamples comprising 10% of the original data; in all the cases, the null was never rejected, providing reassurance on the validity of the chosen instruments.[26]

Since a high instrument count may imply a downward bias in the two-step GMM-SYS standard errors (see Roodman, 2009b, pp. 140–141), to be on the safer side we opted for a one-step methodology; however, a robustness check using a two-step methodology is reported in the Appendix B (Table B2). As can be seen, results are virtually unchanged.

Table 4
Results from GMM-SYS analysis.

	Employment	Employment
Employment $_{t-1}$	0.673***	0.670***
	(0.016)	(0.016)
Value added	0.301***	0.302***
	(0.015)	(0.015)
Patents	0.051	
	(0.040)	
Weighted patents		0.050**
		(0.021)
Gross investments	0.135***	0.131***
	(0.037)	(0.037)
Labor cost per employee	−0.287***	−0.304***
	(0.095)	(0.096)
Constant	0.839***	0.851***
	(0.074)	(0.075)
Time, industry and country dummies	included	included
Observations	104,074	104,074
Number of firms	19,978	19,978
Wald test	6.35***	6.29***
AR(1)	−24.85***	−24.89***
AR(2)	3.01***	2.99***
AR(3)	0.95	0.97
Number of instruments	159	159
Hansen test	535.81***	537.25***

Note: One-step GMM robust standard errors in parentheses. Instrumental variables compromise 3-year lags. *, **, *** indicate 10%, 5% and 1% significance levels. Wald test expressed in millions. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

In order to investigate possible peculiarities of the impact of innovation activity over employment across different sectoral groups, we tested our specification on various subsamples. Table 5 reports the results for the manufacturing and service firms respectively, while results for high-tech and medium-tech manufacturing *versus* low-tech manufacturing firms are presented in Table 6.

As far as the labor demand variables are concerned, estimation results for the manufacturing and services subsamples are very similar to those obtained from the full sample, with the exception of the loss of significance for gross investments in manufacturing.[27]

Focusing our attention on the estimates using the preferred weighted indicator, while the positive effect of innovative activity on employment remains highly significant for the manufacturing subsample, innovation does not seem to play a relevant role in labor demand in the service sectors.

When splitting the samples across high-tech and low-tech

Table 5
Results from GMM-SYS analysis: manufacturing *vs* services.

	Employment			
	Manufacturing		Services	
Employment $_{t-1}$	0.687***	0.686***	0.589***	0.585***
	(0.015)	(0.015)	(0.030)	(0.030)
Value added	0.285***	0.284***	0.397***	0.399***
	(0.014)	(0.014)	(0.030)	(0.030)
Patents	0.045		0.098	
	(0.045)		(0.091)	
Weighted patents		0.048**		0.058
		(0.024)		(0.040)
Gross investments	0.041	0.043	0.170***	0.160***
	(0.036)	(0.036)	(0.052)	(0.051)
Labor cost per employee	−0.204**	−0.211**	−0.826***	−0.859***
	(0.102)	(0.103)	(0.156)	(0.152)
Constant	0.922***	0.936***	0.899***	0.907***
	(0.058)	(0.058)	(0.061)	(0.061)
Time, industry and country dummies	included	included	included	included
Observations	75,546	75,546	28,528	28,528
Number of firms	13,841	13,841	6,137	6,137
Wald test	5.02***	4.98***	0.32***	0.33***
AR(1)	−24.57***	−24.52***	−14.89***	−15.18***
AR(2)	2.18**	2.18**	1.81*	1.78*
AR(3)	1.08	1.09	0.45	0.44
Number of instruments	149	149	147	147
Hansen test	19,000***	9.817***	40,000 ***	7,600 ***

Note: One-step GMM robust standard errors in parentheses. *, **, *** indicate 10%, 5% and 1% significance levels. Wald and Hansen test respectively expressed in millions and thousands. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

Table 6
Results from GMM-SYS analysis: high-tech *vs* low-tech manufacturing.

