Dynamics of Technological Innovation and Employment

Panel Evidence from Luxembourg

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Ni Zhen* and Wladimir Raymond†

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Abstract

This paper studies the dynamic relationship between technological innovation and employment using an unbalanced panel enterprise-level data from four waves of the Luxembourgish Community Innovation Survey (CIS) merged with data from the Structural Business Statistics (SBS) over the period 2003-2010. We estimate a great deal of dynamic panel data models using a wide range of estimation techniques from ordinary least squares, maximum likelihood and instrumental variables to the generalized method of moments and the system generalized method of moments. In addition to accounting for the autoregressive structure of the model, we take account of the endogeneity of technological innovation and find that employment growth is negatively and significantly affected by technological innovation, a rather surprising result that is at odds with the majority of the empirical literature.

Keywords: Innovation, Employment, Dynamics, Panel Data, System GMM

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*CREA, Université du Luxembourg, 162A, avenue de la Faïencerie, L-1511; Tel.: (+352) 466 644 68 26; *email*: ni.zhen@uni.lu. The views expressed in this paper are those of the authors and not those of Université du Luxembourg or STATEC.

†STATEC, B.P. 304 L-2013 Luxembourg. Tel.: (+352) 247 843 51; *email*: wladimir.raymond@statec.etat.lu.

1 Introduction

The endogenous growth models identify innovation, or more broadly technical change, as the main driver of a nation's productivity and income growth (Romer, 1990; Aghion and Howitt, 1992). Furthermore, the preservation of (full) employment in a capitalist economy requires a growing income, an idea that dates back at least to Karl Marx. For instance, in the then EU-12 between 1987 and 1990, an average growth rate of output of 3.4% was reached and accompanied by a growth rate of employment of 1.4% with annual productivity gains of 2% (see Drèze and Malinvaud, 1994). Since Griliches's (1979) seminal work, R&D and innovation have also been recognised by scholars and policy makers as major drivers of firm productivity growth. However, the question whether technical change creates or destroys jobs, albeit age-old (see Ricardo, 1821), remains an unsolved issue. Ricardo's quote '*[...] the opinion entertained by the labouring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy*' reflects the public perception regarding the effect of technical change on employment.

In order to predict the effect of technical change on employment, economic theory usually distinguishes between product and process innovation (e.g. Stoneman, 1983). Product innovation is expected to change upward the demand curve for goods or services, which will raise the demand for labour (compensation effect). Of course, if a firm produces multiple products, new goods may simply drive out old goods so this will reduce the overall expansion in labour demand. Process innovation, on the other hand, is expected to reduce production costs by increasing the productivity of labour or capital. Although the resulting required labor per unit of output is lower (displacement effect), technical progress that reduces the effective cost of labor will cause a firm to increase output. The net effect of process innovation on employment depends on which of these two effects dominates. Overall, product innovation is expected to have a positive net effect on employment while the net effect of process innovation is less clear-cut.

Against popular conceptions, the empirical literature usually identifies a positive relationship between technological innovation and employment. For instance, Meghir et al. (1996) find that, during booms, more jobs are created by technologically dynamic firms in the UK because they face lower adjustment costs in employment. Furthermore, technological innovators are more flexible and more capable of moving to their equilibrium levels of employment when faced with shocks. Using similar data, van Reenen (1997) finds that, even after controlling for fixed effects, dynamics, and endogeneity, technological innovations have a positive and significant effect on employment, which persists over several years. This positive effect is confirmed by, among other studies, Lachenmaier and Rottmann (2011) for German manufacturing, Piva and Vivarelli (2005) for Italian manufacturing and Harrison et al. (2014) for manufacturing and services in France, Germany, Spain and the UK. The studies of Brouwer et al. (1993) and Klette and Førre (1998) are worth mentioning because they belong to the very few empirical studies that do not report a clear-cut positive relationship between technological innovation and employment. Brouwer et al. (1993) find that firms' R&D intensity growth has a (slightly) negative effect on employment growth while firms with a high share of R&D devoted to the implementation of new products experience above average employment growth in The Netherlands over the period 1983-1988. Klette and Førre (1998) find no evidence of a positive relationship between firm R&D intensity and net job creation in Norwegian manufacturing in the late 80s and early 90s. If anything, their results show less net job creation and less job security in R&D-intensive firms. As for Luxembourg, one of the most dynamic economies of the EU-28, we know nothing about such a relationship as no study has been done on that matter, hence the motivation of this study.

We consider a dynamic relationship between technological innovation and employment using an unbalanced panel enterprise-level data stemming from four waves of the Luxembourgish Community Innovation Survey (CIS) merged with data from the Structural Business Statistics (SBS) and pertaining to the period 2003-2010. We estimate a great deal of dynamic panel data models using a wide range of estimation techniques from ordinary least squares (OLS), maximum likelihood (ML) (e.g. Anderson and Hsiao, 1981) and instrumental variables (Anderson and Hsiao, 1982) to the generalized method of moments (GMM) (Arellano and Bond, 1991; Arellano and Bover, 1995) and the system GMM (Blundell and Bond, 1998). In addition to accounting for the autoregressive structure of the model, we take account of the endogeneity of technological innovation and find that employment growth is negatively and significantly affected by technological innovation, a rather surprising result that is at odds with the majority of the empirical literature.

The remainder of the paper is organised as follows. Section 2 presents the theoretical framework upon which the empirical model is based and Section 3 presents the resulting dynamic model to be estimated. Section 4 describes the data used to estimate the models, Section 5 discusses the results and Section 6 concludes.

