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Abstract

This paper investigates the implication of innovation on employment at the firm and industry levels. The paper contributes to the literature in two respects. First, it proceeds from the data of a catch-up country undergoing a very rapid economic development. Most of the empirical investigations use data from developed and technologically leading countries. The second contribution concerns the nature of the data in use; we develop a unique database merging the data of the Estonian Commercial Register with two consecutive Estonian Community Innovation Surveys (CIS), the CISIII for 1998–2000 and CISIV for 2002–2004. Our results coincide with the results on developed economies in the respect that innovation activity has a positive effect on employment and that product innovation has a stronger and a more positive employment effect. Both of these effects are consistent over firm and industry levels. This result is also confirmed by the insignificance of the spillover effects of an industry's innovation on employment by firms.

JEL Code: J23, O33, D21

Keywords: innovation (technological change), employment, catch-up economy

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Non-technical summary

This paper investigates the implication of innovation on employment at firm and industry level. Two different specifications are used, one capturing the effect of the total innovative activity and one capturing the effect of distinguished product and process innovation. The paper contributes to the literature in two respects. First it proceeds from the data of a catch-up country undergoing a very rapid economic development. Most of the empirical micro level investigations use data from developed and technologically leading countries. Besides, the paper gives a comprehensive treatment of innovation employment effects: investigating firm and industry level effects as well as spillovers from the industry and region to the firm level. The second contribution concerns the nature of the data in use; we develop a unique panel merging the data of the Estonian Commercial Register with two consecutive Estonian Community Innovation Surveys (CIS), CISIII for 1998–2000 and CISIV for 2002–2004.

For the firm level estimations the labor demand equation has been derived using similar specification to Van Reenen (1997). The Arellano and Bond (1991) dynamic panel data GMM estimation method has been used to estimate the labour demand equation. Arellano and Bond (1991) propose an instrumental variable estimation for differenced dynamic panel data specification. The lagged differenced dependent variable and other predetermined or endogenous variables are instrumented by their earlier values in levels and by other strictly exogenous or additionally specified instruments. This approach is often called also as a GMM-DIF estimator ("differenced" GMM). For the industry level estimations the industries' job flow indicators have been regressed by industries' innovation activity. Similarly to Greenan and Guellec (2001) the Davis and Haltiwanger (1992) method has been used to calculate industry's job creation and job destruction rates.

The estimation results indicate that in firm and also in industry level innovation activity has positive and statistically significant effect on employment. This confirms the results found on developed world (see Pianta, 2005). Distinguishing between product and process innovation reveals that product innovation tends to have stronger and significant positive effect on employment than process innovation. The latter is robust to the level of analysis in terms of firms or industries. Previous studies have not found this effect to be that consistent over firms and industries. This result is also confirmed by the insignificant spillover effects from firm's main industry's innovation to firm's employment. Weak linkages between industry and individual firm refer to the small importance of business stealing effect from one firm to the rest of the industry. Although controlling for export makes the spillover effects somewhat stronger, but these remain still insignificant.

Contents

1. Introduction

The relationship between technology and employment is discussed extensively in the discipline of economics. The industrial revolution driving workers to destroy new "competitors", the advent of machines, or the utilisation of computers increasing the demand for skilled workers in 1970–80s are well known examples of the implications of technological change on the labour force. In this day and age, the life-cycle of products has shortened, while production technologies are replaced more and more frequently and are often seen spreading all over the world. Innovativeness has become a target of any firm that wants to keep its market share or of any country that wants to become or remain wealthy. Under this "run to the top" manner of innovation activity the implications of innovation have become even more vital. Hence, although the level of employment at a firm is a combination of various supply and demand side factors, we concentrate on the effect of innovation (technological changes) on employment.

The firm-level evidence from developed economies usually finds a positive relationship between employment and innovation, but negative relationships have also been found. Distinguishing between product and process innovation allows for a more thorough investigation of the relationship in question. Pianta (2005:572) quoted Schumpeter who defined product innovation as "the introduction of a new good . . . or a new quality of a good," and process innovation as "the introduction of a new method of production . . . or a new way of handling a commodity commercially." Most of the empirical firm-level studies find a positive relationship between product innovation and employment; see e.g., Van Reenen (1997), Harrison et al. (2006), Rennings et al. (2004), and Greenan and Guellec (2001). In terms of process innovation the results are more varied. Fung (2006) and Harrison et al. (2006) found the relationship to be positive, Van Reenen (1997) found there to be a weak positive or no significant relationship, while Evangelista and Savona (2003) found this relationship to be negative.

As expected, these results depend on the method and data in use and the type of firms included.[1] Taking into account the high persistence of employment and the lengthy impact of innovation, the dynamic panel estimation of the impact of innovation on employment has been a favourable methodology for the analysis at firm-level (Van Reenen, 1997; Piva and Vivarelli, 2005; Fung, 2006; Lachenmaier and Rottman, 2007). The industry-level impact of innovation on employment can differ from firm-level effects. There are not many studies analysing the impact of innovation on employment at the firm

[1] See Appendix 1 for an overview of firm-level studies and Appendix 2 for an overview of studies on industry-level.

and sectoral levels (see Greenan and Guellec, 2001; Evangelista and Savona, 2003).

The purpose of this paper is to investigate the implication of innovation on employment in a rapidly developing EU catch-up economy, such as Estonia. This paper contributes to the literature in two respects. First, it proceeds from the data of a catch-up country instead of a high-income country and provides a comprehensive analysis about firm- and industry-level effects. Second, it merges two rounds of CIS data with the Commercial Register to form a six-year panel based on CIS innovation variables. Although with some limitations, this dynamic panel data enables us to extend the cross-section manner of CIS data and account for the high persistence of employment; while using the direct measure of innovativeness.

Most of the empirical studies use data from developed, technologically leading countries, while the developing, transitional countries are less well investigated. The situation in developing countries is different in many respects, as firms are often oriented towards low value-added production, or subcontracting from abroad. The inward FDI is often a North-South type attracted by low employment costs. In a European Union context, the new members (which joined in 2004 and 2007) hold a considerably lower share of enterprises with innovative activities. In the EU12 (EU member states before 2004, except Ireland, Luxembourg and the UK), the share of enterprises with innovative activities was 44% in 1998–2000. In 8 of the new EU member states, the same share was 24%, while the country under investigation, Estonia, held the highest share of 36% within this group. In terms of the type of innovation that is unlike those in developed countries, process innovation dominates in post-soviet countries. (Eurostat, 2004)

The second contribution concerns the nature of the data in use. We develop a unique database merging the data of the Estonian Commercial Register from 1994–2005 with two consecutive Estonian innovation surveys, the CISIII for 1998–2000 and CISIV for 2002–2004. The resulting database gives us a micro panel of 1122 firms for the period of 1998–2004, with the exception of 2001, which was not covered in the CIS surveys. The advantage of this dataset is that we can incorporate the detailed information on the innovation process from innovation surveys and the background variables of every firm back to the year 1994 from the Commercial Register. So far the literature has not used the joint data of consecutive CIS surveys. The high respond rates of the Estonian survey and the small size of the economy allowed the CIS to survey the whole population in many sectors making many respondents to overlap in both surveys. This enabled us to obtain a representative number of objects to use on the panel.