	Employment			
	High-tech manufacturing		Low-tech manufacturing	
Employment $_{t-1}$	0.676***	0.671***	0.692***	0.694***
	(0.017)	(0.017)	(0.020)	(0.019)
Value added	0.291***	0.293***	0.289***	0.283***
	(0.016)	(0.016)	(0.018)	(0.018)
Patents	0.115***		−0.015	
	(0.043)		(0.079)	
Weighted patents		0.080***		0.001
		(0.025)		(0.038)
Gross investments	0.069**	0.063**	0.035	0.041
	(0.030)	(0.030)	(0.036)	(0.036)
Labor cost per employee	−0.375***	−0.408***	−0.255**	−0.229*
	(0.113)	(0.113)	(0.130)	(0.130)
Constant	0.858***	0.875***	0.340***	0.370***
	(0.118)	(0.121)	(0.077)	(0.073)
Time, industry and country dummies	included	included	included	included
Observations	40,059	40,059	35,487	35,487
Number of firms	7,374	7,374	6,467	6,467
Wald test	2.85***	2.82***	0.68***	0.67***
AR(1)	−19.11***	−19.18***	−17.21***	−17.25***
AR(2)	1.37	1.34	1.51	1.58
Number of instruments	238	238	238	238
Hansen test	422.55***	413.01***	1163.56***	1606.22***

Note: One-step GMM robust standard errors in parentheses. Instrumental variables compromise 2-year lags. *, **, *** indicate 10%, 5% and 1% significance levels. Wald test expressed in millions. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

[26] Results are available from the authors upon request.

[27] This outcome may suggest that in manufacturing the labor-saving process innovation incorporated in capital formation fully counterbalances the expansionary employment impact of new investments. As obvious from reading the following Table 6, this seems to be particularly true in low-tech manufacturing, where labor-saving embodied technological change is more common (for evidences pointing to the possible labor-saving impact of the embodied technological change see Haile et al. (2017), Meschi et al. (2011, 2016), and Piva and Vivarelli (2018).

manufacturing sectors, we find a significant effect of innovation on labor demand for the former category while no significant evidence is observed for the latter category. These results are strongly consistent with prior literature (see Section 2) and further support the view that the labor-friendly impact of innovation is concentrated in the most advanced economic sectors.

6. Conclusions

In this paper we have investigated the impact of innovative activity – proxied by citation-weighted patents – on employment, using a system-GMM approach applied to European microdata. Our findings confirm the labor-friendly nature of innovation at the firm level, in line with prior empirical research (see Section 2).

However, our sectoral estimates show that this positive employment impact is statistically significant only in high- and medium-tech manufacturing sectors, while irrelevant in low-tech manufacturing and in services. Therefore, it seems that patented innovations fully display their labor-friendly nature in the new and emerging sectors, characterized by higher technological opportunities, by higher demand elasticity and by a likely dominance of the “welfare effect” over the “substitution effect” (see Section 1).

These outcomes prove that the aim of the EU2020 strategy (European Commission, 2010) – that is to develop an European economy based on knowledge and innovation – points in the right direction also in terms of job creation. Moreover – since our impact variable takes into account the quality of the introduced innovation – for policy makers it is also reassuring to know that the demand for labor may further increase as the quality of innovation increases. However, European policy makers should also pay attention to the fact that the labor-friendly nature of new technologies appears obvious in only high and medium-tech manufacturing, while, unfortunately, Europe is specialized in more traditional and mature manufacturing and service sectors.

As final remarks, the main limitations of our study have to be recalled, also in order to suggest future avenues of research. Firstly, it is important to keep in mind that this study has only tested the labor-friendly nature of patented innovation, while neglecting the possible labor-saving impact of non-patented process innovation (see Section 3.2); in this respect, the innovation activity considered in this study is conceived in a narrow sense (technical and patentable), while other forms of “embodied technological change” and “soft” innovation are not explicitly taken into account. Secondly, and related to the previous point, patents are surely a better proxy for innovation with regard to manufacturing sectors rather than services; this limitation has to be taken into account in interpreting the non-significant employment impact of innovation in services. Thirdly, our citation-weighted patent indicator may be a more sophisticated measure of innovation than sheer patent counts, but it should be noted that patents are just one of the possible indicators of innovation. In a future study, it may be therefore interesting to investigate the possibility to jointly collect additional and complementary indicators of innovation activity. Fourthly, this study has been conducted on a sample of patenting firms; therefore, generalizing our results to more aggregate levels is not straightforward and must take into consideration possible biases in our data coverage. Finally, this contribution – dealing with the aggregate employment impact of innovation – cannot disentangle the proposed analysis in terms of skills and tasks which can be differently affected by the technological transformations; therefore, the emerging positive overall employment impact may hide relevant (and possibly contrasting) dynamics occurring within the skills/task structure of the labor force.