2 Theoretical framework

The relationship between innovation and employment is taken from a traditional labour demand theory Hamermesh (1996); Cahuc and Zylberberg (2004) where a perfectly competitive firm maximizes its profits under a constant elasticity of substitution (CES) production function (van Reenen, 1997)

$$Y = A[(\alpha N)^\rho + (\beta K)^\rho]^{\frac{1}{\rho}}, \tag{2.1}$$

where Y denotes output, N and K are respectively employment and capital input, and A is the potential Hicks-neutral technological change which does not affect the balance of labour and capital in the production function. The parameters α and β represent respectively labour augmenting Harrod-neutral technology and capital-augmenting Solow-neutral technical change. Both parameters measure the reaction of labour and capital to a technological shock. If W denotes wage and P is the output price, real wage (W/P) equals the marginal product of labour under the first-order condition. In logarithm terms,

$$ln(N) = ln(Y) - \sigma ln(W/P) + (\sigma - 1)ln(\alpha), \tag{2.2}$$

where $\sigma = \frac{1}{1-\rho}$ is the elasticity of substitution between capital and labour. Then the labour elasticity of α is given by

$$\frac{\partial ln(N)}{\partial ln(\alpha)} = \frac{\partial ln(Y)}{\partial ln(P)} \frac{\partial ln(MC)}{\partial ln(\alpha)} + (\sigma - 1). \tag{2.3}$$

Since competitive price is equal to marginal cost (MC), we obtain

$$\eta_N = \eta_p \theta + (\sigma - 1). \tag{2.4}$$

Equation (2.4) indicates that the employment-technology elasticity can be expressed with the price elasticity of demand (η_p), the elasticity of marginal cost with respect to technology change (θ) and elasticity of substitution between capital and labour (σ). The parameter η_p captures the positive demand effect of passing on the cost reduction to the product price. The overall effects also depend on the elasticity between capital and labour. If the elasticity is high ($\sigma > 1$), it is more likely to observe a positive employment effect. In the case of low elasticity of substitution ($\sigma < 1$) and inelastic demand, a negative employment effect is more likely to occur. Those influential factors will be further illustrated below by distinguishing between product innovation and process innovation. As mentioned earlier, product innovation affects employment through the demand function while process innovation affects employment through the production function.

2.1 Employment effect of product innovation

Product innovation is expected to change upward the demand curve for goods or services, which will raise the demand for labour. However, if a firm produces multiple products, new products may simply drive out old products, which will reduce the size of the compensation effects if both old and new products are substitutes. As a result, the net employment effect of product innovation depends upon the degree of complementarity between existing and new products. Furthermore, if the firm introduces a radical product innovation, then it will gain monopoly power until other firms introduce similar or better products. In a monopoly situation, the firm may decide to maximize its profits by reducing output, which may reduce employment. If the firm has multiple products, the net employment effect depends upon whether the compensation or the displacement effect dominates.

2.2 Employment effect of process innovation

Process innovation is expected to reduce production costs by increasing the productivity of labour or capital, which yields a displacement effect. Although the resulting required labor per unit of output is lower, technical progress that reduces the effective cost of labor will cause a firm to increase output in order to meet the demand for cheaper products. This increase in output will be accompanied with an increase in employment. The actual positive employment effect depends on the price elasticity of demand. In the case of an elastic demand ($\eta_p < -1$), small change in price will result in significant demand expansion and employment growth, which will be higher in the case of a radical innovation than for an incremental innovation. The positive employment effect may outweigh the direct negative effect in the case of elastic demand. Furthermore, in the case of labour-augmenting technological progress, labour is relatively more efficient than capital. Therefore, firms are prone to substitute labour for capital. The magnitude of this effect depends on the elasticity of substitution between capital and labour, as shown in equation (2.4). Higher elasticity of substitution results in employment growth, is associated with positive employment effect. Finally, the structure of the product and labour markets that the firm operates in exerts an essential impact on the innovation and employment relationship. In a competitive market, entry is relatively easy and reduction in unit cost is fully transmitted to price reduction, leading to further demand expansion and employment growth. Closed markets (e.g. regional markets), on the other hand, tend to be of low price elasticity of demand and monopolistic, whereas an open market is more likely to be of high price elasticity of demand and competitive(Stoneman, 1983; Katsoulacos, 1984).

3 Empirical strategy

The dynamic model of employment is written as

$$n_{it} = \pi_1 n_{it-1} + \pi_2 n_{it-2} + \sum_{j=0}^{5} \pi_{3j} innov_{it-j} + \pi_4 \mathbf{x}_{it} + \gamma_i + T_t + \nu_{it}, \tag{3.1}$$

$i = 1, ..., N$; $t = 1, ..., T$, where n_{it} is the employment level (in log) of firm i at time t, $innov$ consists of technological product or process innovations (TPP) that are included separately as regressors in some specifications or in combination with each other in some other specifications, $\mathbf{x}_{it}$ is a set of additional explanatory variables such as wage, output, market competitiveness, and education level of staff, γ_i denotes time-invariant firm-specific effect, T_t denotes time dummies to control for general macroeconomic demand shocks, and $\nu_{it} \sim iid(0, \sigma_\nu^2)$ denotes idiosyncratic disturbances that are independent across firms and over time.

