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ECONOMIC RESEARCH AND POLICY ANALYSIS BRANCH

Working Paper Series

Drivers of Innovation, Complementarity of Innovation, and Performance of Enterprises in Canada

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Working Paper 2014-01

Canada

This publication is also available online in HTML:
http://www.ic.gc.ca/eic/site/eas-aes.nsf/eng/h_ra02225.html

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Cat. No. Iu172-1/2014-1E-PDF
ISBN 978-1-100-22791-7

Aussi offert en français sous le titre *Déterminants de l’innovation, complémentarité de l’innovation et performance des entreprises au Canada*.

Government of Canada Gouvernement du Canada

Canada

Industry Canada

Economic Analysis and Statistics

Drivers of Innovation, Complementarity of Innovation, and Performance of Enterprises in Canada

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Industry Canada

Abstract

A rich enterprise-level data set is used to shed light on the complexity of the innovation process, identify the most important inputs to innovation and investigate the relationship between innovation and labour productivity in Canada. The main results are as follows: 1) evidence supports the idea that innovation is a complex process involving more than just R&D; 2) past innovation is the most important input for current innovation, supporting the presence of persistence in innovation; 3) a process/organizational and product/marketing classification seems to describe well the dynamic relationships among innovation types; and 4) the marginal effects of process innovation on labour productivity growth is positive.

February 19, 2013

* Now with the Bank of Canada

Table of Contents

1. Introduction

In recent years, the question of business innovation and productivity has been at the centre of the political debate in Canada. Some reports have identified the low level of business innovation in Canada as a likely explanation for the labour productivity gap observed with other countries such as the United States (see for example, the Expert Panel on Business Innovation, 2009; Institute for Competitiveness and Prosperity, 2011; McFetridge, 2008). These reports emphasize that enterprises in Canada are the key players in introducing innovation, but at the same time little enterprise-level empirical work has been undertaken to understand business innovation.

In the meantime, the complexity of innovation has been recognized. Today's innovation is much more than a research and development (R&D) story. Many other factors such as information and communication technologies (ICT) investments, use of advanced technologies, competition intensity and access to global markets are now considered to be usual suspects that affect firms' innovation behaviour and performance. More recently, investments in intangible assets, such as skills, management practices and organizational changes, have also made their way into the policy discussion about business innovation. Likewise, the definition of innovation itself has evolved as marketing and organizational innovations are now considered to be distinct of product and process innovations (OECD, 2005).

Generally, this paper will shed light on the complexity of the innovation process and investigate the relationship between innovation and labour productivity growth in Canada. To achieve this, a Crépon-Duguet-Mairesse (CDM) model is used. More precisely, the objective is three-fold. First, the most significant inputs to innovation are identified for each type of innovation—process, product, organizational and marketing —from a wide array of inputs. Second, the marginal effect of each type of innovation on labour productivity growth is computed to assess how different types of innovation correlate with productivity. Third, complementarity tests are performed to identify which combination of innovation types increase the most labour productivity growth.

The main findings are: i) innovation is a complex process that involves different inputs (e.g. use of advanced technologies; R&D; training); ii) incidence of past innovation is the most significant variable that explains both the incidence and level of current innovation which suggests there is persistence in innovation-related activities; iii) in contrast to the traditional technological versus non-technological dichotomy of innovation, a product-marketing and process-organizational classification seems more appropriate to describe the dynamic relationships among innovation types; iv) the marginal effect of process innovation on labour productivity growth is positive; v) process-organizational and process-marketing combinations of innovation are substitutes in the labour productivity growth equation while the organizational-product combination is complement.

In terms of policy implications, the results raise the question of how to better support business innovation in Canada. Currently, the largest share of innovation support is devoted to R&D tax credits. One might wonder how this could help enterprises adopting better management practices or making better use of their ICT capital or intangible assets. More research is needed to investigate whether there is an economic case to support non-R&D activities as it is currently done with R&D and whether this would contribute to increased labour productivity in Canada in the long run.