Disclaimer

The views expressed are those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

Acknowledgements

This research benefitted from funding under the European Union’s FP7 project “Innova Measure” [grant number 632806]. The authors are grateful to Nathan Wajsman and Michal Kazimierczak from the Office for Harmonization in the Internal Market (OHIM) for providing access to the EPO/OHIM concordance tables, and to three anonymous Referees, Mariacristina Piva and Dieter Somers for their useful suggestions.

Appendix A. Data sources, merging and cleaning procedures, sample composition

This Appendix describes the main steps taken to compile the firm-level dataset used in this study. This involved (a) merging accounting information from the ORBIS database with the OECD PATSTAT at firm level and matching with sectoral deflator data from Eurostat National Accounts and Structural Business Statistics SDdata (see Fig. A1); and (b) cleaning the merged dataset by removing firms with missing or unreliable information.

Our merging relied on firm-level harmonization tables developed by the authors of the EPO-OHIM (2013) study which used sophisticated algorithms to match company entries with that of patents. This relied on three main steps. First, names were harmonized in both the EPO PATSTAT and ORBIS datasets separately, following the Leuven/Eurostat methodology (Data Production Methods for Harmonised Patent Statistics: Patentee Name Harmonisation, Eurostat 2006). This involved converting all names to upper case, converting special characters into Latin characters (and applying the “NFKD unicode normalization”), removing double spaces, cleaning legal form information (by applying a country-by-country basis and an overall dictionary of 480 items), and removing non-distinctive words. In a second phase, the matching cleaned and harmonised PATSTAT data was merged with the ORBIS database. If multiple matches were obtained, preference was given to the most complete name, the same name root, the

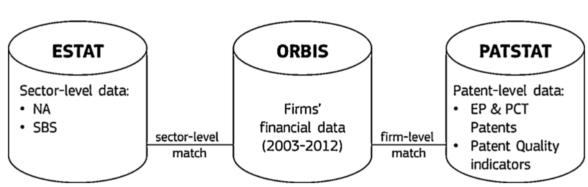

Fig. A1. Diagram on database mergers.
Note: Eurostat (ESTAT) sectoral databases refer to: NA = National Accounts, SBS = Structural Business Statistics, OECD PATSTAT database refer to: EP = patents filed at the European Patent Office, PCT = patents filed as an international application under the Patent Cooperation Treaty.

Table A1
Distribution of firms across sectors before cleaning.

	Number	Percentage (%)
Manufacturing		
Food	786	1.24
Textile	1,003	1.58
Paper	1,123	1.77
Chemistry	3,893	6.12
Pharmaceutical	932	1.47
Minerals	971	1.53
Metal	4,314	6.79
Electronics	4,937	7.77
Machinery	6,460	10.16
Transport	1,366	2.15
Other Manufacturing	2,963	4.66
Services		
Electricity/Water	527	0.83
Retail trade	7,291	11.47
Transport Services	373	0.59
Hotel & Catering	210	0.33
Telecommunication	2,601	4.09
Finance	1,371	2.16
Real Estate	1,020	1.60
Scientific	10,298	16.20
Administration/Education	2,136	3.36
Other services	1,068	1.68
No sector available	7,918	19.84
Total	63,561	100.00

Table A2
Distribution of firms across countries before cleaning.