As Arellano and Bond (1991) point out, if firms endure a costly employment adjustment, the actual employment may deviate from the equilibrium level in the short run. In particular, European firms suffer from high costs of hiring and firing workers. As a result, a dynamic model of employment is called for, which includes one-year and two-year lags of employment and five lags of innovation along the lines van Reenen (1997). As pointed out by Nickell (1984), the first lag of employment arises from quadratic adjustment costs in employment changes. The second lag is due to aggregation over skilled and unskilled workers. Moreover, innovation activities are potentially dynamic and bring about long-lasting effects. It may lead to a time interval between the implementation of innovation and its actual effect on employment, hence the inclusion of lags of technological innovation up to 5 years.[1]

Nickell (1981) shows that the fixed-effects estimator is biased downward in dynamic panel data models. In particular, this bias is serious for panel with short time dimension. Above all, the lagged dependent variable n_{it-1} is correlated with the individual effect γ_i by construction, therefore correlates with $\delta_{it} = \gamma_i + \nu_{it}$ and induces inconsistent estimation. The common solution is to transform the equation (3.1) to first difference form in order to wipe out the fixed effects

$$\Delta n_{it} = \pi_1 \Delta n_{it-1} + \Delta n_{it-2} + \sum_{j=0}^{5} \pi_{3j} \Delta innov_{it-j} + \pi_4 \mathbf{x}_{it} + \Delta T_t + \Delta \nu_{it}. \tag{3.2}$$

However, the differenced lagged dependent variable Δn_{it-1} correlates with $\Delta \nu_{it}$, considering Δn_{it-1} contains n_{it-1} and $\Delta \nu_{it}$ contains ν_{it-1}. Endogeneity arises and OLS method leads to inconsistent estimation in the first-differenced model. To solve the problem, we have to rely on the instrumental

[1] Lags up to 6 years give rise to insufficient number of observations.

variables of differenced lagged dependent variable. Arellano and Bond (1991) propose the GMM-DIF (first-differenced generalized method of moments) estimator by constructing instruments for the lagged dependent variables from the second and third lags. More specifically, the orthogonality condition writes as follows:

$$E(n_{i,t-s}\Delta\nu_{it}) = 0;\ t = 4, 5.......T. \tag{3.3}$$

The system generalized method of moment estimators (GMM-SYS), developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998), is quite similar to first-differenced GMM. Both estimators correspond to the dynamic panels with small time horizon and large cross-section dimension, which means short time periods and many individuals. More specifically, the first-differenced and system GMM are designed for panel analysis with the following assumptions:

- the process is dynamic, one left-hand-side variable is dynamic and depends on the past realizations.
- some regressors may be endogenous.
- small time horizon and large cross-section dimension panels
- linear functional relationship

In contrast to the approach of GMM-DIF, GMM-SYS uses lagged differences of dependent variables as instruments for equation in levels, in addition to lagged level of dependent variable as instruments for equation in first difference. In particular, it imposes the restriction on moment conditions:

$$E(\delta_{it}\Delta n_{i,t-1} = 0);\ t = 4, 5.......T. \tag{3.4}$$

The system GMM further requires a restriction on the initial condition:

$$E(\delta_{i3}\Delta n_{i,2} = 0). \tag{3.5}$$

One additional requirement which is weaker than requiring the level of regressors to be uncorrelated with the individual effects writes:

$$E(\Delta X_{it}\gamma_i = 0). \tag{3.6}$$

GMM-SYS obtains the additional moment conditions and exploits all the information with regard to the levels and difference equation. Therefore GMM-SYS is more efficient than GMM-DIF, especially when the autoregressive parameter is moderately large and the time dimension is short.

For short panels, GMM-DIF can suffer from a downward bias when the autoregressive parameter is high.

4 Data

The empirical analysis is based on an unbalanced longitudinal dataset with 1203 firms over the period 2003-2010. This dataset is constructed by merging two different datasets, Community Innovation Survey (CIS) and Structural Business Statistics (SBS) of Luxembourg. CIS is a questionnaire collected biennially over the period 2002-2010. It consists of four waves of firm-level data which covers all economic activities. The questionnaire contains information on firm innovation activities, in particular, product innovation and process innovation during the reference period. It also includes the introduction of new market products and new firm products, the percentage of employees with higher education, the degree of market competition, past patenting activities. Although only 4 waves of observations are available, the innovation question is proposed in a way that we can fill in the gap between two waves. For example, in the second wave of CIS it is asked that during the three years 2004 to 2006, whether the enterprise has introduced the process or product innovation. Consequently, if the answer is positive, we encode innovation variables of both 2005 and 2006 as 1. If the answer is negative, we consider firm did not implement innovation in 2005 and 2006. The innovation information of 2003 and 2004 can be deduced in the same way. The boundary years such as 2004 and 2006 are more problematic. Mistakes only arise when one wave reports negative innovation activities proceeding with a positive response, as questions relevant to a three-year period. However, it turns out that no wave reports negative innovation activities proceeding with a positive response in the dataset. It leads to 8 waves of innovation information over the period 2003-2010.

Structural Business Statistics (SBS) is an annual database which includes observations on employment, production value, wages, value added at factor cost, number of hours worked, gross value added per employee, gross value added per hour worked, gross investment rate.

In order to focus on the sample of CIS, we delete the enterprises that only appear in SBS but not in CIS. Moreover, since Luxembourg earns the reputation as the European top tax haven where certain taxes are levied at a low rate, there are abundant shell corporations. We further remove firms with less than 10 employees and firms with negative output and zero wage to avoid unreasonable results.