Our results indicate that overall innovation activity has a positive and statistically significant employment effect at the firm and industry levels. Similarly, product innovation also has a stronger and a more positive employment effect at the firm and industry levels. Our estimations indicate no spillover effect from industry or region.

The paper is organized as follows: The next section gives an overview of the literature and describes innovation activities in European countries. Section 3 derives a labour demand function and presents the estimation strategy. Section 4 introduces and describes the data. Section 5 presents the results of the empirical estimations and, finally, Section 6 summarizes the results.

2. Literature and background

2.1. Related literature

A popular proxy of the change in technology has been the notion of innovation. Innovation is considered to be the first attempt to carry an invention into practice (Fagerberg, 2005:4). As already mentioned, the usual conclusion of the studies on the impact of innovation on employment is that there is a positive relationship between innovation and employment. Nevertheless, the theoretical derivation behind the reduced form of equation(s), empirical estimation methods and data characteristics differ.

Most of the studies differentiate between process and product innovation, but there are studies that estimate only the overall effect. The result of process innovation is a greater efficiency in production. As a result, production inputs can be saved or production prices reduced. The usual outcome is a decrease in employment, but when product quality is increased or the output price is reduced, it can also result in higher employment due to increased demand. New products or services, radical innovation or imitation, usually enhance quality and the variety of goods opening new markets as well as increasing production and employment. The result can also be other way around — new goods are innovated to reduce costs and in this way have similar effects to process innovation. Product innovation can also have no effect on employment, such as when new products replace old ones with minor economic effects. (Pianta, 2005:572–573; Smolny, 1998:365–366)

Van Reenen (1997) used the UK dynamic panel to derive the impact of innovation on employment. Van Reener controlled for fixed effects, dynamics and endogeneity, and found a significant positive effect that persists over several years. He claimed that his positive relation could partly be a result of the higher share of product innovations in the sample, as product innovation "will be expected to have a stronger effect on employment" (Van Reenen, 1997:275). In terms of product innovation, he found the impact on employment to be positive; in terms of process innovation, he found no significant effect. The production function was assumed to be a constant elasticity of substitution production function; the demand for labour was derived and the dynamic form of it estimated by GMM-DIF (Arellano and Bond, 1991). The sample consisted of 598 UK manufacturing firms during the period of 1968–1982. The proxy for innovation was the innovation count per firm.

Piva and Vivarelly (2005) used a specification similar to Van Reener (1997) to derive and estimate the labour demand function. They found a positive, although small, statistically significant effect of innovation on employment. They also used a dynamic labour demand specification. As an extension to the approach of Van Reenen (1997), Piva and Vivarelly used the GMM-SYS as their estimation method, which is more suitable for the estimation of short panels and in cases where a dependent variable is less persistent. The panel data used covers 575 Italian manufacturing firms over the period of 1992–1997. The innovation proxy was innovative investments.

At the European level, the cross-country comparable Community Innovation Surveys (CIS) have been used for the investigation of the impact of innovations on employment. The disadvantage of this data is that CIS data measures innovation as a discrete variable of firms' innovation activity over a three-year time period. This makes a single round CIS survey just a cross-section in estimation terms. Although this cross-section counts differences over a three-year time period and also collects information on firms' future expectations about the change in employment. However, the impact of innovation on employment can be sluggish; that is why dynamic panel data approaches have an advantage over the single-round CIS data approaches. That is why a single-round CIS estimates can also underestimate the impact of innovation on employment.

Nevertheless, various efforts are undertaken to estimate the impact of innovation on employment based on CIS data. Evangelista and Savona (2003) estimated the Italian service sector CISII (1993–95) data, trying to determine "the direct effect" of innovation on employment. They used a logit model where the dependent variable is the increase in employment due to innovation. They found that overall innovation expenditures and product innovation had a positive impact on employment, while process innovation had no significant impact.

Harrison et al. (2006) proceeded from four CIS innovation surveys of the European Union's largest countries — France, Germany, Spain and the UK — to compare the impact of process and product innovation on employment at the firm level. Harrison et al. (2006) proceeded from the production function where old and new products are produced. The labour demand equation was derived in such a way as to identify both the process and product innovation impact on employment. The estimation method was two-stage least squares and its data originated from CIS3 1998–2000. They concluded that the effects on employment were similar across countries. Process innovation brought on the replacement of workers, but the compensation effect due to the reduction of production prices dominated, resulting in a positive total effect. Product innovation brought on no displacement effects and a significant compensation effect dominated even when the decrease in the production of the old product was taken into account. In the service sector, the displacement effect was less evident and the total employment effect was weaker.

In this paper we address the limitations of CIS surveys by merging two consecutive CIS surveys. This enables us to use a direct measure of innovativeness from CIS surveys and also introduce a longer time-span. Unfortunately, CIS surveys do not provide innovation count data. Innovation count data can be a supreme measure of innovativeness, but so far CIS data is the best innovation data available for Estonia.

In terms of the type of economy analyzed, empirical investigations usually proceed from the data of high-income countries. Among the low income economies Lundin et al. (2007) found there to be no effect of science and technology investments on employment in China. This was firm-level study from a panel of manufacturing firms. Pradhan (2006) found a negative relation between technology variables and share of unskilled workers in India. This analysis was conducted at subindustry level of manufacturing sector. There are also some studies of developing countries estimating the impact of innovation on aggregated employment. Kang (2007) found that technological innovation has positive impact on overall employment in Korea and that this effect is stronger in manufacturing. Kang (2007) used structural VAR for estimations. Üçdoğruk (2006) found that innovators have higher employment growth in Turkish manufacturing sector. Overall, it is difficult to generalize these results as estimation techniques differed a lot. The study using the most sophisticated estimation technique found the impact of innovation on employment to be insignificant (Lundin et al., 2007, for China).

