80

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Keywords: Perceived competition, technological innovation, panel data

How Does Firms' Perceived Competition Affect Technological Innovation in Luxembourg?*

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January 29, 2015

Abstract

This paper revisits the competition-innovation relationship using an unbalanced panel of enterprise data stemming from various waves of the Luxembourgish innovation survey and pertaining to the period 2002-2010. Using four measures of perceived competition and three indicators of technological innovation, we estimate by full-information maximum likelihood a nonlinear dynamic simultaneous-equations model with pseudo-fixed effects and find that competition for better products increases innovation activities and eventually innovation success. We also find that firms active in markets with rapid product obsolescence often consider their markets to be characterised by rapidly-changing technologies where higher competition is also related to higher innovation.

Keywords: O31, O32, O38, C33, C35

JEL classification: Perceived competition, technological innovation, Panel Data

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1 Introduction

This paper revisits the competition-innovation relationship using an unbalanced panel of enterprise data stemming from various waves of the Luxembourgish innovation survey and pertaining to the period 2002-2010. Given the small and open economy of Luxembourg, the firms operating therein are more likely to face fierce competition especially from internationally-operating firms with possibly high innovation standards. It is therefore important for policy makers in this country to know how firms perform technologically over time when faced with competition. This has motivated the Luxembourgish government in its National Reform Program to consider innovation and competitiveness as two of its priorities. The analysis differentiates itself from other studies on that topic by using the rather new concept of *perceived* competition for which various measures exist in the innovation survey.[1] As we shall see, the competitive environment of the enterprise operating in Luxembourg is better described by these subjective measures than by traditional measures such as market concentration (e.g. Herfindhal index), the price-cost margin or even the newly-suggested price elasticity index of Boone (2008). To better uncover the effect of competition on innovation, we isolate the effect of past innovation behaviour which may be due to true persistence in innovation activities or intrinsic characteristics of the firm also known as individual effects.[2] Our study again stands out from existing empirical papers on the competition-innovation relation as the dynamic feature of the innovation process has largely been neglected.[3]

The literature on the relation between competition and innovation dates back at least to Schumpeter (1942) who studies the link between market structure and innovation and concludes that competitive markets are not necessarily the most effective organisations to promote innovation. This view is later challenged by Arrow (1962) who finds instead that there is a greater incentive to innovate in more competitive environments. The theoretical models that result from these views predict a large range of results depending on the type of innovation (product versus process), the appropriability strategy of the innovation (patenting versus licensing), and the characteristics of the firm such as its quality and its motivation towards escaping competition (see e.g. Bonanno and Haworth, 1998; Boone, 2000; and

[1] Luxembourg is one of the few countries, together with Germany and Canada, whose innovation survey includes measures of perceived competition.

[2] The focus here is not on distinguishing between true and spurious persistence, see Heckman (1981).

[3] The majority of empirical studies on the relation between competition and innovation are based on cross-sectional data, see for instance Peroni and Gomes Ferreira (2012) in the case of Luxembourg. Two notable exceptions are the studies by Bérubé et al. (2012) and Tingvall and Poldhal (2006) that are based on panel data. They do not, however, account for the dynamic characteristic of the innovation process.

Gilbert, 2006 for a survey). Scherer (1967) predicts an inverted-U relationship between competition and innovation, a view that is later popularised by Aghion et al. (2005) who show that the Arrowian effect, also referred to as the *escape-competition* effect, applies when competition is low and the Schumpeterian effect applies when competition is high. The inverted-U relation has since been put to test in a great deal of empirical studies with unambiguous results (see e.g. Tingvall and Poldhal, 2006; Peneder, 2012; Peroni and Gomes Ferreira, 2012; Polder and Veldhuizen, 2012).

One of the main issues that arises when studying the relation between competition and innovation is concerned with measuring competition. Market concentration variables, such as the Herfindhal index or 4-firm concentration ratio, and the price-cost margin (PCM) also known as the Lerner index have for a long time been the main measures of competition used in empirical studies. The shortcomings of these measures are by now widely known (see e.g. Boone, 2008; Boone et al., 2013). In our case, given the size and the degree of openness of the Luxembourgish economy, the geographic and product markets on which concentration measures of competition are based are particularly difficult to define. Market concentration measures based on Luxembourgish data are more likely to indicate an overall low level of competition, as shown in Peroni and Gomes Ferreira (2012), whilst the reality may be different especially in the knowledge-intensive service sector. As for the PCM, its use as a measure of competition is not recommended when the time dimension is involved. Boone et al. (2013) explain that an increase of PCM over time, due to a decrease in costs, does not necessarily indicate market power but may simply reflect efficiency of the firm. If competition is intensified due to more aggressive behaviour from competitors, this will increase the PCM of efficient firms at the expense of inefficient ones. This reallocation also increases market concentration measures. Unlike the PCM and market concentration measures, the profit elasticity (PE) index proposed by Boone (2008) is shown to be able to discriminate between market power and efficiency. In other words, when the previously-mentioned reallocation is strong implying an increase in the PCM, the latter will wrongly indicate an increase in market concentration whilst the PE will rightly indicate an increase in more aggressive competition. In our case, however, the PE is also more likely to fail for the same reason as for concentration measures, i.e., the very concept of market is difficult for the analyst to identify in Luxembourg.

Like Tang (2006) for Canada,[4] we use firm-specific perception of competition for many

[4]Perception measures adequately apply to Canada and Luxembourg for similar reasons. In other words,

reasons. First, the perception measures, albeit subjective, are more likely to reflect the actual competition that the firm faces. Indeed, these measures are provided by the firm manager who, unlike the analyst, knows very well the operating market and the competitors of the firm. Second, the traditional objective measures, namely market concentration variables, PCM and PE, are outcomes of competition and do not capture the underlying process influencing the firm decision making. Third, given a competitive environment, different firms may have different perceptions of competition, which is more likely to induce different innovative reactions to these perceptions. Fourth, the perception measures capture better the competitive environment of diversified firms that operate in various product markets. Firms in the same industry do not necessarily operate in the same market. Overseas markets are also captured by the perception measures, which may not be the case for market concentration variables, PCM or PE. Finally, competition is multidimensional by nature, see e.g. Wright (2011), which makes its measurement by a single variable unlikely. Instead, we use four perception measures with respect to the threat of new competitors' arrival, rapidly-changing technologies, obsolete products and easy substitution of products.[5] Thus, our perception measures reflect competition in terms of entry barriers, new processes, new products and substitutability of products. We estimate by full-information maximum likelihood a nonlinear dynamic simultaneous-equations model with pseudo-fixed effects and find that perceived competition with respect to obsolete products Granger-causes innovation activities and eventually innovation success. Furthermore, the threat of seeing the arrival of new competitors and easy substitution of products has no significant effect on innovation activities and innovation success. As for the enterprise facing rapidly-changing technologies, it eventually faces the threat of seeing its products obsolete. That enterprise has a higher propensity to invest in innovation and eventually becomes more successful in achieving product or process innovations.

The remainder of the paper is organised as follows. Section 2 presents the data and shows descriptive statistics on the main variables of interest. These descriptive statistics are reported across sectors and over time. In Section 3, we explain the empirical strategy. More specifically, we describe the model, motivate its specification and present the estimation method. We discuss the empirical results in Section 4 by emphasising the role of perceived competition on innovation and by suggesting policy recommendations. Section 5 summarises

both countries can be considered as a small and open economy, given the size of their respective economy with respect to that of their neighbors.

[5] A product pertains to a good or a service throughout the analysis.

the results and concludes.