In order to handle with missing values, we replace the missing values of employment of SBS by its counterpart from CIS. We replace the missing values of the measure of introduction of new market products and new firm products by zero when firms do not implement product innovations. In addition, the percentage of employees with higher education and competitiveness of the market have more than 50% missings and vary little along the time. We replace the missing values by their respective mean values.

It leads to a dataset of 1203 firms over the period 2003-2010. The dataset consists of 65.55% of small enterprises, 27.14% of medium-sized enterprises, and 7.31% of large enterprises. We take the double natural log transformation (both dependent variables and continuous explanatory variables) in order to have elasticity interpretations. Moreover, we calculate the log growth rate for all continuous variables (turnover, wages, output, working hours, investment rate). Two dummy variables which measure the product innovation and process innovation are created. We also create a dummy variable as a general index of innovation *TPP (Technological Product and Process Innovation)*, which takes the value 1 if firms implement either product or process innovation. We also create sector dummies according to the NACE 2-digit level to account for the sector effects.

4.1 Descriptive Statistics

Before presenting the results of the econometric analysis, some descriptive statistics are given in Table 1. We can see about 27% of enterprises implement product innovation, 22% of enterprises implement process innovation whereas 33% of enterprises implement either type of innovation. Averagely speaking, 30% of employees are with higher education (including post-secondary college diplomas and university graduates diplomas). Market competition is a categorical variable, defined on a 1-4 scale, where 1 indicating low market competition and 4 indicating high market competition. Therefore the value 3.38 suggests that the average degree of market competition is intense. Moreover, 10% of firms implement product innovation which is new to the market. The average employment growth, turnover, wage, output growth rate are not particularly high.

The sample is further divided in three sub-samples according to the "innovation frequency" over the period 2003-2010. The innovation frequency ranges from 0 to 8 and only takes even numbers from the way TPP is constructed. In the group of non-innovators, 516 firms do not innovate throughout 8 years. In the group of occasional innovators, 388 firms innovate twice during the 8-year period. In the group of persistent innovators, 299 firms innovate at least 4 times over the period 2003-2010. Table 2 contains the information on innovation groups, which comprises 42.88 % of non-innovators, 32.26% of occasional innovators, 24.86% of persistent innovators. Therefore, the number of non-innovative firms is substantial in the sample.

Table 3 illustrates the innovation frequency across all sectors of the economy. As shown below, manufacturing, transportation and storage and wholesale and retail trade, repair of motor vehicles

Table 1: Descriptive statistics

Variable	Mean	Sd.	Min	Max
Employment, growth rate	0.03	0.20	-2.47	2.19
Product innovation, dummy	0.27	0.44	0	1
Process innovation, 0/1	0.22	0.42	0	1
TPP, dummy	0.33	0.47	0	1
Employees with higher education, percentage	0.30	0.34	0	1
Market competitiveness	3.38	0.80	1	4
Patent, dummy	0.12	0.32	0	1
New to the market, dummy	0.10	0.30	0	1
Turnover, growth rate	0.05	0.35	-8.80	4.42
Wage, growth rate	0.05	0.32	-2.28	2.09
Output, growth rate	0.05	0.40	-8.80	4.64
Value added at factor cost, growth rate	0.05	0.45	-6.00	3.96
Hours of work, growth rate	0.03	0.22	-2.52	2.19
Gross investment, growth rate	0.12	2.49	-10.40	12.65
Number of observations		9620		

Table 2: Percentage of non-innovators, occasional innovators and persistent innovators

Variable	Percentage	Number of firms
Non-innovator	42.88	516
Occasional innovator	32.26	388
Persistent innovator	24.86	299
Total	100.00	1203
Number of observations	9620	

and motorcycles are the main industries in the sample. 40.35% of persistent innovators are from manufacturing, followed by information and communication (20.54%). Moreover, 30.55% of non-innovators are from the sector of transportation and storage, followed by manufacturing (23.62%).

Table 4 illustrates the relationship between innovation group and firm size. According to the definition of the European Commission (Recommendation 2003/361/EC: SME Definition), there are three broad parameters which define small, medium and large enterprises:

- Micro-entities are companies with up to 10 employees.
- Small companies employ up to 50 workers.
- Medium-sized enterprises have up to 250 employees.
- Large enterprises have 250 or more persons employed.

For the aforementioned reason, we exclude micro-entities from the current sample. As shown below, 80.62% of non-innovators are small firms. By contrast, only 1.68% of non-innovators are large enterprises. In particular, 83.98% of large enterprises are persistent innovators whereas 72.39% of medium-sized enterprises innovate at least twice over the period 2003-2010. It suggests that the medium-sized and large enterprise innovate more frequently than small enterprise, which

Table 3: Percentage of non-innovators, occasional innovators and persistent innovators across sectors