The net effect of innovations on employment at the aggregate industry level can differ from survey-based firm-level results. The firm-level analysis does not allow for the expanding of these results to the whole industry. There are several reasons why these firm-level results cannot be applied to the industry level (Harrison et al., 2006; Piva and Vivarelli, 2005):

- it is not possible to distinguish between market expansion and the business stealing effect; e.g., if employment is increased by an innovating firm, the market share of other firms will diminish;

- the entering and exiting of firms is not observed, innovators may close down non-innovators;
- totally new economic branches may surface and create completely new jobs.

Piva and Vivarelli (2005) gave an overview of the advantages and disadvantages of the microeconometric estimation of the employment effects of innovation. The main disadvantage was that the results of the micro studies cannot be generalized, because all the sectoral and macroeconomic effects were not captured. For instance, if one uses a sample with only innovating firms, "business stealing" effects will be neglected. The advantage of micro studies is that innovation can be measured more precisely; for example, process and product innovation can be distinguished.

There is evidence that innovation has a positive effect on employment at the firm level as well at the sectoral level. Innovative firms and sectors create more employment compared to non-innovative ones (Greenan and Guellec, 2000; on a French panel). However, the positive effect of process innovation dominates at the firm level and the positive effect of product innovation dominates at the industry level (the possible effect of market expansion). Similarly, Antonucci and Pianta (2002) found on a panel of manufacturing industries of the developed European countries that process innovation had a negative effect on employment, while product innovation had a positive, but insignificant effect. Evangelista and Savona (2003) found that in the Italian service sector firm-level estimations showed more positive results on employment due to innovation than industry-level estimations. In sum, the simultaneous surveys on firm and industry levels do not equally give the same results across the level of analysis undertaken, especially when distinguishing between product and process innovation.

2.2. Innovation patterns of high- and middle-income countries

There have been disagreements about the causality between the innovativeness and income of the economy. According to one version, innovativeness determines economic growth (endogenous growth theory); the other version states that the level of economic development determines innovativeness. Differentiation between product and process innovation does not provide a clearer picture. On the one hand, empirical literature suggests that product and process innovation are interdependent; see e.g., Reichstein and Salter (2006) about UK manufacturing industries. On the other hand, microeconometric studies find that the determinants of product and process innovation differ. Product innovation is related to disembodied forms of technology (a stock of knowledge or a set of capabilities), while process innovation benefits from capital embodied technology (fixed productive capital) (Rouvinen, 2002).

Figure 1 presents the relation between the share of product and process innovative firms in the 25 European countries. There is a positive relation between the share of product and process innovative firms, but this relation tends to be non-linear. The share of process innovative firms increases faster at lower levels of innovativeness and the share of product innovative firms increases faster at higher levels of innovativeness. These country-level observations are weighted by countries' GDP *per capita* in euros; the larger the country marker is in Figure 1, the higher the country's GDP per capita also is. Evidently, countries with a higher level of income tend to have more innovative firms and tend to create more product rather than process innovations.

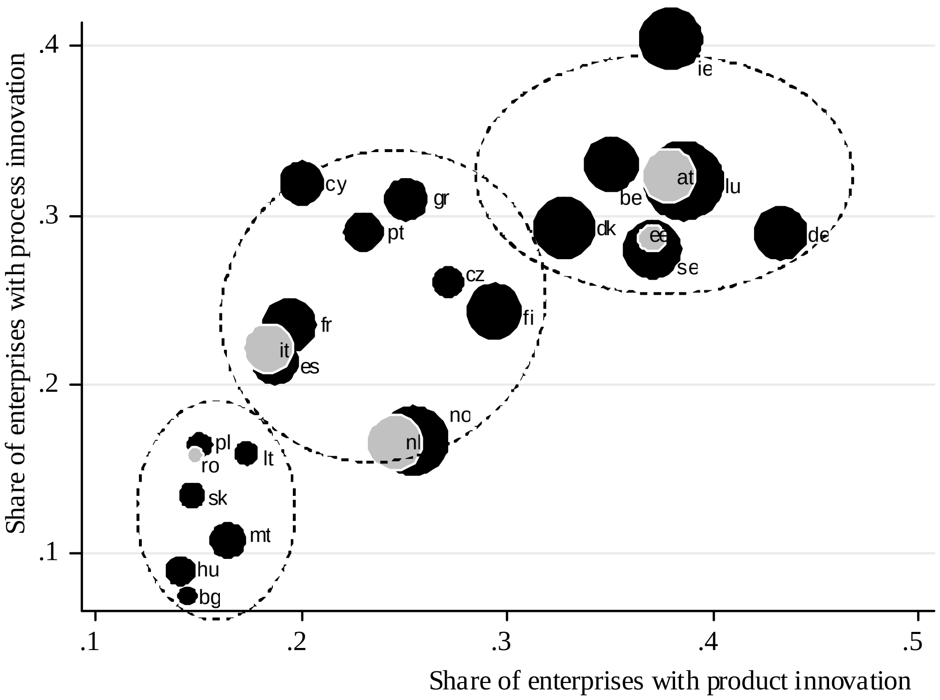

Figure 1: Relationship between product and process innovativeness, weighted by GDP per capita (2004, in euros).

Note: The process innovation numbers drawn from the Eurostat database do not contain process innovation created jointly by firms and outside partners.
Source: IV European Community Innovation Surveys, 2002–04 (Eurostat, 2008).

Three groups of countries emerge from the figure. The first group comprises countries with a fixed low level of product innovation and varying low level of process innovation. These countries all have relatively low income levels in the European context and consist of Bulgaria, Hungary, Malta, Slovakia, Romania, Poland and Lithuania. The second group contains countries with middle levels of product and process innovation. This group includes countries where process innovation dominates and which are characterised by middle and high levels of income: Spain, Italy, France, Portugal, Cyprus and Greece. There are also countries in the second group where product innovation dominates and this group includes high income countries: The Netherlands, Norway, Finland, and as an outlier, the Czech Republic. The final group comprises countries with high innovativeness dominated by product innovation. This group contains high income countries such as Denmark, Belgium, Sweden, Austria, Luxembourg, Germany and Ireland. Ireland is an exception that possesses a remarkably high share of process innovative firms. The country under investigation in this paper, Estonia, is also a part of this group. Estonia is a clear outlier there having high rates of innovativeness, but a low level of income.