2 Data

The data used in the analysis stem from four waves of the Luxembourgish Community Innovation Survey (CIS) pertaining to all sectors covered by the survey for the periods 2002-2004, 2004-2006, 2006-2008 and 2008-2010. The data are collected at the enterprise level by CEPS/INSTEAD in collaboration with STATEC.[6] A combination of census and stratified random sampling is used where the strata are based on employment and economic activity defined by NACE Rev. 2. All enterprises with employment, in headcounts, equal to or greater than 250 or belonging to strata with less than 20 enterprises are included in the census, whilst those with at least 10 but less than 250 employees or belonging to strata with 20 enterprises or more are sampled.

Our sample consists of 480 enterprises with at least ten employees and positive sales at the end of each period covered by the innovation survey. These enterprises are present in at least two consecutive waves of the CIS, which constitutes a necessary condition in order to be included in the dynamic analysis. Figure 1 shows the various sub-categories of the unbalanced panel where roughly one third of the firms of the sample are present in all four waves.[7] Figure 2 shows the enterprise average size, as measured by employment in headcounts and turnover in millions of euros, in each sub-category of the unbalanced panel. The enterprises of the balanced panel are on average larger than those of the remaining sample. This is explained by the fact that enterprises whose number of employees exceeds 250 are censused and are also more likely to survive during the whole period 2002-2010 (see e.g. Agarwal and Audretsch, 2001). Using the unbalanced panel allows us to obtain more accurate estimates as more observations for broader types of enterprises are used and also to control partly for survivorship biases as enterprises are allowed to enter and exit the sample at any (sub-)period. Figure 3 shows the number of observations by industry and category of industries taken respectively at the two-digit level of NACE Rev. 2 and according to the taxonomies of Eurostat.[8] Over 60% of the sample belong to the KIS and low-tech sectors

[6]CEPS/INSTEAD is a Luxembourgish public research institute and stands for *'Centre d'Études de Populations, de Pauvreté et Politiques Socio-Économiques/International Networks for Studies in Technology, Environment, Alternatives and Development'*, and STATEC is the national statistical office of Luxembourg.

[7]These firms belong to what is referred to as the balanced panel in the econometric literature.

[8]Eurostat classifies the manufacturing industries into four categories of "high technology" and "medium-high technology" which form our "high-tech" category, and "low technology" and "medium-low technology" which form our "low-tech" category. These categories are defined on the basis of R&D intensity computed

with the remaining 40% belonging to the LKIS, high-tech and utilities sectors.

Figure 1: Number of enterprises in each sub-category of the unbalanced panel

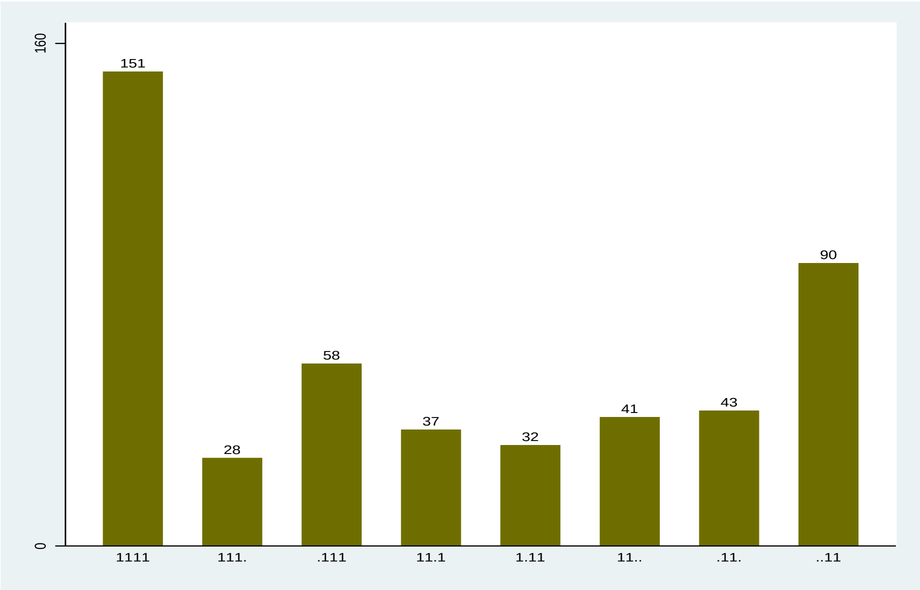
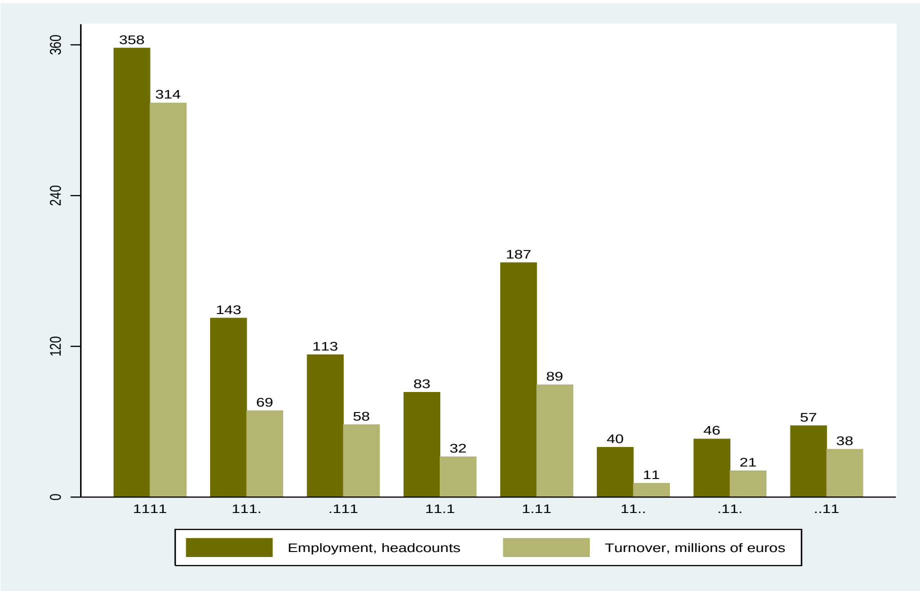
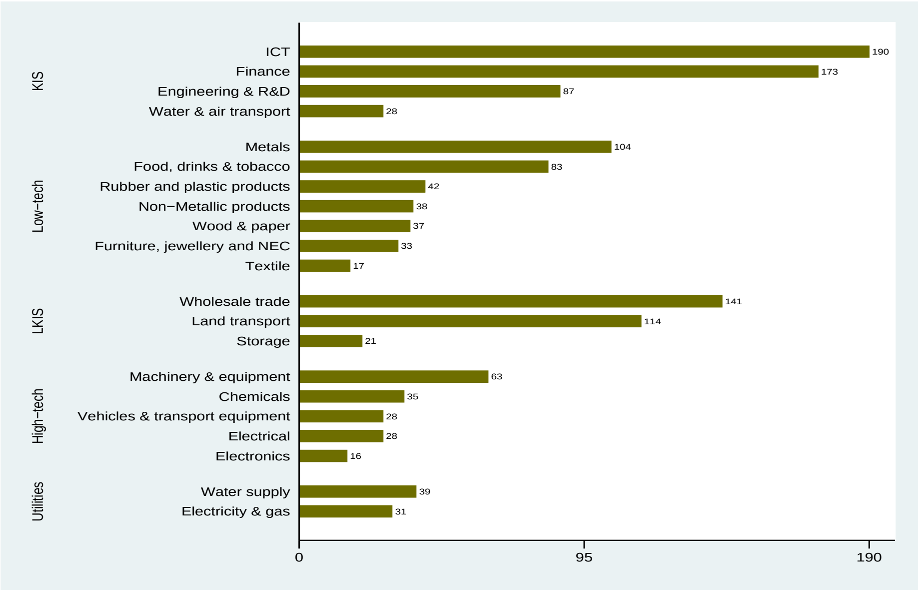


Figure 2: Enterprises' average size in each sub-category of the unbalanced panel



as the ratio of R&D expenses over valued added. Similarly, Eurostat classifies the service sector into "knowledge-intensive services" (KIS) and "less knowledge-intensive services" (LKIS) on the basis of the level of tertiary educated persons. For more details on these taxonomies, see http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/EN/htec_esms.htm and http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an3.pdf.