Sector	NACE	Non-innovator		Occasional		Persistent		Total	
		row	column	row	column	row	column	row	column
Support services	77-82	17.39	0.28	65.22	1.53	17.39	0.41	100	0.68
Construction	41-43	68.12	1.65	31.88	1.12	0.00	0.00	100	1.02
Electricity and gas	35	33.33	0.84	25.00	0.92	41.67	1.56	100	1.07
Financial activities	64-66	17.31	2.03	28.66	4.90	54.03	9.39	100	4.97
Health and social work	86-88	100.00	0.04	0.00	0.00	0.00	0.00	100	0.01
Information & communication	58-63	25.40	8.37	32.52	15.63	42.08	20.54	100	13.96
Manufacturing	10-33	34.28	23.62	26.14	26.25	39.57	40.35	100	29.17
Mining & quarrying	05-09	34.69	0.60	48.98	1.23	16.33	0.41	100	0.73
Science & technicals	69-75	42.37	9.15	32.63	10.27	25.00	7.99	100	9.14
Real estate	68	100.00	0.46	0.00	0.00	0.00	0.00	100	0.19
Transportation & storage	49-53	64.69	30.55	24.41	16.80	10.91	7.62	100	20.00
Water supply & sewerage	36-39	46.74	1.51	22.83	1.07	30.43	1.45	100	1.36
Trade & repair of vehicles	45-47	50.59	20.88	33.28	20.02	16.13	9.85	100	17.48
Other services	94-96	7.14	0.04	35.71	0.26	57.14	0.41	100	0.21
Total	05-96	42.34	100.00	29.05	100	28.61	100.00	100	100.00
Number of observations					6740				

Table 4: Percentage of non-innovators, occasional innovators and persistent innovators and firm size

Innovation status	Small		Medium-sized		Large		Total	
	row	column	row	column	row	column	row	column
Non-innovator	80.62	52.08	17.69	27.61	1.68	9.74	100	42.34
Occasional innovator	71.50	31.69	26.92	28.81	1.58	6.29	100	29.05
Persistent innovator	33.33	0.84	25.00	0.92	41.67	1.56	100	1.07
Total	65.55	100.00	27.14	100.00	7.31	100.00	100	100.00
Number of observations				6740				

is consistent with previous studies (see van Reenen, 1997; Lachenmaier and Rottmann, 2011; Piva and Vivarelli, 2005). It may be as a result of more favourable R&D research environment, better access to external financing channels and less risk of market failures.

Table 5 depicts the descriptive statistics by innovation groups. Persistent innovators (236.41) tend to have higher average employment level than non-innovators (39.39) and occasional innovators (49.34). However, there is no substantial difference in growth rate of employment. The percentage of employees with higher education is slightly higher for persistent innovators (38%) than occasional innovators (32%) and non-innovators (23%). Moreover, persistent innovators use patent to protect their innovation results more frequently (22%) and tend to introduce the new market products (26%) more often than less innovative counterparts. However, there are no significant differences in growth rate of output, wage, turnover, hours of work, value added at factor cost and degree of market competition. In addition, the investment rate suffers a below-average growth rate for persistent innovators. Although medium and large sized firms tend to innovate more frequently, the lack of significant difference in growth rate of employment suggests no clear-cut positive effect. Instead, it may be interpreted as a hint for a negative impact of innovation on employment at the firm level.

Going back to the above-mentioned data, it is worth mentioning that the innovation strategies are highly correlated. Firms which implement product innovation are more likely to implement process innovation. The correlation between total frequency of product innovation and process innovation is 0.718. As pointed out by van Reenen (1997), product innovation often takes place along with process innovation. The effect of product innovation turns out to be difficult to disentangle from process innovation, since many innovations consist of both elements.

5 Estimation results

As the first step for the econometric analysis, Table 6 contains OLS regression of employment on innovation and patents. The preliminary results do not include time dummies and sector

Table 5: Descriptive statistics for non-innovators, occasional innovators and persistent innovators

Variable	Non-innovator	Occasional	Persistent	Total
Employment	39.39	49.34	236.41	98.64
Employment, growth rate	0.03	0.03	0.04	0.03
Employees with higher education	0.23	0.32	0.38	0.30
Market competitiveness	3.36	3.40	3.38	3.38
Patent, dummy	0.03	0.07	0.22	0.12
New to the market, dummy	0.00	0.09	0.26	0.10
Turnover, growth rate	0.04	0.05	0.05	0.05
Wage, growth rate	0.04	0.05	0.05	0.05
Output, growth rate	0.05	0.06	0.06	0.05
Value added at factor cost, growth rate	0.04	0.07	0.06	0.05
Hours of work, growth rate	0.03	0.04	0.04	0.03
Gross investment, growth rate	0.16	0.15	0.04	0.12
Turnover, log	15.13	15.42	16.54	15.60
Wage, log	13.76	14.03	15.00	14.18
Output, log	14.69	14.99	16.24	15.20
Value added at factor cost, log	14.06	14.28	15.43	14.50
Hours of work, log	10.72	10.90	11.71	11.04
Gross investment, log	10.68	10.99	12.41	11.29
Number of observations		6740		

dummies. Each column adds additional lag variable of innovation. The last column includes lags up to five years for both innovation and patent, although some variables are dropped out due to collinearity. The contemporaneous coefficient of *TPP* is not significant, nonetheless lagged *TPP* shows a significant and positive effect. The second lag shows a significant positive effect as well when lags up to 1 and 2 years are included in the fix effect model. By contrast, the estimates of patent are insignificant and less clear-cut. This suggests that conditional on innovation, changes in firm patenting activity have no significant impact on employment growth. In other words, patents do not contribute to explain the variation in the growth rate of employment directly. The wage and output show significant positive effects. One alternative method apart from the fix effect is to use the first differencing estimators. Nevertheless, it gives rise to insignificant results therefore we leave out here.