These differences in cross-country product and process innovativeness can be a result of different industry mixes in these countries. Antonucci and Pianta (2002) concluded on the example of European countries' manufacturing industries that the same industries across countries were characterised by similar shares of new or improved products in sales or share of process innovation in sales. In other words, the distribution of countries between product and process innovativeness can be explained by industry specificity rather than by country factors (Antonucci and Pianta, 2002:300). Their estimations were based on CISII data from 1994–96. Contrary to our paper, they found a negative relationship between product and process innovation. This may be a result of a different measure of innovativeness; they used the share of new or improved products in sales or share of process innovation in sales. It can also be a result of different levels of aggregation; they used the manufacturing industry level instead of the country level.

The empirical analysis of this paper employs Estonian data. One must notice that in terms of the level of innovativeness Estonia is the most innovative among the group of low income new EU members. Additionally, the share of product innovative firms in Estonia is higher than the share of process innovative firms. The high share of innovative firms may also show that these innovations are far from major technological shifts. The CISIV survey for Estonia shows that most of the firms' innovation activity is related to the purchasing of machines and equipment or computer hard- and software (Viia et al., 2007:9). Another EU-wide innovation survey, the European Innovation

Scoreboard, has also ranked Estonia as one of the most innovative countries among the new EU members. Still, the Estonian innovation system is very unbalanced. Estonia has developed its innovation drivers (tertiary education), innovation and entrepreneurship (SMEs innovation activity) well, but performs badly in transferring these into knowledge creation (low R&D activity) (Pro Inno Europe, 2007).

3. The labour demand function of firms

The empirical literature investigating the employment effects of innovation (or technological change) usually proceeds from the neoclassical production theory with a predetermined shape of the production function. The labour demand is derived from profit maximizing conditions and estimated using various econometric methods.

The specification used in this paper proceeds from the one employed by Van Reenen (1997). There the constant elasticity of substitution (CES) production function has been used to derive the labour demand function. A perfectly competitive firm operates according to a CES production function:

$$Q = T\left[(AN)^{(\sigma-1)/\sigma} + (BK)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} \tag{1}$$

where Q is output, T is the Hicks-neutral technology parameter, A is labour augmenting Harrod-neutral technology, B is the Solow-neutral technical change, N is employment, and K is capital. In a perfectly competitive world without distortions, the marginal product of labour should equal real wages (W/P). Proceeding from this assumption and solving for labour demand results in the following labour demand function:

$$\log N = \log Q - \sigma \log{(W/P)} + (\sigma - 1)\log A \tag{2}$$

Next, equalizing the marginal product of capital with the real price of capital and substituting via this second order condition for the output in the labour demand function (2), gives the following labour demand function:

$$\log N = (\sigma - 1)\log{(A/B)} - \sigma\log{(W/P)} + \log K + \sigma \log R \tag{3}$$

Next, Van Reenen (1997) replaced the unobserved technology variables with innovation and produced the stochastic form of the labour demand function. In our paper the first part of the right hand side variables in (3) is proxied by technology level instead of innovations (change in technology). Our labour demand function is derived as follows:

$$n_{it} = \alpha_1 TECH\_level_{it} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it}. \tag{4}$$

Lower case letters stand for logarithms, $TECH\_level$ indicates the level of technology, τ_t represent time dummies, and u_{it} is a white noise error term. The superscript i indicates the firm and t the time period. The price of capital is assumed to be constant across firms, but variable over time; i.e., proxied by time dummies.

In empirical studies the latter static specification of labour demand should be extended with dynamic adjustment for employment and innovation. The database used for this paper reports innovation as a discrete variable over two 3-year periods, 1998–2000 and 2002–2004. Hence, the simultaneous introduction of the yearly lagged innovation variables is not possible here $(cor\,(INNOV_{it}, INNOV_{it-1}) = 1)$. Assuming that any adjustment in employment due to a development in technology is gradual, the technology variable is lagged by one time period. After counting for employment persistence[2] the following labour demand equation results:

$$n_{it} = f + \alpha_1 TECH\_level_{it} + \beta_1 n_{it-1} + \beta_2 n_{it-2} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it}, \tag{5}$$

where the constant f represents a unified constant for every firm at every period of time and two AR terms of employment have been added. As usual in a panel data models, the residual u_{it} has two components, a traditional white noise one and a firm specific part.

4. Data

This paper uses data from three different sources: The Estonian Commercial Register (register) of 1994–2005, the third Community Innovation Survey of 1998–2000 (CISIII) and the forth Community Innovation Survey of 2002–2004 (CISIV). The Estonian Ministry of Justice collects the register data and as it is compulsory for enterprises to report their economic indicators correctly, this database is taken to be the most reliable one. Thus, when a variable like employment is reported in both databases (in both the register and innovation surveys) the register data has been used.

[2] The lagged time periods introduced go up to 2 periods as employment lags become insignificant after this lag length (yearly estimates).

The Estonian Community Innovation Surveys' data is collected by Statistics Estonia. The methodology of CIS surveys proceeds from the methodology suggested by the European Commission (see European Commission Oslo manual 1997 for details). The CIS survey is conducted every 4 years. In Estonia, the first survey was conducted for 1998–2000. Enterprises are asked to report information on their innovation activities retrospectively; i.e., reporting innovation activity from 1998 to 2000 in 2000, and innovation activity from 2002 to 2004 in 2004. (Kurik et al., 2002; Viia et al., 2007)

The CIS survey sample has been made selecting firms by the size and the field of their activities. The field of activities included are mining and selected manufacturing and service sectors (the traditional public sectors in services sectors are excluded). Not all production sectors are included in the innovation surveys; e.g., agriculture, construction, hotels, education, and health care are excluded from the sample (see Table 1). Thus, the CIS survey does not represent the innovativeness of all Estonian enterprises. Table 1 shows that the manufacturing and transportation sectors are overrepresented, while wholesale and retail trade, real estate and rentals are underrepresented. Nevertheless, employing a comparable methodology in different countries (following the Oslo manual) ensures the comparability of the data across countries (Kurik et al., 2002:21; Viia et al., 2007:18).