Figure 3: Number of observations by industry and category of industries



2.1 Measures of perceived competition and technological innovation

Perceived competition

Four binary variables of competition are considered. They are denoted by PC 1-PC 4 and take the value one if the extent of the following characteristics describing the competition context is deemed *high* or *medium* by the enterprise:

PC 1: your position on the market is threatened by the arrival of new competitors.

PC 2: your technologies for producing goods and providing services are changing rapidly.

PC 3: your products are rapidly becoming obsolete.

PC 4: your products can easily be replaced by the products of your competitors.

Technological innovation

A binary variable of innovation spending directed towards technological innovation and two binary variables of product and process innovation achievement are considered. Innovation spending includes in-house and extramural R&D, acquisition of machinery and equipment, acquisition of computer hardware and software, and acquisition of external knowledge such as patents, non-patented inventions and knowhow. This variable takes the value one if the enterprise reports positive figures on either spending at the end of each period covered by the innovation survey. Product innovation refers to goods or services that are new (to the enterprise, not necessarily to the market) or significantly improved, and process innovation refers to new or significantly improved production methods, logistics, delivery and distribution methods, and supporting activities such as maintenance systems.

Descriptive statistics

Table 1 reports descriptive statistics on perceived competition and technological innovation for the categories of industries and for the whole sample.[9] The numbers represent shares of enterprises that deem the previously-listed characteristics describing the competition context high or medium, and shares of enterprises that undertake innovation activities and achieve successfully product or process innovations.[10] We observe the following patterns. Firstly, competition is deemed lower overall in the utilities sector than in the manufacturing and the service sector. These statistics reflect the actual competition in the utilities sector which is known to be almost monopolistic in Luxembourg.[11] Similarly, the percentage of innovative enterprises and that of innovators are lower in the utilities sector. Secondly, the arrival of new competitors (PC 1) constitutes less of a threat to incumbents in high-technology manufacturing and knowledge-intensive services than in low-technology manufacturing and less knowledge-intensive services. The enterprise perception of competition with respect to that component also confirms the observed fact that entry costs are generally higher in high-technology and knowledge-intensive sectors than in low-technology and less knowledge-intensive sectors. However, the perception of competition with respect to rapidly-changing technologies (PC 2), products that become obsolete rapidly (PC 3), and products that can be easily replaced by competitor's products (PC 4) is higher in high-technology and knowledge-intensive sectors than in low-technology and less knowledge-intensive sectors, which is also to be expected. Last but not least, the percentage of innovative enterprises is higher in high-technology and knowledge-intensive sectors than in low-technology and less-knowledge intensive sectors. Furthermore, since innovation input (e.g. R&D) is closely related to in-

[9]All sectors of the Luxembourgish economy covered by the CIS are analysed. Because of insufficient number of observations, the following sectors have been removed from the analysis, namely mining and quarrying (NACE 05-09), construction (NACE 41-43), real estate activities (NACE 68), legal and accounting activities (NACE 69), activities of head offices and consultancy (NACE 70), other professional, scientific and technical activities (NACE 74), rental and leasing activities (NACE 77), travel agency, tour operator reservation service and related activities (NACE 79), human health activities (NACE 86), and repair of computers and personal and household goods (NACE 95).

[10]We make a distinction between an innovative enterprise and an innovator. The former refers to enterprises that undertake innovative activities regardless of whether they are successful or not. The latter refers to enterprises that manage to achieve successfully product or process innovations.

[11]Market concentration is very high in the electricity and gas sector. In 2010, for instance, the dominant player in the retail market for electricity, Enovos, had a market share of 85% and the three largest electricity distribution companies controlled 94% of the market. Furthermore, supplier switching rate was very low, no more than 0.2%, one of the lowest in the EU27.

novation output (e.g. new product), we also observe higher percentages of innovators in the former sectors than in the latter.

Table 1: Perceived competition, innovation input and innovation output by sector[†]

Sector	Perceived competition				Innovation		
	PC 1	PC 2	PC 3	PC 4	Spending	Product	Process
Manufacturing	0.64	0.56	0.47	0.70	0.58	0.48	0.42
Low-tech	0.66	0.51	0.44	0.68	0.47	0.39	0.39
High-tech	0.63	0.65	0.53	0.75	0.82	0.66	0.49
Services	0.62	0.56	0.53	0.63	0.50	0.46	0.40
LKIS	0.70	0.51	0.48	0.63	0.32	0.28	0.29
KIS	0.58	0.59	0.57	0.64	0.61	0.57	0.46
Utilities	0.47	0.32	0.26	0.45	0.37	0.26	0.26
Whole sample	0.62	0.55	0.50	0.65	0.53	0.46	0.40
# observations	1017				1348		

[†]The perceived competition variables are available only in the first three waves of the CIS.

Table 2 shows similar descriptive statistics on perceived competition and technological innovation by CIS for enterprises that are present in at least two consecutive waves, our unbalanced panel (see Figure 1). With the exception of PC 4, we observe a non-monotonic decrease in the enterprise perception of competition between 2002 and 2008. The overall decrease is not significant whereas the increase between 2002 and 2006 and the decrease between 2006 and 2008 are. The evolution over time of PC 4 is at odds with the other competition measures. In other words, it increases between 2002 and 2006 and reverts to its original level between 2006 and 2008. As for technological innovation, we observe a non-monotonic decrease in the share of innovative enterprises and innovators between 2002 and 2010.

2.2 Relation between perceived competition and technological innovation

Table 3 shows tetrachoric correlations between perceived competition, innovation input and innovation output. The various components of competition are positively and significantly

Table 2: Perceived competition, innovation input and innovation output by CIS

CIS	# enterprises	Perceived competition				Innovation		
		PC 1	PC 2	PC 3	PC 4	Spending	Product	Process
2002-2004	257	0.62	0.54	0.42	0.75	0.61	0.47	0.44
2004-2006	358	0.65	0.59	0.66	0.46	0.54	0.49	0.36
2006-2008	402	0.60	0.51	0.40	0.75	0.48	0.42	0.45
2008-2010	331	-	-	-	-	0.50	0.46	0.36

correlated, which reflects its multidimensional nature (see e.g. Wright, 2011). This correlation is particularly high between perceived competition through rapidly-changing technologies, PC 2, and perceived competition through outdated products, PC 3. The various components of innovation also exhibit a positive correlation which is much higher than the correlation between the competition variables. Innovation is observed to be unambiguously positively and significantly related to competition only when the latter is measured by PC 2 or PC 3. In other words, in Luxembourg the enterprise is prone to undertake innovation activities and to introduce product or process innovations when it feels threatened by competitors that use more advanced technologies or that offer better products.