The estimate relative to equation (3.1) is presented in Table 7, which builds up a more complex and theoretically satisfactory specification by adding lagged employment, time and sector dummies. The first 4 columns report the results based on OLS estimations and columns (5) and (6) are based on dynamic panel estimators. In the first column OLS is carried out without time dummies and sector dummies. The second column adds time dummies and the third column includes additionally sector dummies. In the forth column product innovation and process innovation enter the employment equation jointly in place of *TPP*. The column 5 uses Arellano-Bond GMM-SYS estimator and column 6 uses Anderson-Hsiao MLE estimator. First of all, time dummies capture

Table 6: OLS estimates of the static model of employment

Regressor	Dependent variable, Log employment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Higher education	0.054	0.058	0.038	0.033	-0.090	-0.108	0.025
	(1.05)	(1.15)	(0.63)	(0.58)	(-1.03)	(-1.20)	(0.09)
Competitiveness	-0.010	-0.010	0.006	0.006	0.008	0.006	0.000
	(-1.09)	(-1.06)	(0.45)	(0.49)	(0.46)	(0.36)	(0.01)
Wage	0.466^{***}	0.454^{***}	0.438^{***}	0.430^{***}	0.460^{***}	0.456^{***}	0.410^{***}
	(56.80)	(50.25)	(43.40)	(36.30)	(32.74)	(24.38)	(14.43)
Output	0.167^{***}	0.169^{***}	0.168^{**}	0.163^{***}	0.148^{***}	0.147^{***}	0.243^{***}
	(27.11)	(25.82)	(24.09)	(21.00)	(17.22)	(13.82)	(12.89)
TPP_t	0.009	-0.003	0.015	0.010	0.008	0.001	
	(1.41)	(-0.38)	(1.63)	(0.90)	(0.54)	(0.03)	
TPP_{t-1}		0.021^{**}	0.007	0.017	0.011	0.025	
		(2.75)	(0.90)	(1.48)	(0.99)	(1.40)	
TPP_{t-2}			0.030^{***}	0.021^{*}	0.022	0.024	
			(3.49)	(2.02)	(1.41)	(1.37)	
TPP_{t-3}				0.016	0.016	0.023	
				(1.67)	(1.60)	(1.29)	
TPP_{t-4}					-0.002	-0.002	
					(-0.18)	(-0.10)	
TPP_{t-5}						0.007	0.044^{*}
						(0.47)	(1.99)
Patent_{t-5}							-0.042
							(-0.36)
Constant	-5.488^{***}	-5.364^{***}	-5.149^{***}	-4.946^{***}	-5.104^{***}	-5.015^{***}	-5.897^{***}
	(-51.44)	(-45.19)	(-36.63)	(-30.34)	(-26.15)	(-20.17	(16.52)
# observations	5572	4872	4058	3280	2505	1827	867
adj. R-squared	0.565	0.526	0.476	0.418	0.400	0.296	0.372

t-statistics in brackets; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

the macroeconomic trend and decrease the magnitude of most estimates considerably. However, the incorporation of sector dummies results in the same outcome, hence left out for the following analysis. The first lag of employment, wage and output show significant and positive effects, however, the estimation of *TPP* along with product innovation and process innovation remain insignificant. Therefore we suspect that some variables are potentially endogenous, such as the innovation variable itself.r

5.1 Instrumenting the variable of interest

In order to check for causality and obtain more reliable inference, we further investigate the case of innovation as endogenous variable. We instrument the variable of interest using the past patenting activities, as adopted by van Reenen (1997). The idea behind is that firms build up a stock of technologies which facilitates current innovation activities and enhances the probability of successful innovation when the internal and external economic conditions are favourable. It is plausible to believe that past patenting activities have no impact on current employment, however exert a

Table 7: OLS, ML and GMM estimates of the dynamic model of employment

Regressor	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) ML	(6) GMM
Employment$_{t-1}$	0.200**	0.192**	0.192**	0.191**	0.502**	0.757**
	(7.24)	(6.88)	(6.88)	(6.82)	(16.12)	(2.92)
Employment$_{t-2}$	-0.021	-0.005	-0.005	-0.005	0.034	-0.128
	(-0.80)	(-0.18)	(-0.18)	(-0.19)	(1.42)	(-1.46)
Higher education	-0.098	-0.103	-0.103	-0.107	-0.147**	-0.168*
	(-1.13)	(-1.19)	(-1.19)	(-1.23)	(-5.76)	(-1.68)
Competitiveness	0.017	0.015	0.015	0.015	(0.007)	-0.002
	(0.99)	(0.86)	(0.86)	(0.86)	(0.94)	(-0.16)
Wage	0.426**	0.427**	0.427**	0.427**	0.368**	0.262
	(23.24)	(23.18)	(23.18)	(23.09)	(23.59)	(1.35)
Output	0.126**	0.126**	0.126**	0.127**	0.040**	0.017
	(11.88)	(11.84)	(11.84)	(11.82)	(5.49)	(0.61)
TPP$_{t}$	-0.002	-0.002	-0.002		0.003	-0.102
	(-0.13)	(-0.11)	(-0.11)		(0.17)	(-0.22)
TPP$_{t-1}$	0.020	0.020	0.020		0.013	0.259
	(1.17)	(1.16)	(1.16)		(0.77)	(0.51)
TPP$_{t-2}$	0.017	0.017	0.017		0.015	-0.058
	(1.02)	(1.02)	(1.02)		(0.64)	(-0.15)
TPP$_{t-3}$	0.0146	0.013	0.013		0.013	0.324
	(0.86)	(0.78)	(0.78)		(0.78)	(0.67)
TPP$_{t-4}$	-0.004	-0.004	-0.004		-0.007	-0.243
	(-0.27)	(-0.27)	(-0.27)		(-0.50)	(-1.39)
TPP$_{t-5}$	0.002	0.000	0.000		-0.000	0.200
	(0.16)	(0.03)	(0.03)		(-0.04)	(0.60)
Product innov$_{t}$				0.002		
				(0.11)		
Product innov$_{t-1}$				-0.002		
				(-0.11)		
Product innov$_{t-2}$				0.029		
				(1.45)		
Product innov$_{t-3}$				0.003		
				(0.14)		
Product innov$_{t-4}$				0.009		
				(0.56)		
Product innov$_{t-5}$				0.002		
				(0.13)		
Process innov$_{t}$				0.000		
				(0.01)		
Process innov$_{t-1}$				0.010		
				(0.52)		
Process innov$_{t-2}$				0.002		
				(0.10)		
Process innov$_{t-3}$				-0.005		
				(-0.23)		
Process innov$_{t-4}$				-0.012		
				(-0.70)		
Process innov$_{t-5}$				-0.007		
				(-0.39)		
Year dummies	no	yes	yes	yes	yes	yes
Sector dummies	no	no	yes	yes	yes	yes
Constant	-4.992*	-5.019*	-5.019*	-5.022*	-4.097*	-5.897***
	(-18.96)	(-18.96)	(-18.96)	(-18.93)	(-23.79)	(16.52)
# observations				1816		
adj. R-squared	0.272	0.274	0.274	0.271		