Table 1: Distribution of Estonian enterprises across fields of activity in the Estonian Commercial Register and in innovation surveys

	Register 1999		CIS 1998–2000		Register 2003		CIS 2002–2004	
NACE	Count	Share	Count	Share	Count	Share	Count	Share
A	1.727	4.45			2.359	4.64		
B	171	0.44			163	0.32		
C	103	0.27	24.5	0.79	97	0.19	19.8	1.13
D	5.103	13.16	1.490.1	48.19	6.046	11.89	883.9	50.59
E	301	0.78	104.0	3.36	281	0.55	49.8	2.85
F	2.593	6.69			3.884	7.64		
G	13.859	35.75	517.8	16.75	14.623	28.76	370.2	21.19
H	1.544	3.98			1.811	3.56		
I	2.977	7.68	396.2	12.81	3.962	7.79	295.6	16.92
J	530	1.37	102.6	3.32	1.226	2.41	24.4	1.40
K	7.724	19.92	456.7	14.77	13.412	26.38	103.3	5.91
L	0	0			5	0.01		
M	404	1.04			511	1		
N	521	1.34			876	1.72		
O	1.211	3.12			1.591	3.13		
Total	38.768	100	3.092	100.00	50.847	100	1.747	100.00
CIS sample			3.161				1.747	

Note: The numbers for CIS are weighted by weights supplied by data collectors (later estimates proceed from unweighted numbers).
Source: Estonian Commercial Register, CISIII and CISIV, own calculations.

In CISIII, all enterprises employing more than 10 employees were questioned. A random sample was made for smaller firms. In CISIV, all enterprises employing more than 50 employees were questioned, and a random sample was made of firms employing 10–49 employees. In CISIV, the smallest enterprises, with 0–10 employees, were not covered. The response rate was high in both surveys; namely, 74.3% in CISIII and 79.3% in CISIV. The response to the CISIII was voluntary, while the CISIV was a part of the compulsory national collection of enterprise statistics (Kurik et al., 2002:21; Viia et al., 2007:18).

In this paper information on innovation comes from the CIS data, while register data provided information on capital and employment costs. Employment was covered in both data sets; primarily register data was used. If an observation was not available in the register data but was available in the CIS, then the information from the CIS was used.

The information on innovation is collected for a period of three years, so it is unclear in which exact year within the 3-year period the innovation took place. Innovation is presented as a discrete variable in CIS surveys; i.e., whether the firm innovated within the 3-year period or not. Based on this information we calculate an innovation variable that takes the value 1 for every year within the 3-year period being considered if the firm was innovating and takes the value 0 for every year within the 3-year period if the firm was not. The constructed innovation variable can be interpreted as a summary proxy for a firm's average innovation activity over the 3-year period in question.

Table 2 presents the descriptive statistics of innovative and non-innovative firms. The capital stock is calculated by summing tangible fixed assets and intangible fixed assets, and subtracting goodwill. The capital stock measure is in the prices of the year 2000. The GDP deflator at the one-digit NACE level has been used to deflate the capital stock. The NACE codes are taken from the register data; in cases where register data is missing, observations have been drawn from CIS data.

The wage is calculated by dividing total remuneration costs of the enterprise (including social security and pension payments) by the number of workers in the firm. The real wage is calculated by deflating with GDP deflator at the one-digit NACE level. All the variables are reported at the firm level.

The number of observations after merging CIS and register data is 3161 for CISIII and 1747 for CISIV. The number of enterprises that are covered in both CIS rounds is 1122. The larger and innovative firms are somewhat overrepresented in this merged data set. The descriptive statistics of these 1122 firms in the panel are presented in Table 2. The share of product and process innovators is of the same magnitude, amounting to one third in the

Table 2: Descriptive statistics, 1998–2000 and 2002–2004

	All firms		Innovators		Non-innovators	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Innovation (%)	46.2					
Product innovation (%)	34.4					
Process innovation (%)	33.9					
Employment	100	331	139	422	66	222
Real wage [a)]	102333	282438	111751	89443	96041	396473
Real capital stock (in millions of EEK)	35.3	365	61.3	537	14.1	110
Number of observations						

Note: a) Yearly real remuneration costs per employee in Estonian kroons (EEK) (1 EEK = 1/15.65 EUR).
Source: Estonian Commercial Register, CISIII and CISIV, own calculations.

sample. The share of firms with any innovative activity amounts to 46%. The innovators are bigger firms in terms of employment and capital stock and their remuneration costs per employee are higher. The empirical analysis uses a panel of 830 enterprises, for which all the information needed is available.

5. Empirical results

5.1. Firm-level evidence

This paper proceeds from a labour demand specification similar to Van Reenen (1997), see Section 3. A simple OLS estimation of the labour demand of equation 5 will give a biased estimator for the lagged dependent variable AR as the firm specific part of the error term will be positively correlated with lagged dependent variable. The standard way out is to use within group estimation or model in differences to get rid of object-specific effects. However, neither of these strategies will give satisfactory estimates for our dynamic labour demand equation. For the within group estimator, the transformed lagged employment (deviation from within group mean) would be negatively correlated with the transformed error terms (deviation from within group mean). This bias, also called the Nickell bias, diminishes when $T \to \infty$ (Nickell, 1981), but in our sample T is small. Estimating the dynamic panel model in differences would again give a correlation between lagged differenced employment and the error term, but this correlation can be addressed by introducing instruments to lagged differenced employment.[3]

Considering the above complications, instrumental variable techniques are

[3]For a good methodological description of the estimation of labour demand equations, see Lachenmaier and Rottmann (2007).

the most preferable ones for dynamic panel data estimations. The Arellano and Bond (1991) dynamic panel data GMM estimation method has been used in this paper. They proposed an instrumental variable estimation for differenced dynamic panel data specification. The lagged differenced dependent variable and other predetermined or endogenous variables are instrumented by their earlier values in levels and by other strictly exogenous or additionally specified instruments. This approach is also often called as a GMM-DIF estimator ("differenced" GMM).

Table 3 presents the results of the panel estimates. The second and the third columns in Table 3 present the result of the OLS estimations. The technology variables have been lagged by one year as compared to the immediate effect; the effects were more significant in this case.

Table 3: Employment and R&D activity or innovation, R&D and innovation variables from 1999–2001 and 2003–2005

	OLS (pooled) [a)]		Within estimator [a)]		Two-step Arellano-Bond (GMM) [a) b)]		Two-step Arellano-Bond (GMM) [a) b)]	
	Estimator	Robust Std. Err.	Estimator	Robust Std. Err.	Estimator	Std. Err.	Estimator	Std. Err.
R&D activity $(t-1)$	0.0440	0.0077	0.0284	0.0102				
Innovation $(t-1)$					0.0127	0.0079		
Product innovation $(t-1)$							0.0148	0.0081
Process innovation $(t-1)$							0.0011	0.0099
Employment $(t-1)$	0.7961	0.0495	0.4202	0.0553	0.5616	0.0511	0.5608	0.0500
Employment $(t-2)$	0.0996	0.0446	0.0963	0.0379	0.0477	0.0209	0.0464	0.0207
Real wages	-0.1276	0.0259	-0.5495	0.0584	-0.4633	0.1255	-0.4373	0.1230
Real capital	0.0481	0.0053	0.1102	0.0108	0.3006	0.0785	0.2764	0.7405
Sargan test (20)					27.87		28.47	
p-value					0.1124		0.0988	
AR(1): no autocorrelation					-3.68		-3.72	
p-value					0.0002		0.0002	
AR(2): no autocorrelation					0.67		0.74	
p-value					0.5053		0.4579	
No. of observations	3962		3962		3521		3521	
No. of groups			845		830		830	

Note: a) Time dummies have been used as additional explanatory variables.
b) Estimation on differences. The set of instrumented variables includes: lagged differenced employment, differenced real wages and differenced real capital stock. The set of exogenous variables includes: innovation variables and time dummies. The set of instruments includes: lagged employment, real wages, real capital in levels and lagged differenced exogenous variables. The maximum lag length for instruments is 2 to satisfy Sargan test of no over identification.