Table 3: Tetrachoric correlations between perceived competition, innovation input and innovation output

	Perceived competition				Innovation		
	PC 1	PC 2	PC 3	PC 4	Spending	Product	Process
Perceived competition							
PC 1	1						
PC 2	0.17^{**}	1					
PC 3	0.18^{**}	0.73^{**}	1				
PC 4	0.33^{**}	0.18^{**}	$0.10^{\dagger}$	1			
Innovation							
Spending	0.05	0.28^{**}	0.30^{**}	0.08	1		
Product	0.04	0.22^{**}	0.22^{**}	0.14^{*}	0.87^{**}	1	
Process	0.04	0.19^{**}	0.22^{**}	0.06	0.80^{**}	0.60^{**}	1

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

The tetrachoric correlations reported in Table 3 do not take into account the effect of other explanatory variables on the firm innovative behaviour. In order to account for that effect, we shall estimate a nonlinear dynamic simultaneous-equations model where the dependent variables are the three binary variables of innovation spending, product innovation and process innovation, the main explanatory variables are the four measures of perceived competition, and the other explanatory variables consist of the conglomerate status of the enterprise,[12] its size, the university degree of its employees and whether or not the enterprise receives financial support from local or national government or from the European Union. These additional explanatory variables are all binary with the exception of size, captured by employment in headcounts, which is continuous. Descriptive statistics on these variables are reported in Table 4. They indicate that the majority of enterprises of our sample are either independent (42%) or belong to multinationals (36%). The mean and median values

[12] Independent enterprises are defined as those who do not belong to any conglomerate. Local conglomerate and multinational enterprises are those for which the conglomerate's head office is located respectively in Luxembourg and abroad.

of employment are 211 and 70 respectively. For a quarter of the enterprises, the percentage of staff with a university degree is less than 5%, for almost half of them this percentage lies between 5% and 50%, and for 28% of them this percentage is greater than 50%. Finally, 34% of innovative enterprises receive financial support from local or national government or from the European Union. This percentage almost halves when non-innovative enterprises are also considered.

Table 4: Descriptive statistics on size, university degree of employees, conglomerate status and subsidies

Variable	Mean	Median	Std. Dev.	Min.	Max.
Conglomerate status					
Independent	0.417	-	-	0	1
Local conglomerate	0.222	-	-	0	1
Multinational	0.361	-	-	0	1
Employment, headcounts	211	70	509	10	6491
% of staff with univ. degree					
<5%	0.253	-	-	0	1
[5%, 50%]	0.465	-	-	0	1
>50%	0.282	-	-	0	1
Subsidies					
Innovating enterprises	0.335	-	-	0	1
All enterprises	0.180	-	-	0	1

3 Empirical strategy

The model is written as

$$spend_{it} = \mathbb{1}[\gamma_1 spend_{i,t-1} + \boldsymbol{\beta}'\mathbf{compet}_{i,t-1} + \boldsymbol{\delta}_1'\mathbf{x}_{it} + \epsilon_{1it} > 0], \tag{3.1}$$

$$prod_{it} = \mathbb{1}[\gamma_2 prod_{i,t-1} + \vartheta spend_{it} + \boldsymbol{\delta}_2'\mathbf{z}_{it} + \epsilon_{2it} > 0], \tag{3.2}$$

$$proc_{it} = \mathbb{1}[\gamma_3 proc_{i,t-1} + \lambda spend_{it} + \boldsymbol{\delta}_3'\mathbf{z}_{it} + \epsilon_{3it} > 0], \tag{3.3}$$

where $\mathbb{1}$ denotes the indicator function which takes the value one if its argument is positive, and zero otherwise.

Equation (3.1) explains enterprise i's decision to engage in innovation activities at period t,[13] which depends upon some latent innovation incentive that can be expressed as a function of past innovation spending, $spend_{i,t-1}$, perceived competition in the previous period, $\mathbf{compet}_{i,t-1}$, observed enterprise and industry characteristics, $\mathbf{x}_{it}$, and other unobserved

[13] According to our notations, t corresponds to the periods 2002-2004, 2004-2006, 2006-2008 and 2008-2010. Since we use a first-order autoregressive model with an unbalanced panel, the minimum and maximum number of time periods equals respectively 2 and 4, see Figure 1.

factors summarised in the error, ϵ_{1it}. If the incentive is positive, the enterprise is observed to carry out innovation activities, in which case $spend_{it}$ is equal to one, otherwise it is equal to zero. The coefficients to be estimated are γ_1 which captures persistence in innovation spending, and $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ which capture respectively the effect of perceived competition and other observed enterprise and industry characteristics on innovation spending.

Equations (3.2) and (3.3) explain respectively product and process innovation. The ability to achieve these innovations is unobserved but defined as a function of past product and process innovation, respectively $prod_{i,t-1}$ and $proc_{i,t-1}$, innovation spending, $spend_{it}$, observed enterprise and industry characteristics, $\mathbf{z}_{it}$,[14] and other unobserved factors, ϵ_{2it} and ϵ_{3it}. The reasoning underlying the link between the unobserved ability to achieve product or process innovation and the actual achievement of these innovations is similar to that of equation (3.1). In equation (3.2), γ_2 captures the persistence of product innovation, and ϑ and $\boldsymbol{\delta}_2$ the effect of innovation spending and other observed enterprise and industry characteristics on product innovation. The coefficients of equation (3.3), namely γ_3, λ and $\boldsymbol{\delta}_3$, are interpreted similarly.

3.1 Model specification

The four measures of perceived competition enter equation (3.1) with a lag of one period so as to avoid any simultaneity between competition and innovation (see e.g. Futia, 1980). In addition to competition, we explain the probability of innovation spending and innovation success in period t by lagged counterparts to capture persistence, which is an inherent characteristic of the innovation process (see e.g. Geroski et al., 1997; Cefis and Orsenigo, 2001). Persistence in innovation spending can be explained by the existence of "sunk costs" (see e.g. Máñez et al., 2009). In other words, resources that are spent, for instance, on scientists to carry out R&D cannot be recovered. As a result, carrying out innovation activities is likely to be time dependent. Persistence in innovation success can be observed for several reasons. First, because of information asymmetry, firms may be more willing to rely on retained earnings rather than to seek external funding for their future innovations (Bhattacharya and Ritter, 1983). Second, Mansfield's (1968) "success breeds success" postulates that innovation success confers advantages in technological opportunities that make further success more likely. Third, according to the evolutionary theory (see e.g. Nelson and Winter,

[14] The observed enterprise and industry characteristics, $\mathbf{z}_{it}$, explaining product and process innovation are assumed to be the same.

1982), radical innovations are often followed by a succession of incremental innovations along a technological trajectory. Furthermore, in a process similar to Arrow's learning-by-doing, firms learn by innovating and develop organisational competencies along that trajectory (see e.g. Dosi and Marengo, 1994).

The vectors of explanatory variables, $\mathbf{x}_{it}$ and $\mathbf{z}_{it}$, include as common components two binary variables for local conglomerate and multinational enterprise with the reference being the category of the independent enterprise, and employment in headcounts. The latter variable is log-transformed in the estimation. Firms that are part of a conglomerate are expected to be more innovative as they benefit from knowledge spillovers, internal access to finance, and synergies in marketing (Veugelers and Cassiman, 2004). According to Schumpeter (1942), firm size is expected to affect positively innovation behaviour as larger corporations have more and better resources to invest and wield more monopolistic power that enables them to capture the benefits of their innovation output. Two additional explanatory variables that are not in $\mathbf{z}_{it}$, namely university degree of employees and public financial support, are also included in $\mathbf{x}_{it}$. Human capital, proxied by university degree of employees, affects the firm's absorptive capacity which increases the ability to undertake innovation activities and to eventually introduce product or process innovations (Vinding, 2006). Two binary variables for enterprises with percentage of employees with a university degree between 5% and 50%, and greater than 50% are included in the estimation, the reference category being that of enterprises with percentage of educated employees smaller than 5%. As for public financial support, we expect enterprises that receive subsidies for innovation to be more innovative, although evidence on this score is mixed (David et al., 2000). In order to estimate a causal effect of subsidies on innovation activities and avoid potential endogeneity of subsidies (see e.g. Wallsten, 2000), we include in equation (3.1) a lagged dummy variable for enterprises that receive public financial support. Finally, equations (3.2) and (3.3) can be seen as knowledge production functions where the main input to innovation output is innovation spending.