The remainder of the paper is organized as follows. Section 2 surveys the literature on the CDM model and on complementarity between innovation types. In Section 3, the empirical model is presented while the dataset used is described in Section 4. The main results are shown in Section 5. Section 6 concludes.

2. Literature Review

Link between innovation and productivity
It is generally accepted in the economic literature that innovation is positively related to productivity (see for example Hall, 2011). Several methods are available to assess this relationship, two examples being the growth accounting method and econometric regressions techniques. The second approach is adopted in this paper in the form of a Crépon-Duguet-Mairesse (CDM) model, an enterprise-level system of equations (Crépon et al., 1998).

The CDM model was developed to go beyond the R&D-productivity relationship pioneered by Griliches (1979). The idea is to introduce an intermediate stage between the input to innovation (R&D) and the ultimate outcome (productivity) to reflect the uncertain nature of the transformation process of R&D into productivity. This intermediate stage takes the form of a knowledge-generating, or innovation output equation which naturally links R&D and productivity. Typical examples of innovation output variables used are the share of sales from innovative products, patent rate or a binary indicator of the incidence of innovation. See for example Mairesse and Mohnen (2010) for a review.

CDM models have been widely used in recent years, in particular for crosscountry comparison purposes (OECD, 2009; Griffith et al., 2006; Mairesse and Mohnen, 2003). Overall, there is evidence that product innovation is positively correlated with productivity, but the case of process innovation is more complex. Most results indeed suggest that process innovation is not or negatively correlated with productivity. This result may be due to the presence of a disruptive effect: in the short run, the enterprise's limited resources are used to integrate the new process into the existing organization rather than to actually produce more efficiently. Another explanation is related to the definition of productivity used which usually involves sales. If product innovation mainly affects revenue and process innovation mainly affects costs, the absence of a positive link betwen process innovation and productivity (based on sales) makes sense. Moreover, in most studies, the problem is compounded by the short time period considered between the introduction of innovation and the measurement of productivity.

Complementarity in innovation
The available empirical evidence suggests the presence of complementarity between process and product innovations. This relationship has been analyzed using several different techniques, most of them using indirect tests. For example, Rouvinen (2002) based his test on the estimated correlation from a bivariate Probit on product and process innovations while Reichstein and Salter (2006) used the correlation between the Logit regression residuals (see Arora and Gambardella, 1990). Martinez-Ros (1999) reached a similar conclusion by including past innovation in his empirical specifications. A more direct test of complementarity was performed by Miravete and Pernias (2004) who used a structural model. They found that product and process innovations are complement (for the ceramic industry in Spain) and that this complementarity is mostly due to unobserved factors. The authors suggest that organizational changes and other intangibles, such as management practices, are key to unleashing the full potential of the combination of product and process innovations. Note these studies used a framework where only two types of innovation (product and process) were available

Consistent with the view of Miravete and Pernias, non-technological (organizational and marketing) innovation has been found to complement technological innovation (product and process). Using an empirical strategy similar to Rouvinen (2002), Schmidt and Rammer (2007) concluded that technical and nontechnical innovations are complement. Other indirect evidence of complementarity between organizational and technological innovation has been reported by Faria and Lima (2009) and Sapprasert (2008). Using the 1999 Canadian Survey of Innovation, Cozzarin and Percival (2006) reported results that support as well the hypothesis of complementarity. Their results suggest that product innovation and several organizational strategies, such as hiring graduate or skilled workers and promoting firm/product reputation, are complement in the profit/productivity equation.

Results on complementarity between innovation and productivity using a CDM model are mixed. Robin and Mairesse (2008) found that both product and process innovations are positively correlated with productivity, but that the impact of process innovation is stronger when combined with product innovation. Other evidence of complementarity is found by Polder et al. (2010). Their results are consistent with complementarity of organizational-process innovations on productivity for the Netherlands. This means that introducing both organizational and process innovations increase productivity more than introducing each of them separately. Note that this concept is different from the correlation measure between innovation types cited above as it measures how productivity changes when different combinations of innovation are used. Polder et al. also found that product-process innovations are complement, but that product-organizational innovations are substitute.