	Number	Percentage (%)
Austria	2,211	3.48
Belgium	1,688	2.66
Bulgaria	19	0.03
Cyprus	13	0.02
Czech Republic	242	0.38
Denmark	1,887	2.97
Estonia	64	0.10
Finland	1,682	2.65
France	7,104	11.18
Germany	19,543	30.75
Greece	121	0.19
Hungary	209	0.33
Ireland	1,099	1.73
Italy	10,235	16.10
Latvia	26	0.04
Lithuania	16	0.03
Luxembourg	244	0.38
Malta	1	0.00
Netherlands	128	0.20
Poland	287	0.45
Portugal	181	0.28
Romania	37	0.06
Slovakia	30	0.05
Slovenia	110	0.17
Spain	2,710	4.26
Sweden	4,097	6.45
United Kingdom	9,577	15.07
Total	63,561	100.00

same legal form, and the same postcode (in this order). Finally, a manual matching process was implemented to ensure that the frequency distribution in the sample matched the overall population. This focused on those applicants that were underrepresented in the sample (most often those with a lower number of IP rights). For the manual process, applicant information from sources other than ORBIS was used, *i.e.* national business registers or company websites, in order to find the reason for the non-match (*i.e.*, recent name change).

In order to deal with distortions caused by the common business practice of concentrating intellectual property portfolios at the head offices of large companies, patents reported in industries “Activities of head offices”, “Activities of holding companies” and “Other business support service activities n.e.c.” (NACE codes 7010, 6420 and 8299, respectively) were assigned to bona fide industry codes, in case a given head office or holding company was flagged as a domestic ultimate owner. This was carried out by equally distributing to each subsidiary a fraction of the patents owned by

Table A3
Distribution of firms across size.

Firm size	Number	Percentage (%)
Micro	2,854	14.29
Small	5,461	27.34
Medium	6,740	33.74
Large	4,923	24.64
Total	19,978	100.00

Note: Firm size groups are denoted as: micro: 0–10 employees, small: 11–50 employees, medium: 51–250 employees and large: more than 250 employees.

Table A4
Distribution of firms across sectors.

	Observations		Firms	
	Number	Percentage (%)	Number	Percentage (%).
Manufacturing				
Food	2,539	2.44	430	2.15
Textile	2,825	2.71	510	2.55
Paper	3,286	3.16	587	2.94
Chemistry	11,072	10.64	1,997	10.00
Pharmaceutical	2,321	2.23	397	1.99
Minerals	2,639	2.54	480	2.40
Metal	12,279	11.80	2,266	11.34
Electronics	10,640	10.22	2,039	10.21
Machinery	17,460	16.78	3,212	16.08
Transport	3,954	3.80	706	3.53
Other Manufacturing	6,531	6.28	1,217	6.09
Services				
Electricity/Water	1,148	1.10	208	1.04
Retail trade	11,406	10.96	2,341	11.72
Transport Services	963	0.93	172	0.86
Hotel & Catering	166	0.16	47	0.24
Telecommunication	2,586	2.48	587	2.94
Finance	1,061	1.02	229	1.15
Real Estate	647	0.62	157	0.79
Scientific	8,408	8.08	1,909	9.56
Administration/ Education	1,388	1.33	314	1.57
Other services	755	0.73	173	0.87
Total	104,074	100.00	19,978	100.00

the head office (for further details, see the Methodology Appendix of the EPO-OHIM study, Section 9.1, pp. 99–115).

We extracted data for 70,549 patenting firms identified by that study. It has to be noticed that, while the focus of the EPO-OHIM study was 2004–2008, we had access to patent data for an extended set of firms over the period 2003–2012. However, the need to refer to the EPO-OHIM identification procedure implied the exclusion of all the firms that have only filed patents in 2003 or over the period 2009–2012. Since both ORBIS and PATSTAT were updated by the time we made our data extraction, we could merge 65,720 firms with patent and economic information; however, we decided to focus on manufacturing and services and so to exclude the construction sector from the analysis, which resulted in an uncleaned dataset of 63,561 firms. The sectoral distribution of these companies is shown in Table A1, while their cross-country distribution is shown in Table A2. We note that of the companies with information on core NACE activity, the distribution between manufacturing and service sectors was rather balanced (45.2 and 42.3%, respectively). Within these two groups, patenting firms were more concentrated to a few of the sectors: scientific services (16.2%), retail trade (11.5%), machinery (10.2%) and electronics (7.8%). Almost a third of the firms in the uncleaned dataset were located in Germany, 16.1% in Italy, 15.1% in the United Kingdom and 11.2% of them in France.