3.2 Estimation

Since we consider a panel data framework, individual and time effects must be accounted for. Hence, the error terms of equations (3.1)-(3.3) are written as

$$\epsilon_{kit} = \alpha_{ki} + \mu_{kt} + \nu_{kit}, \qquad k \in \{1, 2, 3\}, \tag{3.4}$$

where α_{ki} and μ_{kt} denote respectively individual and time effects, and ν_{kit} denotes the idiosyncratic errors. Equation (3.4) is referred to as two-way error components disturbances in the econometric literature (Baltagi, 2008). We consider a two-way pseudo fixed-effects approach which consists in writing α_{ki} and μ_{kt} as

$$\alpha_{ki} \simeq \sum_{j=1}^{J} \alpha_{kj} D_i^j, \tag{3.5a}$$

$$\mu_{kt} = \sum_{s=2}^{T} \mu_{ks} D_t^s, \tag{3.5b}$$

where j denotes the industry to which the enterprise belongs with J being the total number of industries,[15] s is the period of the CIS to which the enterprise belongs with T being the total number of periods, and D_i^j and D_t^s are binary variables defined respectively as

$$D_i^j = \begin{cases} 1 & \text{if } i \in j \\ 0 & \text{if } i \notin j \end{cases} \tag{3.6a}$$

$$D_t^s = \begin{cases} 1 & \text{if } s = t \\ 0 & \text{if } s \neq t \end{cases}. \tag{3.6b}$$

The pseudo fixed-effects approach of dealing with the individual effects has various appealing features in the context of our data. First, given the size of Luxembourg, many industries consist of very few firms so that the extent of heterogeneity within industries is limited, albeit large across industries. Furthermore, some industries are known to be quasi-monopolistic where a dominant player and its subsidiaries control the market.[16] Heterogeneity is also likely to be limited within these industries. Second, this approach avoids the incidental parameters problem (see Neyman and Scott, 1948) since the number of intercept parameters to be estimated, α_{kj}, does not increase with i. As for the time effects, we are in the case

[15] In the estimation, we include 2-digit industry dummies defined according to NACE Rev. 2.
[16] This is the case of Enovos, for instance, in the electricity and gas sector.

of a small T panel so that the incidental parameters problem is not an issue. As a result, the presence of individual and time effects in equations (3.1)-(3.3) does not bring additional difficulty to the estimation procedure.

The model is estimated by full information maximum likelihood (FIML) which requires distributional assumptions regarding the idiosyncratic errors ν_{kit}. Conditional on the regressors, the individual pseudo fixed-effects and the time effects, the errors are assumed to be independently identically distributed (iid) according to the normal distribution with mean vector $\mathbf{0}$ and covariance matrix $\boldsymbol{\Sigma} = \begin{pmatrix} 1 & & \\ \rho_{12} & 1 & \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix}$. The parameters ρ_{kl} $(k, l \in \{1, 2, 3\})$ pick up the correlations amongst the unobserved factors that affect innovation spending, product innovation and process innovation, and are also to be estimated. The log-likelihood consists of $2^3 = 8$ components calculated over various subsamples of innovative firms and innovators defined by equations (3.1)-(3.3), i.e.,

$$\ln L = \sum\nolimits_{000} \ln L_{000} + ... + \sum\nolimits_{111} \ln L_{111}, \tag{3.7}$$

where $\ln L_{pqr}$ $(p, q, r \in \{0, 1\})$ denotes the individual contributions to the log-likelihood and $\sum_{pqr}$ defines the observations of the various subsamples.[17]

Since the model exhibits nonlinear conditional means, the coefficients of equations (3.1)-(3.3) only pick up the sign and significance of the effects of the explanatory variables. To quantify them, we need to calculate average partial effects (APEs). Because of the simultaneous-equations characteristic of the model, three types of APEs, namely *direct*, *indirect* and *total*, can be computed. For instance, competition is assumed to have a direct effect on innovation spending, as is usually the case in theoretical and applied studies (see e.g. Gilbert, 2006; Levin et al., 1985), and only an indirect effect on innovation success, which operates through the effect of innovation spending on innovation success.[18] The total effect on innovation success of any explanatory variable common to all three equations is the sum of the direct effect of that variable on innovation success and the indirect effect transmitted to innovation success via the effect of that variable on innovation spending and the effect of the latter on innovation success.[19]

[17]The summations $\sum_{pqr}$ actually consist of a double summation where the inner summation is taken with respect to time, i.e. $\sum_t$, and the outer summation is taken with respect to the cross-sectional unit, i.e. $\sum_i$.

[18]In Tang's (2006) study, the 'knowledge production function' relating innovation output to competition does not control for innovation input. As a result, any seemingly significant direct effect of competition on innovation output may actually be an indirect effect via the effect of innovation input on innovation output. In our study, there is no evidence of a direct effect of competition on innovation output.

[19]In the case at hand, the total effect of competition on innovation success is simply the indirect effect,

The derivation of the individual likelihood functions and the calculation of the APEs are given in Appendix A.

4 Results

We now turn to the estimation results of the model. We present in Tables 5 and 6 the core results of interest, namely the role of perceived competition in explaining technological innovation. Some policy recommendations derived from these results and based upon Figure 4 and Table 7 are suggested. In Table 8, we present the estimated effect of current and lagged innovation spending on product and process innovation as well as the persistence of innovation, all of which is referred to as dynamics of innovation. Table 9 shows the effects of additional determinants of innovation such as conglomerate status, size of enterprise, university degree of employees and subsidies.

4.1 The role of perceived competition

Table 5 shows average partial effects of perceived competition on technological innovation in a specification of the model where all measures of perceived competition but PC 3 are included. All else equal, perceived competition for better technologies (PC 2) in period t-1 increases significantly the likelihood of innovation spending, product innovation and process innovation in period t by respectively 0.068, 0.045 and 0.042 in the unit interval.[20] An enterprise that perceives that its technologies of production are outperformed by those of its competitors is more likely to engage in innovation activities, which eventually translates into a larger probability to achieve product or process innovations. This result is somewhat in accordance with Tang (2006) who finds a positive correlation between this measure of perceived competition and innovation activities in Canada. However, our model is richer as it uncovers causality, in lieu of correlation, between perceived competition and innovation accounting for several inherent features of innovation such as dynamics and firm heterogeneity. Furthermore, we consider a recursive structural model where a 'knowledge production function' relating innovation output to innovation input is estimated, unlike Tang (2006) who does not account for innovation input when studying the relation between innovation output and perceived competition.

since competition does not enter equations (3.2) and (3.3).

[20] According to equations (3.1)-(3.3), the effect of perceived competition on innovation spending is a direct effect whilst the effect on product and process innovation is an indirect effect.