The parameter estimates have expected signs and are of reasonable magnitude. As expected, the GMM estimator of lagged employment lies between the upward biased OLS estimator and the downward biased within estimator. The same applies for the estimator of real wages. In the estimations, R&D activity has been used as a proxy for the level of technology (see the second and the fourth columns in Table 3). R&D activity is a three-year average discrete variable similar to innovation activity. In the estimations of differences, innovation activity has been used as a proxy for change in the level of technology (see the sixth and the eight columns in Table 3). R&D activity has a strong positive effect on innovation in OLS and within group estimations. In GMM estimation the impact of innovation on employment weakens, but it still remains significant around an acceptable level of significance.

In this paper innovation is taken as a differenced level of technology in the Arellano and Bond approach. Intuitively, innovation reflects an applied change in technological level. As principle choices on capital and wages can affect the next period's employment decisions, capital and wages are treated as endogenous. Sargan tests indicated the use of a maximum of two time lags for employment and endogenous predetermined variables as instruments. For example, differenced employment in 2003 is instrumented by employment levels in 2002 and 2001, plus other instruments arising from predetermined endogenous variables and exogenous variables introduced by the same logic.

In order to check the results for robustness, innovation was also instrumented. In this case patents were used as an additional instrument as these are correlated with innovation, but not with employment. Van Reenen (1997) used patents as a successful instrument for innovations. Nevertheless, in our estimations, instrumenting innovation did not change the estimation results. Hence, innovation was taken to be strictly exogenous in the baseline case.

The next step is to distinguish between process and product innovation in the labour demand equation. The estimation results are presented in Table 3. In this specification both product and process innovation are positively related to employment. The impact of product innovation is much stronger, but this estimator is significant within the weakest bounds of significance. Other parameter estimates remain broadly unchanged compared to the first specification with either of the innovation activities.

5.2. Industrial and regional spillover effects

Overall innovation activity in a firm's parent industry or around its geographical location can also alter a firm's employment. Tentatively it is impossible to predict these effects. On one side, a positive spillover could emerge as a high innovation activity of the enterprises in the same industry or within a particular geographical region making it easier (cheaper) to copy the innovation. As a result, firms may experience a higher net effect from innovation and experience a stronger impact from innovation on employment. On the other side, the higher an industry's innovation activity is, the lower its firms' ability to gain a relative advantage in the market due to innovation will be.

Table 4 presents the results of exercises on possible spillover effects. Neither the parent industry's innovation nor its region's innovation has any significant effect on a firm's employment.

Table 4: Innovation spillovers from the parent industry and within the same region, GMM, innovation variables from 1999–2001 and 2003–2005

	Two-step Arellano-Bond (GMM)[a)]		Two-step Arellano-Bond (GMM)[a)]		Two-step Arellano-Bond (GMM)[a)]	
	Estimator	Std. Err.	Estimator	Std. Err.		
Innovation ($t-1$)	0.0133	0.0078			0.131	0.0079
Product innovation ($t-1$)			0.0115	0.0080		
Process innovation ($t-1$)						
Employment ($t-1$)	0.5634	0.0505	0.5657	0.0481	0.5650	0.0521
Employment ($t-2$)	0.0470	0.0211	0.0440	0.0205	0.0476	0.0209
Real wages	-0.4656	0.1255	-0.4116	0.1180	-0.4591	0.1214
Real capital	0.2869	0.0765	0.2342	0.0694	0.2970	0.0771
Industry export *(t-1)*					0.0024	0.0038
Innovation in industry [b)]	-0.0068	0.0249			-0,0071	0,0258
Product innovation in industry [b)]			0.0115	0.008		
Process innovation in industry [b)]			0.0054	0.0093		
Innovation in region [b)]	0.0003	0.0300			-0,0020	0,0306
Product innovation in region [b)]			0.0319	0.0224		
Process innovation in region [b)]			-0.0383	0.0230		
No. of observations	3509		3509		3493	
No. of groups	830		830		830	
Sargan test (20)	28.28		29.72		28.73	
p-value	0.1028		0.0744		0.0932	
AR(1): no autocorrelation	-3.68		-3.72		-3.75	
p-value	0.000		0.000		0.000	
AR(2): no autocorrelation	0.65		0.82		0.75	
p-value	0.5157		0.4097		0.4508	

Note: a) Estimation of differences. The set of instrumented variables includes lagged differenced employment, differenced real wages and differenced real capital stock. The set of exogenous variables includes innovation variables and time dummies. The set of instruments includes lagged employment, real wages, real capital in levels and lagged differenced exogenous variables. The maximum lag length for instruments is 2 to satisfy Sargan test of no over identification.

b) Industry's and region's innovation has been calculated as the share of employment of innovating firms in a specific industry or region. The firm's own employment has been excluded from its industry's or region's innovation variable to avoid any in-built multicollinearity with firms innovation variables. The number of industries is 46 (at 2-digit NACE) and the number of regions 20 (the 5 biggest cities and 15 counties).

****, ** ,* denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% levels.*

This picture changes only slightly when product and process innovation have been distinguished. In the latter case, statistical significance of innovation variables slackens slightly, while an industry's process innovation becomes significant at a weak significance level. Hence, despite what firm's own innovation activity is, when its parent industry is experiencing process innovation, it also reduces the firm's own employment. Overall, there seems to be no significant spillover effect on a firm's employment from its parent industry or from its regional location. Van Reenen (1997) found a similar result in terms of an establishment's main field of activity. Controlling for export weakens this result only slightly. This weak business stealing effect actually indicates that firms do not have to "steal" positions from other firms.