t-statistics in brackets; $^{*}p < 0.10$, $^{**}p < 0.05$.

strong influence on current innovation activities. Additionally, patent is available in the Community Innovation Survey of Luxembourg over the period 2004-2010. Firms are required to answer the following question: During the reference period, did your enterprise make use of patent to protect your enterprises knowledge or innovations? If yes, how efficient or important was it on your enterprises activity? One further point to report concerns the correlation between patent and *TPP*, which is far from perfect. The main reason is nevertheless by cause of missing values of patent. There are 49.03% of missing values for *TPP* and 57.48% of missing values for patent. Therefore, in spite of validity, too much missing values may undermine the power of instruments and blur the conclusion.

Table 8: GMM estimates of the dynamic model of employment instrumenting innovation output

Regressor	(1)	(2)	(3)	(4)	(5)	(6)
Employment_{t-1}	0.736^{**}	0.741^{**}	0.730^{**}	0.736^{**}	0.750^{**}	0.734^{**}
	(5.99)	(5.72)	(5.92)	(5.65)	(5.44)	(5.65)
Employment_{t-2}	-0.122^{**}	-0.123^{**}	-0.122^{**}	-0.128^{**}	-0.129^{**}	-0.128^{**}
	(-4.34)	(-4.29)	(-4.32)	(-4.77)	(-4.73)	(-4.79)
Higher education				-0.171^{**}	-0.161^{**}	-0.179^{**}
				(-2.91)	(-2.60)	(-3.09)
Competitiveness				0.013^{**}	0.013^{*}	0.015^{**}
				(1.97)	(1.86)	(2.21)
Wage	0.288^{**}	0.284^{**}	0.293^{**}	0.310^{**}	0.299^{**}	0.314^{**}
	(4.00)	(3.74)	(4.06)	(3.66)	(3.33)	(3.71)
Output	0.047^{**}	0.047^{**}	0.047^{**}	0.040^{**}	0.040^{**}	0.040^{**}
	(3.83)	(3.77)	(3.86)	(3.74)	(3.68)	(3.71)
TPP	-0.046^{**}			-0.056^{**}		
	(-2.56)			(-3.49)		
Product innov		-0.052^{**}			-0.065^{**}	
		(-2.32)			(-3.28)	
Process innov			-0.076^{**}			-0.088^{**}
			(-2.75)			(-3.57)
Year dummies	yes	yes	yes	yes	yes	yes
# observations	3745	3745	3745	3305	3305	3305
AR(1)	-6.26^{***}	-6.12^{***}	-6.31^{***}	-6.10^{***}	-5.91^{***}	-6.17^{***}
AR(2)	0.21	0.26	0.17	0.08	0.13	0.02
Hansen test	15.64	17.15	14.06	16.38	18.00	15.17

t-statistics in brackets; $^{*}p < 0.10$, $^{**}p < 0.05$.

Table 8 reports results of system GMM estimation based on instrumenting innovation with the two-period lagged patent. Columns (4)-(6) contain control variables such as employees with higher education and degree of market competition whereas columns (1)-(3) leave out those control variables. Columns (2) and (5) show the employment effect of product innovation whereas columns (3) and (6) show the effect of process innovation. It's worth noting that coefficients of dummy variables represent the growth rate. To illustrate, the coefficient of *TPP* (-0.0464) in column (1) indicates that for a representative firm, the introduction of innovation will reduce the employment by 4.64%. In addition, coefficients of logarithm value of continuous variables represent the elasticity. To illustrate, the coefficient of wage (0.288) in column (1) indicates that 10% increase in wage will lead to 2.88% increase in employment. The first lag of employment shows a significant and positive sign, which is consistent with previous studies (see van Reenen, 1997; Lachenmaier and Rottmann, 2011; and Piva and Vivarelli, 2005). The magnitude of the coefficient is considerably large and close to 1, which suggests the presence of strong persistence. Together with the short time dimension, it further justifies our application of system GMM rather than first-differenced GMM. The second lag enters with a significant and negative sign, which is consistent with the studies of Nickell and Wadhwani (1991) and van Reenen (1997). Moreover, for stability of the dynamic equation, the inverses of all roots of the lag operator polynomial must be inside the unit circle. The stability of the dynamic model is confirmed as the sum of the lag coefficients is less than 1. In addition, as expected, output and wage enter the employment equation with a significant and positive sign. The percentage of employees with higher education shows a significant negative sign, which is reasonable and expected. It relates to the heated debate on skill-biased technological change which favours skilled and often more educated labour over unskilled labour. The degree of competitiveness also shows the positive significant effect, in regard to aforementioned statement. The market competition boosts the positive employment effect.