Table 5: FIML estimates of the nonlinear dynamic model: Perceived competition except PC 3

Variable	Spending$_t$		Product$_t$		Process$_t$	
	APE	Std. Err.	APE	Std. Err.	APE	Std. Err.
Competition$_{t\text{-}1}$						
PC 1	0.005	0.030	0.003	0.020	0.003	0.019
PC 2	0.068*	0.029	0.045*	0.020	0.042*	0.019
PC 4	-0.009	0.031	-0.006	0.020	-0.005	0.019
Industry dummies			yes			
Time dummies			yes			
Log-likelihood			-1139.087			
# observations			868			
Significance levels :	† : 10%	$*$: 5%	$**$: 1%			

Table 6: FIML estimates of the nonlinear dynamic model: Perceived competition

Variable	Spending$_t$		Product$_t$		Process$_t$	
	APE	Std. Err.	APE	Std. Err.	APE	Std. Err.
Competition$_{t\text{-}1}$						
PC 1	0.002	0.030	0.001	0.019	0.001	0.018
PC 2	0.018	0.033	0.012	0.022	0.011	0.021
PC 3	0.103**	0.035	0.068**	0.023	0.065**	0.022
PC 4	-0.015	0.031	-0.010	0.020	-0.009	0.019
Industry dummies			yes			
Time dummies			yes			
Log-likelihood			-1134.506			
# observations			868			
Significance levels :	† : 10%	$*$: 5%	$**$: 1%			

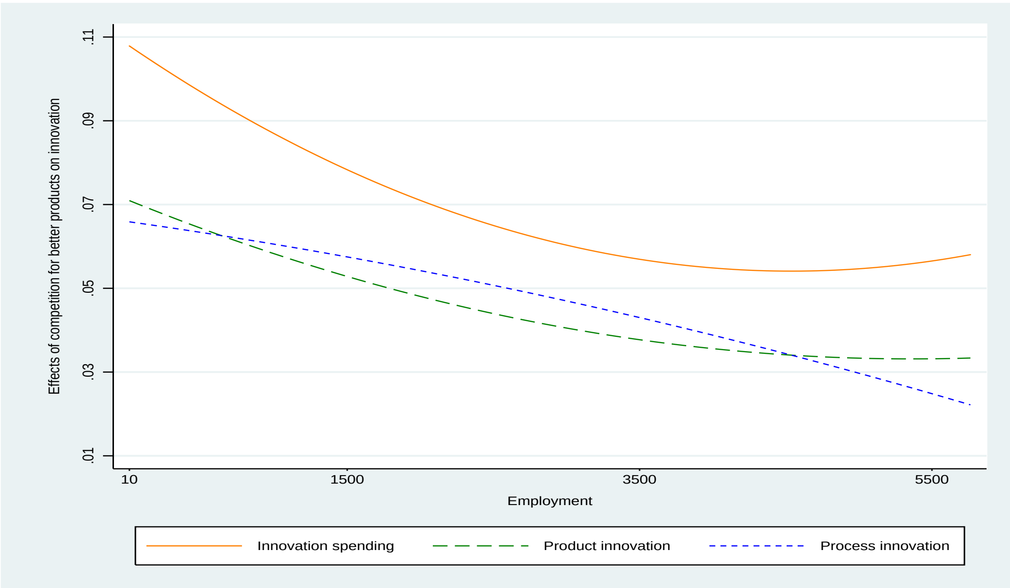
When PC 3 is also included in the specification, the above-mentioned result disappears, i.e., perceived competition for better technologies is no longer significant, see Table 6. Instead, we observe that perceived competition for better products, PC 3, affects positively and significantly the likelihood of innovation spending, product innovation and process innovation. The results of Tables 5 and 6 indicate that the enterprise's fear of being outperformed because of rapidly-changing technologies is eventually translated into the fear of seeing its products obsolete. The effect of PC 2 is taken over by that of PC 3, which can be explained by the fact that PC 2 and PC 3 exhibit a very large correlation, the largest amongst the competition variables, see Table 3.[21] In both specifications, perceived competition related to the arrival of new competitors, PC 1, does not spur innovation activities. It is argued that the intensity of competition is not necessarily linked to the number of rivals of the firm, but rather to advantages related to product quality or production cost that these rivals may gain by introducing product or process innovations (Metcalfe and Boden, 1993). As for easy

[21]The specification of Table 5 is rejected against the specification of Table 6 on the basis of a likelihood ratio test. Thus, the variation of the effect of perceived competition over firm employment (Figure 4) and across sectors (Table 7) is shown only for PC 3. Furthermore, the remaining APEs of Tables 8 and 9 are shown only for the preferred specification.

substitution of products, PC 4, the effect possesses an expected negative sign. Indeed, easy substitution of products creates uncertainty and does not guarantee high expected profits generated by 'monopoly power' which is the very reason to innovate. As a result, easy substitution of products tends to reduce firms' incentive to innovate even though the effect is insignificant in our case.

Figure 4 shows that the effect of perceived competition for better products decreases with firm size. In other words, small and medium enterprises (SMEs) have more the urge to spend in innovation and to upgrade their technologies of production and their products as a response to this measure of competition. Indeed, these enterprises are known to be less diversified than large corporations and hence are more compelled to keep their (rather narrow) range of products up to date. Thus, SMEs should primarily be encouraged to innovate, for instance via tax credits, when the perception level of competition for better products is rather high.

Figure 4: Partial effects of perceived competition for better products (PC 3) on technological innovation versus employment



Finally, Table 7 shows that the high-tech manufacturing sector has the lowest propensity to invest in innovation and to introduce new products or processes as a response to higher competition for better products. This can be explained by the fact that the high-tech sector already has the highest perception of competition for better products and the highest level of innovation (see Table 1). On the other hand, the utilities sector is observed to have the lowest level of competition and innovation, and one of the highest potentials to respond to higher competition. All else equal, a rather high perception of competition in the utilities sector yields a 0.049 higher probability of innovation spending, a 0.03 higher probability of product innovations and a 0.025 higher probability of process innovations than in the high-tech sector.

Table 7: Average partial effects of perceived competition for better products (PC 3) on technological innovation per sector: OLS regression estimates†

Variable	Effects on spending		Effects on product innov.		Effects on process innov.	
	APE	Std. Err.	APE	Std. Err.	APE	Std. Err.
Manufacturing						
Low-tech	0.040**	0.004	0.028**	0.003	0.032**	0.003
High-tech	-	-	-	-	-	-
Services						
LKIS	0.035**	0.004	0.022**	0.003	0.029**	0.003
KIS	0.049**	0.004	0.037**	0.003	0.029**	0.003
Utilities	0.049**	0.006	0.030**	0.004	0.025**	0.004
Intercept	0.066**	0.003	0.042**	0.002	0.039**	0.002
Adj. R-squared	0.182		0.190		0.155	
$F(4, 863)$	47.974		50.750		39.666	
P-value	0.000		0.000		0.000	
# observations	868					

†The high-tech sector is the reference category. Significance level : ** : 1%

4.2 Dynamics of innovation

Because of the autoregressive and simultaneous-equations structure of the model, see equations (3.1)-(3.3), the average partial effects reported in Table 8 resemble those of an autoregressive distributed lag (ARDL) model where current innovation output is related to lagged innovation output and to current and lagged innovation input.[22] Thus, various types of dynamics are captured by these APEs. Firstly, they pick up a lagged effect of innovation input on innovation output, which reflects 'time to build', opportunity cost and uncertainty inherent to the innovation process (Majd and Pindyck, 1987). As expected, the results indicate that current innovation spending has a significantly larger effect on innovation output than lagged innovation spending, which is consistent with Pakes and Griliches (1980) and with Hall et al. (1986), in some specifications, who estimate a distributed lag regression of patents on R&D. Secondly, persistence in innovation spending is estimated, which reflects the existence of sunk costs in the investment decision. The results show that firms that have innovation spending in period t-1 are more likely to have innovation spending in period t,

[22]The difference between our model and a 'true' ARDL model is that the former consists of direct and indirect APEs while the APEs are all direct in the latter model.

which is consistent with Máñez et al. (2009) who find persistence in R&D investment for Spanish manufacturing. Finally, we also estimate the persistence of innovation output which reflects Mansfield's 'success breeds success' (see e.g. Flaig and Stadler, 1994). The results show that firms that have succeeded in achieving product innovations in the past are more likely to achieve so in the present, whereas the lagged effect of process innovation is hardly significant economically and statistically. Our pattern of persistence in product and process innovation is at odds with Roper and Hewitt-Dundas (2008) who find strong persistence in both types of innovation output for manufacturing plants in Ireland and Northern Ireland. Overall, our results show significantly larger persistence in innovation input than in innovation output, which is at odds with Peters (2009) who finds a similar pattern of persistence in both types of innovation for German manufacturing and services enterprises.