In summation, firm-level estimations indicate that innovation has a positive effect on employment. Distinction between the types of innovation uncovers a positive relationship between product innovation and employment. However, these relations are significant only at the lowest acceptable significance levels.

5.3. Industry-level evidence

Different methodologies have been used to analyse industry-level innovation impact on employment. See Appendix 2 for the selection of industry-level studies. If information about the direct effect of innovation on employment was available, the weighted share of firms with a positive effect per industry could be calculated straightforwardly. This estimation strategy was used by Evangelista and Savona (2003) on Italian services CISII (1993–1995) data. They found a positive employment effect in knowledge-intensive industries and a negative impact in traditional service sectors. Their firm-level results were much more positive in terms of employment.

Unfortunately, direct information about innovation employment's impact is often lacking from the data. Hence, the consequent strategy is to calculate industry-level employment changes and regress these with an industry's innovation activity. The identification of the innovation effect is the bottleneck in this approach. Antonucci and Pianta (2002) employed this strategy on 8 old EU countries manufacturing CISII data. They estimated the industry's rate of change of employment for 1994–1999 depending on innovation and other control variables from 1994–1996. They found a negative impact of innovation on European manufacturing employment.

In addition to the extension of the leads of the employment variable one can enhance the measurement of an industry's employment change. Greenan and Guellec (2001) disentangled the industry's employment growth rate into a job creation and a job destruction rate. They used the calculation of job flows suggested by Davis and Haltiwanger (1992). There are clear advantages to this approach compared to conventional industry employment growth. Let us take an example where an industry experiences a zero net employment change, but a positive number of jobs are created and abolished in the industry. Consequently, the net employment change is not related to any of the industry's innovation variables; the jobs created in the industry might be due to product innovation and the jobs lost might be due to process innovation. Without a distinction between job creation and job destruction we could easily underestimate the role of innovation in real employment reallocation in the labour market. Greenan and Guellec (2001) found on their French manufacturing panel that firm-level process innovation had a positive dominant effect and industry-level product innovation had a positive dominant effect on employment.

In this paper, we proceed from the latter approach. Similarly to Greenan and Guellec (2001), the Davis and Haltiwanger (1992) method has been used to calculate an industry's job creation and job destruction rates. The advantage of this approach is that the resulting rates are interpretable as ordinary growth rates. The disadvantage is that by definition there is much higher probability of having larger job flows in smaller firms. E.g., if a worker's job is abolished in one firm, the probability of finding a new job in the same firm is much lower in the case of a small firm. The way out is to introduce distinguished firm-size groups for every industry (Greenan and Guellec, 2001).

We distinguish between 15 industries (1 digit NACE level) and 6 size groups.[4] The total number of groups is 90, while some groups remain empty due to a lack of observations. The job flow rates are calculated over a three-year period considering our innovation variable measuring firms' average innovation activity over the three-year period. The job flow rates are calculated as follows (this designation has been adopted from Greenan and Guellec (2001)):

$$g_{st}^{pos} = \sum_{e \in E_{st}} \frac{x_{et}}{x_{st}} g_{et}, g_{et} > 0$$

$$g_{st}^{neg} = \sum_{e \in E_{st}} \frac{x_{et}}{x_{st}} \left| g_{et} \right|, g_{et} < 0$$

$$g_{st}^{net} = g_{st}^{pos} - g_{st}^{neg}$$

where g_{st}^{pos} indicates the job creation rate, g_{st}^{neg} the job destruction rate and g_{st}^{net} the net job flow. The latter equals the conventional sector's employment growth. Subscript e denotes the firm, $e = 1, \ldots, E$; subscript t denotes the time, $t = 1995, \ldots, 2005$; and subscript s denotes the sector (by industry and firm size), $s = 1, \ldots, 90$. The firm's average employment, x_{et}, has been calculated as $x_{et} = (L_{et} + L_{et-1} + L_{et-2})/3$ where L_{et} represents the firm's employment. The sector's average employment, x_{st}, has been calculated as $x_{st} = \sum_{e \in E_{st}} x_{et}$. Finally, the firm's employment growth rate, g_{et}, has been calculated as $g_{et} = (L_{et} - L_{et-2})/x_{et}$.

[4]The size groups are less than 10 employees, 10–19 employees, 20–49 employees, 50–199 employees, 200–499 employees, and 500+ employees.

The job creation and destruction rates are essentially size weighted averages of the growth rate of growing firms and an absolute value of negative growth rates of diminishing firms. One should notice that the calculated flows underestimate actual job flows as employment is reported on a yearly basis, not including job flows within a year (Greenan and Guellec, 2001). For the sake of comparability, the same sample has been used as in firm-level analysis; i.e., including firms participating in both surveys.

Table 5 presents the estimation results between job flows and innovation. It is well evident that product innovation has the strongest and most significant effect on changes in job flows. A higher share of firms with product innovation (weighted by employment) is related to a higher job creation rate and net employment growth in a sector. Process innovation is also related to job flows positively, but this effect is much weaker and less significant. Innovation variables tend to take effect more strongly one year after the innovation period. For example, product innovation tends to have an immediate effect on job creation compared to a more lengthy effect on the job destruction rate. The same applies to process innovation effects, but these estimates are statistically less significant. The sluggish impact on the job destruction rate can also indicate labour market rigidities in workers' dismissal.

Table 5: Industry-level relationship between job flows and innovation$^{a)}$

Dependent variable:	g^{pos}		g^{neg}		g^{net}	
	Coef.	Robust. Std. Err.	Coef.	Robust. Std. Err.	Coef.	Robust. Std. Err.
(1) Innovation $^{b)\,c)}$	0,116	0,189	0,021	0,069	0,095	0,230
(2) Innovation $^{b)}$ (t-1)$^{d)}$	0,168	0,134	-0,191	0,123	0,360*	0,190
(3) Product innovation $^{b)\,c)}$	0,292*	0,159	-0,081	0,062	0,373*	0,190
(4) Product innovation $^{b)}$ (t-1)$^{d)}$	0,194*	0,115	-0,208*	0,108	0,402**	0,166
(5) Process innovation $^{b)\,c)}$	0,244	0,198	-0,005	0,065	0,249	0,236
(6) Process innovation $^{b)}$ (t-1)$^{d)}$	0,190	0,165	-0,181*	0,108	0,371*	0,203

Note: a) The set of control variables includes firm size and time dummies;
b) Innovation variables are a three-year average share of employment of innovating firms to the total employment in a sector. Similarly to job flow variables, innovation variables are calculated by industry- and firm-size groups.
c) Models (1), (3) and (5) are estimated for 1998-2000 and 2002-04 averages.
d) Models (2), (4) and (6) are estimated for 1999-2001 and 2003-05 averages.
****, ** ,* denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% levels. .*

The industry-level results overlap very well with the firm-level results. In both cases product innovation tends to have a stronger positive effect on employment and the overall employment effect from innovation tends to also be positive. These overlapping results have not been the case in previous surveys: Evangelista and Savona (2003) found much more positive innovation effects at the firm level. Greenan and Guellec (2001) found the process innovation effect to be stronger at the firm level and the product innovation effect to be stronger at the industry level.

