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

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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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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 microeconometric 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.).