Table 8: FIML estimates of the nonlinear dynamic model: Dynamics of innovation

Variable	Spending_t		Product_t		Process_t	
	APE	Std. Err.	APE	Std. Err.	APE	Std. Err.
Spending_t	-	-	0.655^{**}	0.050	0.625^{**}	0.041
$\text{Spending}_{t\text{-}1}$	0.262^{**}	0.039	0.173^{**}	0.028	0.164^{**}	0.027
$\text{Product}_{t\text{-}1}$	-	-	0.106^{**}	0.028	-	-
$\text{Process}_{t\text{-}1}$	-	-	-	-	$0.048^{\dagger}$	0.026

Significance levels : † : 10% $*$: 5% $**$: 1%

4.3 Other determinants of innovation

Table 9 shows average partial effects of additional determinants of innovation such as conglomerate status, size of enterprise, university degree of employees and subsidies. The results show that enterprises that belong to a Luxembourgish conglomerate are more likely to spend in innovation and to successfully introduce product or process innovations than stand-alone enterprises. This is in accordance with the theoretical work of Greenwald et al. (1984) and Myers and Majluf (1984) who argue that it is easier for conglomerate enterprises to finance their innovation as they have access to internal financing which is less costly than external financing because of information asymmetry between the firm and outside investors.[23] Foreign-controlled firms are found to be less likely to spend in innovation and to eventually achieve product innovations than those that belong to local conglomerates. Hence, our results reflect the fact that firms tend to undertake innovation activities at their home base (Granstrand et al., 1993). Furthermore, the attractiveness of a country to welcoming

[23] Seru (2014) on the other hand finds that US conglomerates stifle innovation because of inefficiencies in internal capital markets. This finding is not supported by our data.

R&D units is not so much determined by costs and wages but rather by 'dynamic efficiency' (Meyer-Krahmer and Reger, 1999). In other words, the factors driving R&D location decisions have more to do with the value-added effects of transnational learning processes along the whole value-added chain, i.e. from R&D to product sales. The APEs show a monotonic positive relationship between innovation and firm size, a Schumpeterian result, and between innovation and university degree of employees, the latter result confirming the findings of Vinding (2006). Finally, all else equal, receiving subsidies in period t-1 does not affect the likelihood of spending in innovation and achieving product or process innovations in period t. This can be explained by the fact subsidies are usually directed towards firms that already have innovation activities. For instance, González et al. (2005) find that in the Spanish manufacturing sector the bulk of subsidies are primarily given to firms that are already performing R&D so that the absence of such subsidies would only affect a small number of firms. A potential effect of the amount of subsidies is not considered in this paper due to data limitations.

Table 9: FIML estimates of the nonlinear dynamic model: Other determinants

Variable	Spending_t		Product_t		Process_t	
	APE	Std. Err.	APE	Std. Err.	APE	Std. Err.
Local conglomerate	0.089^{*}	0.039	0.088^{*}	0.040	0.096^{*}	0.041
Multinational enterprise	-0.035	0.036	-0.002	0.037	0.081^{*}	0.039
Employment (in log)	0.069^{**}	0.013	0.081^{**}	0.013	0.078^{**}	0.013
% staff with univ. degree						
[5%, 50%]	0.142^{**}	0.039	0.094^{**}	0.027	0.089^{**}	0.025
>50%	0.209^{**}	0.053	0.138^{**}	0.036	0.131^{**}	0.034
$\text{Subsidies}_{t\text{-}1}$	0.041	0.044	0.027	0.029	0.026	0.027

Significance levels : † : 10% $*$: 5% $**$: 1%

5 Conclusion

In this study, we examine how firms that operate in Luxembourg respond technologically to perceived competition using a panel of enterprise data over the period 2002-2010. By making use of four dichotomous measures of perceived competition and three indicators of innovation, we estimate a nonlinear dynamic simultaneous-equations model and obtain the following results. First, in a specification where innovation spending, product innovation and process innovation are explained by the arrival of new competitors, rapidly-changing technologies and easy substitutability of products, we find that an enterprise that fears that its technologies of production are outperformed by those of its competitors is more likely to spend in innovation and to ultimately introduce new products or new processes. Second, when the enterprise perception that its products are outperformed by those of its competitors is also included as an explanatory variable of competition, this additional measure of competition takes over the role of competition for better technologies whilst the remaining three measures of competition are insignificant. In other words, the enterprise that perceives that its products are outperformed by those of its competitors has a larger probability to spend in innovation and to achieve product or process innovations. The fear of seeing its technologies of production being obsolete is ultimately translated into the fear of seeing its products obsolete. Third, the effect of perceived competition on innovation decreases with firm size. SMEs have more the urge to spend in innovation and to upgrade their technologies of production and their products as a response to competition for better products than larger corporation. Hence, the former should primarily be targeted by policy makers if innovation is to be encouraged via competition. Fourth, the high-tech sector has the lowest response to increased competition in terms of spending in innovation and introducing new products or processes. Encouraging further competition to increase innovation in that sector would not be fruitful. As additional results, we find evidence of a time lag between innovation input and innovation, and of persistence of innovation input and innovation output. Finally, local conglomerate enterprises, larger corporations and those with a better skilled labour force have a larger probability to spend in innovation and to be technologically successful.

Appendix A Log-likelihood and average partial effects

A.1 Log-likelihood

The nonlinear dynamic simultaneous-equations model consists of equations (3.1)-(3.3) with two-way error components disturbances defined in equations (3.4)-(3.6b). Under the assumption that the idiosyncratic errors are normally distributed conditional on the regressors, the individual pseudo fixed-effects and the time effects, i.e. $(\nu_{1it}, \nu_{2it}, \nu_{3it}) \overset{iid}{\sim} \boldsymbol{Normal}(\mathbf{0}, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma} = \begin{pmatrix} 1 & & \\ \rho_{12} & 1 & \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix}$, the log-likelihood function is given by

$$\ln L = \sum\nolimits_{000} \ln L_{000} + ... + \sum\nolimits_{111} \ln L_{111}, \tag{A.1}$$

where $\ln L_{pqr}$ $(p, q, r \in \{0, 1\})$ denotes the individual contributions to the log-likelihood and $\sum_{pqr}$ defines the observations of the various subsamples. The individual likelihoods for which $r = 0$ are calculated as

$$L_{pq0} = \int_a^b \int_c^d \int_{-\infty}^{-\boldsymbol{\pi}_3' \mathbf{w}_{3it}} \phi_3(\nu_{1it}, \nu_{2it}, \nu_{3it}) d\nu_{1it} d\nu_{2it} d\nu_{3it}, \tag{A.2}$$

where ϕ_3 denotes the density function of the *trivariate* standard normal distribution, the integral bounds a, b, c, and d are defined as

$$(a, b) = \begin{cases} (-\infty, -\boldsymbol{\pi}_1' \mathbf{w}_{1it}) & \text{if } p = 0 \\ (-\boldsymbol{\pi}_1' \mathbf{w}_{1it}, \infty) & \text{if } p = 1 \end{cases}$$

$$(c, d) = \begin{cases} (-\infty, -\boldsymbol{\pi}_2' \mathbf{w}_{2it}) & \text{if } q = 0 \\ (-\boldsymbol{\pi}_2' \mathbf{w}_{2it}, \infty) & \text{if } q = 1 \end{cases}$$