6. Final comments

In this paper, the effect of firm- and industry-level employment on innovation was investigated using Estonian data. A dynamic panel of Estonian firms was constructed to estimate the employment effects of innovation at the firm level. Industries' job flow indicators were calculated to investigate the effects of industry-level innovation. Two different specifications were used, one capturing the effect of total innovative activity and the other capturing the effect of distinguished product and process innovation.

The estimation results indicate that firm- and industry-level innovation activity have a positive and statistically significant effect on employment. This confirms the results found in the developed world. Distinguishing between product and process innovation reveals that product innovation tends to have a stronger positive effect on employment than process innovation. However, these effects are only moderately significant. The latter is robust to the level of analysis in terms of firms or industries. Previous studies have not found this effect to be that consistent over firms and industries. This result is also confirmed by the insignificant spillover effects from a firm's parent industry's innovation on a firm's employment. Weak linkages between an industry and its individual firms refer to the small importance of the business stealing effect from one firm to the rest of the industry.

The insignificant effect of process innovation on employment probably reflects the very diverse incentives behind the firms' process innovation activities. The enterprises of a catch-up country may be more heterogeneous, varying from non-innovative low-cost production firms to rapidly-developing innovative firms. While the structure of innovation is expected to change towards more product innovation under the catch-up process (i.e., to approach the innovation structure in the developed world), the positive employment effect of innovation will probably get even stronger in the future.

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Appendix 1. Selection of firm-level studies on technological change and employment

Authors, date	Data	Countries	Industries	Innovation variables	Employment variables	Estimation method	Results
Fung, 2006	1992–2003, 79 (out of 100) banking holding companies, US Securities and Exchange Commission, US Patent and Trademark Office	Top 100 banking holding companies	Banking	Process innovation: patented process innovations per firm and per industry, ICT expenditures	Full-time equivalent employees in firm	CES production function, estimated dynamic differenced labour demand function (OLS, IV)	Process innovation and employment positively related, whole industry's employment benefits from patented process innovations (yearly effects)
Piva, Vivarelli, 2005	1992–97, 575 firms, investment bank Mediocredito Centrale questionnaire survey	Italy	Manufacturing	Innovative investments	Firm-level employment	CES production function, estimated dynamic differenced labour demand function (GMM-SYS)	Innovativeness and employment positively related, effect small in size (yearly effects)
Rennings, Ziegler, Zwick, 2004	2000, 1040 environmentally innovating establishments from IMPRESS project telephone interviews	Germany, UK, Italy, the Netherlands, Switzerland	Industry, manufacturing, services	Discrete variables of environmental product (service) or process innovation	Increasing, decreasing or unchanged employment due to environmental innovation in establishment	Not structural models, various discrete choice models	Product innovation has positive effect on employment, process innovation has no significant effect (cross-section effects)
Evangelista, Savona, 2003	1993–95, cross-section of 943 innovative firms from National Statistical Office innovation survey	Italy	Services	Discrete variables of service or process innovation, total innovation expenditures per employee	Increasing, decreasing or unchanged employment due to innovation in firm	Not structural models, logit models for high- and low-skilled and total employment	Product innovation and innovation expenditures per employee have positive effect on employment and on highly-skilled employment, process innovation has no significant effect (effect within 3 years)

Authors, date	Data	Countries	Industries	Innovation variables	Employment variables	Estimation method	Results
Greenan, Guellec, 2001	1986–90, 15186 firms from French annual business survey and survey of technological innovation	France	Manufacturing	Discrete variables of product or process innovativeness during 1986–90	Annual mean of the 5-year change in full-time equivalent employees in firm	Structural model of supply (Cobb-Douglas production function) and demand, estimate labour demand with 2SLS	Process and product innovation have positive effect on employment, process innovation effect is stronger (medium-term effect of 5 years)
Van Reenen, 1997	1976–82, 598 firms listed on London Stock Exchange merged with SPRU innovation count data	UK	Manufacturing	"Successful commercial introduction of new or improved products and processes" specified by experts. Major technological shifts.	Firm employment in UK	CES production function, estimated dynamic differenced labour demand function	Innovation has positive effect on employment. Product innovation has positive effect, process innovation has insignificant effect.

Appendix 2. Selection of sectoral-level studies on technological change and employment

Authors, date	Data	Country	Industries	Level of disaggregation	Employment and innovation measure	Estimation method	Results
Evangelista, Savona, 2003	1993–95, cross-section of 943 innovative firms from National Statistical Office innovation survey	Italy	Services	22 sub-industries at 2- and 3-digit NACE level	Qualitative employment variable (increase, no change or decrease of employment due to firm's innovation activity)	For every sub-industry of services the index of impact of innovation has been calculated (weighted by the number of employees)	Innovation activity has replaced low-skilled jobs with high-skilled jobs, overall effect of innovation on employment in services is negative (effect within 3 years)
Antonucci, Pianta, 2002	1994–96, 10 industries, CISII cross-section	Germany, France, Italy, Denmark, the Netherlands, the UK, Sweden, Finland	Manufacturing	10 sub-industries	Change in sub-industry employment, total innovation expenditures in sales, new or changed product share in sales, process innovations in sales (sales includes all the sales in sub-industry)	Cross-country regression between change in employment (1994–99), innovation variables (1994–96), change in demand (1994–96), change in labour compensation (1994–96)	Innovation has negative impact on employment; process innovation has a negative effect, product innovation has a positive, but insignificant effect
Greenan, Guellec, 2001	1986–90, 15186 firms from French annual business survey and survey of technological innovation	France	Manufacturing	37 manufacturing industries in 7 size categories (255 categories in total)	Net growth employment rate calculated as job creation rate minus job destruction rate, discrete variable of innovation activities between 1986–90	Net growth employment rate regressed with the share of innovative firms across industries (weighted by the number of employees)	Innovativeness and product innovation are positively related to employment, process innovation has no significant effect (yearly effects)