In contrast, Hall et al. (2011) did not find any evidence of complementarity between product, process and organizational innovations in the productivity equation for Italy. Interesting point, despite their opposite conclusions, the last two studies mentioned are comparable because the same inputs (R&D and ICT investments) and the same outputs to innovation are used along with a very similar CDM methodology. As mentioned at the beginning of this section, disruptive short-term effects caused by the introduction of several types of innovation could explain the absence of complementarity evidence in the Hall et al. study.

3. The Model

The model in this paper mainly follows Polder et al. (2010) and Hall et al. (2011) but differs on three major points. First, the range of inputs to innovation is broader. Past innovation, patents owned by the enterprise, the number of advanced technologies used and training are included in addition to R&D expenditures. However, in contrast to the Hall et al. and Polder et al. studies, enterprise-level ICT investments are not available and cannot be accounted for. Second, marketing innovation is included in addition to product, process and organizational innovations. Third, continuous innovation outputs variables are used in one model: the amount spent on process, product or marketing innovation and the percentage of workers affected by organizational innovation.

Although several studies cited in Section 2 used binary indicators of innovation, the use of continuous variables is not new. For example, some studies have used the share of sales from innovative product (see OECD, 2009). Using innovative sales controls for the quality of innovation, but this has the disadvantage of being only available for product innovators. Another example is Peters (2008) who used cost savings due to process innovation as well as innovative sales. The novelty of the present paper is thus to have a continuous variable for each of the four types of innovation.

The model used in this paper is a modified three-stage CDM model. The three parts of the CDM model form a system of equations with a recursive structure. The third stage regresses a measure of productivity on innovation indicators. The indicators come from the second stage, that is the innovation outputs equation. Finally, these second stage innovation outputs are linked to the innovation inputs through the first stage equation.

3.1 Innovation Inputs: R&D Equation

The dependant variable in the first stage is the log of average R&D expenditures from 2005–2007 as shown in Equation (1):

$$\ln\left(RD_i\right) = \alpha \begin{pmatrix} RD_i^{2004} \\ \mathrm{ADVTECH}_i \\ X_i^{2005\text{–}07} \end{pmatrix} + \in_i \tag{1}$$

where i denotes enterprise i and ε_i is the usual error term. Right-hand side variables includes lagged R&D and the number of advanced technologies used. Other control variables (X_i) are enterprise size, province, industry, country of control and multi-establishment binary variables. Sources and definitions of these variables are discussed in Section 4 and in Appendix A.

Since not all enterprises have undertaken R&D activities between 2005 and 2007, a Tobit model is estimated and used to obtain the predicted values of R&D expenditures for all enterprises, even those which reported no R&D activities[1]. This assumes that, as in several other studies (see for example Polder et al., 2010; Griffith et al., 2006), all enterprises have the potential of performing some R&D.

3.2 Innovation Outputs Equation

Model 1: Incidence of innovation
The innovation outputs variables used in the second stage of Model 1 are measured by four discrete variables indicating whether process, product, organizational or marketing innovation has been introduced by the enterprise between 2007 and 2009 (I^k). The four equations are jointly estimated using a multivariate Probit. The latent equations are given by:

$$I_i^k = \beta_1^k \begin{pmatrix} J_i^{\mathrm{PRCS}} \\ J_i^{\mathrm{ORGZ}} \\ J_i^{\mathrm{PRDT}} \\ J_i^{\mathrm{MRKT}} \end{pmatrix} + \beta_2^k \begin{pmatrix} \ln \widehat{RD}_i \\ \mathrm{ADVTECH}_i \\ \mathrm{TRAINING}_i \\ \mathrm{PATENTS}_i \\ X_i^{2005\text{–}07} \end{pmatrix} + \xi_i^k \tag{2}$$

where k denotes process (PRCS), organizational (ORGZ), product (PRDT) and marketing (MRKT) innovations. Since the β are indexed by k, four sets of parameters are estimated.