We then followed a similar cleaning process as described in Hall and Mairesse (1995). As a first step, we removed all the firms with either missing or unavailable information (negative values) concerning at least one variable of interest for all the years of the investigated period. This cleaning step removed 37,805 firms (almost 60% of the initial uncleaned merged sample) and was primarily due to the poor quality of the ORBIS data.

The second step in the cleaning process involved the removal of outliers in both levels and growth rates. This step was considered necessary for three reasons: (1) to remove firms with possible erroneous values in the data; (2) to prevent outliers from heavily affecting the results; and (3) to exclude potential biases due to mergers and acquisitions. Concerning level rates, we trimmed the top 1 percentage of the distribution of the overall

Table A5
Distribution of firms across countries.

	Observations		Firms	
	Number	Percentage (%)	Number	Percentage (%)
Austria	1,733	1.67	520	2.60
Belgium	1,799	1.73	294	1.47
Bulgaria	39	0.04	7	0.04
Czech Republic	649	0.62	116	0.58
Denmark	240	0.23	29	0.15
Finland	3,389	3.26	700	3.50
France	12,707	12.21	2,901	14.52
Germany	23,296	22.38	4,888	24.47
Greece	69	0.07	13	0.07
Hungary	104	0.10	33	0.17
Ireland	144	0.14	36	0.18
Italy	33,177	31.88	5,934	29.70
Latvia	9	0.01	1	0.01
Luxembourg	81	0.08	27	0.14
Poland	431	0.41	103	0.52
Portugal	411	0.39	78	0.39
Romania	143	0.14	23	0.12
Slovakia	41	0.04	8	0.04
Slovenia	201	0.19	41	0.21
Spain	9,249	8.89	1,400	7.01
Sweden	5,003	4.81	851	4.26
United Kingdom	11,159	10.72	1,975	9.89
Total	104,074	100.00	19,978	100.00

firms sample for respectively value added per employee, wage cost per employee and fixed assets per employee. As far as growth rates are concerned, we differentiated cut-off levels for various firm sizes to allow larger growth rates for smaller firms. Hence we defined firm sizes as micro (0–10 employees), small (11–50 employees), medium (51–250 employees) and large (more than 250 employees). Cut-off values have been defined for one-year growth levels in employees, value added, fixed assets and wage costs. This trimming exercise excluded 2645 firms from the sample (about 4% of the initial uncleaned sample).

After this cleaning exercise we ended up with a final workable sample of 23,111 firms (about 36% of the initial one). From this unbalanced panel, 3133 firms were further dropped by applying our GMM-SYS procedure to the specification (3), resulting in a final sample of 19,978 companies.

Table A3 reveals that our final panel database covers the whole range of small-, medium- and large-sized enterprises, although it is biased towards the two latter categories. This bias stems from the fact that we use patent information as proxy for the innovative activities of firms, leading to the exclusion of many micro- and small-sized firms after merging the original firm-level ORBIS dataset with the EPO/OHIM database. Indeed, medium- and large-sized firms account for roughly 64 percent of the panel when analyzing firm size in the first year of appearance of each firm in the sample.

Table A4 shows that the dataset covers all economic activities. Not surprisingly (given our focus on patenting firms) the most represented sectors within manufacturing are the chemical sector (about 10%), the metal industry (12%) and the machinery sector (17%). Retail trade (11%) and scientific research providers (6%) are the most represented services in the sample. Obviously enough, the number of service firms in our sample is significantly lower than their share in the population of firms across Europe; this is due to the fact that service firms are far less involved in patenting.

Table A5 reports the geographical distribution of the retained firms across Europe. Although our original intention was to cover all EU Member States, eventually the cleaned sample provides information for 22 countries due to incomplete financial information in the ORBIS database and/or missing patent information in the EPO/OHIM database. However, larger Member States are all included and the diversity of European regions is well-represented. Nevertheless, we note that Italy – accounting for about 36% of the included firms – is over-presented in the sample due to data quality, as discussed above. To account for this potential bias, we provide estimations excluding Italy in the Appendix B (Table B4); as can be seen, results remain virtually unchanged.

Appendix B. Robustness checks

See Tables B1–B3.

Table B1
Baseline specification: OLS and fixed effects estimations.