and $\boldsymbol{\pi}_1' \mathbf{w}_{1it}$, $\boldsymbol{\pi}_2' \mathbf{w}_{2it}$ and $\boldsymbol{\pi}_3' \mathbf{w}_{3it}$ are defined respectively as

$$\boldsymbol{\pi}_1' \mathbf{w}_{1it} \equiv \gamma_1 spend_{i,t-1} + \boldsymbol{\beta}' \mathbf{compet}_{i,t-1} + \boldsymbol{\delta}_1' \mathbf{x}_{it} + \sum_{j=1}^{J} \alpha_{1j} D_i^j + \sum_{s=2}^{T} \mu_{1s} D_t^s, \tag{A.3a}$$

$$\boldsymbol{\pi}_2' \mathbf{w}_{2it} \equiv \gamma_2 prod_{i,t-1} + \boldsymbol{\delta}_2' \mathbf{z}_{it} + \sum_{j=1}^{J} \alpha_{2j} D_i^j + \sum_{s=2}^{T} \mu_{2s} D_t^s, \tag{A.3b}$$

$$\boldsymbol{\pi}_3' \mathbf{w}_{3it} \equiv \gamma_3 proc_{i,t-1} + \boldsymbol{\delta}_3' \mathbf{z}_{it} + \sum_{j=1}^{J} \alpha_{3j} D_i^j + \sum_{s=2}^{T} \mu_{3s} D_t^s. \tag{A.3c}$$

Similarly, the individual likelihoods for which $r = 1$ are calculated as

$$L_{pq1} = \int_{a}^{b} \int_{c}^{d} \int_{-\boldsymbol{\pi}_3' \mathbf{w}_{3it}}^{\infty} \phi_3(\nu_{1it}, \nu_{2it}, \nu_{3it}) d\nu_{1it} d\nu_{2it} d\nu_{3it}. \tag{A.4}$$

The multiple integrals of equations (A.2) and (A.4) involve multivariate cumulative distribution functions which are evaluated using the Geweke-Hajivassiliou-Keane simulator so that the resulting function to be maximised is a simulated log-likelihood.

A.2 Average partial effects

Given the exogenous linear indexes in equations (A.3a)-(A.3c), the conditional mean associated with equation (3.1) is straightforwardly derived as

$$\mathbb{E}(spend_{it} \big| \mathbf{w}_{1it}) = \Phi_1 \left(\boldsymbol{\pi}_1' \mathbf{w}_{1it} \right), \tag{A.5}$$

where Φ_1 denotes the univariate cumulative distribution function (CDF) of the standard normal distribution. Hence, the partial effect of a certain continuous regressor, say w_{it}, in the innovation spending equation is derived as

$$\partial \mathbb{E}(spend_{it} \big| \mathbf{w}_{1it}) / \partial w_{it} = \pi_{1w} \phi_1(\boldsymbol{\pi}_1' \mathbf{w}_{1it}), \tag{A.6}$$

and the resulting APE is computed as the sample average of that derivative, i.e. $(NT)^{-1} \sum_{it} \pi_{1w} \phi_1(\boldsymbol{\pi}_1' \mathbf{w}_{1it})$.

The conditional mean associated with equation (3.2) requires using the *law of iterated expectations* (LIE), that is

$$\mathbb{E}(prod_{it} \big| \mathbf{w}_{1it}, \mathbf{w}_{2it}) = \mathbb{E}_{spend_{it}} \mathbb{E}(prod_{it} \big| \mathbf{w}_{1it}, \mathbf{w}_{2it}, spend_{it}).$$

Since $spend_{it}$ is a binary variable,

$$\begin{aligned} \mathbb{E}(prod_{it} \big| \mathbf{w}_{1it}, \mathbf{w}_{2it}) = {} & \mathbb{P}\left(spend_{it} = 1\right) \mathbb{E}(prod_{it} \big| \mathbf{w}_{1it}, \mathbf{w}_{2it}, spend_{it} = 1) \\ & + \mathbb{P}\left(spend_{it} = 0\right) \mathbb{E}(prod_{it} \big| \mathbf{w}_{1it}, \mathbf{w}_{2it}, spend_{it} = 0), \end{aligned}$$

which, using the standard normal CDF, is written as

$$\mathbb{E}(prod_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{2it}) = \ \Phi_1\left(\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)\Phi_1\left(\vartheta+\boldsymbol{\pi}_2'\mathbf{w}_{2it}\right)+\Phi_1\left(-\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)\Phi_1\left(\boldsymbol{\pi}_2'\mathbf{w}_{2it}\right). \quad \text{(A.7)}$$

The partial effect of w_{it} in the product innovation equation is calculated as

$$\begin{aligned}\partial\mathbb{E}(prod_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{2it})/\partial w_{it} = & \underbrace{\pi_{2w}\left[\phi_1(\vartheta+\boldsymbol{\pi}_2'\mathbf{w}_{2it})\,\Phi_1(\boldsymbol{\pi}_1'\mathbf{w}_{1it})+\phi_1(\boldsymbol{\pi}_2'\mathbf{w}_{2it})\,\Phi_1(-\boldsymbol{\pi}_1'\mathbf{w}_{1it})\right]}_{\text{direct effect}} \\ & + \underbrace{\pi_{1w}\phi_1(\boldsymbol{\pi}_1'\mathbf{w}_{1it})\left[\Phi_1(\vartheta+\boldsymbol{\pi}_2'\mathbf{w}_{2it})-\Phi_1(\boldsymbol{\pi}_2'\mathbf{w}_{2it})\right]}_{\text{indirect effect}}, \qquad \text{(A.8)}\end{aligned}$$

where we use the symmetry of the normal distribution, that is $\phi_1\left(\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)=\phi_1\left(-\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)$.

The conditional mean associated with equation (3.3) also requires using the LIE, that is,

$$\mathbb{E}(proc_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{3it}) = \mathbb{E}_{spend_{it}}\mathbb{E}(proc_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{3it},spend_{it}),$$

which using similar derivations yields

$$\mathbb{E}(proc_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{3it}) = \ \Phi_1\left(\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)\Phi_1\left(\lambda+\boldsymbol{\pi}_3'\mathbf{w}_{3it}\right)+\Phi_1\left(-\boldsymbol{\pi}_1'\mathbf{w}_{1it}\right)\Phi_1\left(\boldsymbol{\pi}_3'\mathbf{w}_{3it}\right). \quad \text{(A.9)}$$

The partial effect of w_{it} in the process innovation equation is calculated similarly as

$$\begin{aligned}\partial\mathbb{E}(proc_{it}\big|\mathbf{w}_{1it},\mathbf{w}_{3it})/\partial w_{it} = & \underbrace{\pi_{3w}\left[\phi_1(\lambda+\boldsymbol{\pi}_3'\mathbf{w}_{3it})\,\Phi_1(\boldsymbol{\pi}_1'\mathbf{w}_{1it})+\phi_1(\boldsymbol{\pi}_3'\mathbf{w}_{3it})\,\Phi_1(-\boldsymbol{\pi}_1'\mathbf{w}_{1it})\right]}_{\text{direct effect}} \\ & + \underbrace{\pi_{1w}\phi_1(\boldsymbol{\pi}_1'\mathbf{w}_{1it})\left[\Phi_1(\lambda+\boldsymbol{\pi}_3'\mathbf{w}_{3it})-\Phi_1(\boldsymbol{\pi}_3'\mathbf{w}_{3it})\right]}_{\text{indirect effect}}. \qquad \text{(A.10)}\end{aligned}$$

In the case of a binary regressor, say d_{it}^w, the partial effect is calculated by evaluating the conditional means in equations (A.5), (A.7) and (A.9) at $d_{it}^w = 1$ and $d_{it}^w = 0$ and by taking the difference of the evaluated expressions. Standard errors of the partial effects are obtained by the delta method.

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