We test and confirm the assumption of absence of serial correlation of error term, which is essential for consistent results. More specifically, if ν_{it} is not serially correlated, there must be a significant negative serial correlation of first level (AR(1)) and no significant serial correlation in second level (AR(2)). Moreover, in the case of an overidentified model, we use Sargan test and Hansen test to check the validity of instrument sets and overidentified restrictions. Both Sargan test and Hansen test are χ^2 distributed under the null hypothesis with $(p-k)$ degrees of freedom (where p is the number of instruments and k is the number of variables in the regression). Nevertheless, it is worth emphasizing the Sargan test loses the validity and consistency in the case of nonsphericity in the error terms, whereas Hansen test remains robust. The presence of nonsphericity in the error terms is suspected hence Sargan test is misleading. The p-value of Hansen test leads to non rejection of the null hypothesis of joint validity of the instruments, which confirms the validity of set of instruments.

5.2 Robustness check

In this subsection, we extend the analysis by including more control variables such as turnover, gross investment rate and gross value added per hour. Table 9 presents the estimation results. The coefficients of lagged employment change slightly, but the signs remain the same. Moreover, turnover exhibits a significant negative effect. The significant effect of output diminishes due to the presence of investment rate, which shows the significant positive effect. Wage, higher education and degree of market competition slightly change in the magnitude of coefficients. Nevertheless, the coefficients of TPP, product innovation and process innovation vary slightly and remain significant. In all the cases, the coefficients of innovation variables confirm a significant negative relationship between innovation and employment.

Table 9: GMM estimates of the dynamic model of employment: Robustness check

Regressor	(1)	(2)	(3)
Employment_{t-1}	0.803^{**}	0.803^{**}	0.788^{**}
	(4.02)	(4.06)	(3.74)
Employment_{t-2}	-0.099^{**}	-0.104^{**}	-0.089^{**}
	(-2.38)	(-2.56)	(-2.02)
Higher education	-0.128^{*}	-0.118^{*}	-0.146^{**}
	(-1.90)	(-1.75)	(-2.12)
Competitiveness	0.010	0.010	0.013
	(1.18)	(1.13)	(1.42)
Wage	0.268^{**}	0.256^{**}	0.277^{**}
	(3.17)	(3.07)	(3.18)
Output	0.143	0.150	0.169
	(1.40)	(1.46)	(1.52)
TPP	-0.055^{**}		
	(-2.61)		
Product innov		-0.066^{**}	
		(-2.47)	
Process innov			-0.094^{**}
			(-2.78)
Turnover	-0.139^{**}	-0.128^{**}	-0.171^{**}
	(-2.31)	(-2.18)	(-2.59)
Valued added	-0.073	-0.086	-0.063
	(-1.03)	(-1.19)	(-0.87)
Investment	0.011^{**}	0.010^{**}	0.011^{**}
	(2.43)	(2.34)	(2.30)
Year dummies	yes	yes	yes
# observations		2196	
AR(1)	-3.03^{***}	-3.00^{***}	-2.97^{***}
AR(2)	0.89	0.89	0.85
Hansen test	15.79	16.56	14.13

t-statistics in brackets; $^{*}p < 0.10$, $^{**}p < 0.05$.

6 Conclusion

Using a unique longitudinal dataset of 1203 luxembourgish firms over the period 2003 to 2010, we analyse the effect of innovation on employment with the system generalized method of moments estimation. Innovation is instrumented using the past patenting activities, as suggested by the previous studies. We discover that medium-sized and large enterprises tend to implement innovation more frequently. In addition to accounting for the autoregressive structure of the model, we take account of the endogeneity of technological innovation and find that employment growth is negatively and significantly affected by technological innovation, a rather surprising result that is at odds with the majority of the empirical literature.

Although inconsistent with most empirical findings relevant to the innovation effect, it's worth emphasizing that the result is very close to Klette and Førre (1998). Their study suggests that there is no clear-cut positive relationship between innovation and net job creation. Moreover, they find out that the most R&D-intensive firms have declined in terms of employment relative to the rest of the manufacturing sector. This similarity can be traced back to the resemblance of two economies: both are small open economies and high cost countries. Going back to the discussion in regard to competition, the positive employment effect is more likely to emerge in the competitive markets. Although the self-report average market competition is intense, it may not reflect the real market condition. Innovation is regarded as a means to preserve competitiveness. Competition in the product, labour and capital markets is a necessary prerequisite for innovation to exert a positive impact on employment. It can be argued that if the international competition is more fierce, the importance of innovation as a means to preserve competitiveness will be elevated, and a positive relationship between innovation and employment is more likely to arise.

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