	Employment			
	OLS		Fixed effects	
Employment $_{t-1}$	0.785***	0.785***	0.439***	0.439***
	(0.005)	(0.005)	(0.010)	(0.010)
Value added	0.209***	0.209***	0.276***	0.276***
	(0.004)	(0.004)	(0.005)	(0.005)
Patents	0.017***		0.028**	
	(0.004)		(0.014)	
Weighted patents		0.012***		0.020***
		(0.002)		(0.005)
Gross investments	0.065***	0.065***	0.029***	0.029***
	(0.003)	(0.003)	(0.002)	(0.002)
Labor cost per employee	−0.854***	−0.855***	−1.723***	−1.723***
	(0.015)	(0.015)	(0.027)	(0.027)
Constant	0.511	0.511	2.117***	2.117***
	(7.582)	(17.495)	(0.041)	(0.041)
Industry and country dummies	included	included	included	included
Observations	104,074	104,074	104,074	104,074
Number of firms	19,978	19,978	19,978	19,978
R-squared	0.99	0.99	0.98	0.98
F test			(1,319,977)	(1,319,977)
			1351.51***	1354.11***

Note: OLS and FE robust standard errors in parentheses. *, **, *** indicate 10%, 5% and 1% significance levels.

Table B2
Baseline specification: two-step GMM-SYS estimations.

	Employment	Employment
Employment $_{t-1}$	0.683***	0.675***
	(0.018)	(0.017)
Value added	0.296***	0.297***
	(0.017)	(0.016)
Patents	0.032	
	(0.039)	
Weighted patents		0.057***
		(0.021)
Gross investments	0.144***	0.139***
	(0.034)	(0.034)
Labor cost per employee	−0.430***	−0.482***
	(0.092)	(0.091)
Constant	0.784***	1.849**
	(0.076)	(0.842)
Time, industry and country dummies	included	included
Observations	104,074	104,074
Number of firms	19,978	19,978
Wald test	0.72***	0.72***
AR(1)	−24.68***	−24.91***
AR(2)	2.92***	2.82***
AR(3)	1.01	1.05
Number of instruments	159	159
Hansen test	535.81***	537.25***

Note: Two-step GMM robust standard errors in parentheses. Instrumental variables compromise 3-year lags. *, **, *** indicate 10%, 5% and 1% significance levels. Wald test expressed in millions. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

Table B3
Baseline specification: using patent scope as a measure of patent's quality.

	Employment
Employment $_{t-1}$	0.668***
	(0.016)
Value added	0.304***
	(0.015)
Patent scope	0.030**
	(0.015)
Gross investments	0.123***
	(0.036)
Labor cost per employee	−0.315***
	(0.095)
Constant	0.857***
	(0.075)
Time, industry and country dummies	included
Observations	104,074
Number of firms	19,978
Wald test	6.26***
AR(1)	−25.42***
AR(2)	2.95***
AR(3)	0.98
Number of instruments	159
Hansen test	552.72***

Note: One-step GMM robust standard errors in parentheses. Instrumental variables compromise 3-year lags. *, **, *** indicate 10%, 5% and 1% significance levels. Wald test expressed in millions. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

Table B4
Baseline specification: restricted sample excluding Italian firms.

	Employment	Employment
Employment $_{t-1}$	0.677***	0.669***
	(0.018)	(0.018)
Value added	0.286***	0.289***
	(0.016)	(0.016)
Patents	0.107**	
	(0.043)	
Weighted patents		0.083***
		(0.024)
Gross investments	0.098***	0.091**
	(0.036)	(0.036)
Labor cost per employee	−0.306***	−0.342***
	(0.103)	(0.105)
Constant	0.471***	0.905***
	(0.074)	(0.085)
Time, industry and country dummies	included	included
Observations	70,897	70,897
Number of firms	14,044	14,044
Wald test	3.57***	3.37***
AR(1)	−20.69***	−20.81***
AR(2)	1.16	1.10
Number of instruments	158	158
Hansen test	334.50***	328.46***

Note: One-step GMM robust standard errors in parentheses. *, **, *** indicate 10%, 5% and 1% significance levels. Wald test expressed in millions. Instrumental variables compromise 2-year lags. As the Hansen test over-rejects the null in case of very large samples, we performed random sub-sample tests for 10% of the original data. For these samples the null of the Hansen test was never rejected.

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