Past innovation (J^k) is included in the equations. The significance of the estimated parameters β_1^k consists of an indirect test on the complementarity between innovation types. Predictions of R&D expenditures $\ln \widehat{RD}$ come from Equation (1). *PATENTS* denotes the number of Canadian patents an enterprise owns and *TRAINING* is a binary variable equals to 1 if employees were trained following the introduction of advanced technologies.

It is assumed that the ξ^k are correlated as follows:

$$\begin{bmatrix} \xi^{\mathrm{PRCS}} \\ \xi^{\mathrm{PRGZ}} \\ \xi^{\mathrm{PRDT}} \\ \xi^{\mathrm{MRKT}} \end{bmatrix} \sim \mathrm{N}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \Sigma^{\mathrm{PRCS}}_{\mathrm{ORGZ}} & \Sigma^{\mathrm{PRCS}}_{\mathrm{PRDT}} & \Sigma^{\mathrm{PRCS}}_{\mathrm{MRKT}} \\ . & 1 & \Sigma^{\mathrm{ORGZ}}_{\mathrm{PRDT}} & \Sigma^{\mathrm{ORGZ}}_{\mathrm{MRKT}} \\ . & . & 1 & \Sigma^{\mathrm{PRDT}}_{\mathrm{MRKT}} \\ . & . & . & 1 \end{pmatrix}\right]$$

Variances had been normalized for identification purposes. This multivariate Probit is estimated using the algorithm of simulated maximum likelihood developed by Cappellari and Jenkins (2003) [2].

Despite the fact that other inputs to innovation are included, only R&D expenditures are being predicted in the first stage. Treating non-R&D inputs similarly would require much more information and failure to do so is acknowledged to be a limitation.

Aside from this potential endogeneity problem, another issue is the overlap of the innovation periods. Past innovation covers the 2005–2007 period while current innovation is for the 2007–2009 period. Unfortunately, nothing can be done to separate the effect of the common year 2007 as the data are not available by year, but over a three-year period. Finally, although several years of data are available, the panel dimension is not exploited and the other variables are aggregated accordingly to match these periods.

Model 2: Level of innovation
The innovation outputs in this model are measured by four continous variables. For product, process and marketing innovations, it is the amount spent on these types of innovation. For organizational innovation, it is the percentage of workers affected by these changes.

Therefore, the major change in Equation (2) is to replace the discrete dependant variables by their continuous counterparts. All the explanatory variables remain the same as shown in Equation (3).

$$INT_i^{k,2007\text{–}09} = \beta_1^k \begin{pmatrix} J_i^{\mathrm{PRCS}} \\ J_i^{\mathrm{ORGZ}} \\ J_i^{\mathrm{PRDT}} \\ J_i^{\mathrm{MRKT}} \end{pmatrix} + \beta_2^k \begin{pmatrix} \ln \widehat{RD}_i \\ ADVTECH_i \\ TRAINING_i \\ PATENTS_i \\ X_i^{2005\text{–}07} \end{pmatrix} + \xi_i^k \qquad (3)$$

where INT measures the level of innovation and k takes the same value as in Equation (2). The four equations of Model 2 are estimated by using four independant Tobit regressions. This is the other main difference with Model 1 in which the four equations are jointly estimated. But as shown by Table 10, the levels of innovation are less correlated than the incidence, supporting the use of independant regressions. The Tobit also takes into account the corner solution for non innovators.

3.3 Labour Productivity Growth Equation

In the last stage, labour productivity growth is regressed on the predicted innovation indicators obtained from the second stage to assess the correlation between innovation and productivity. Because the second stage is different for Model 1 and Model 2, the third stage equation also differs between models.

Model 1: Incidence of innovation
The productivity equation in the last stage of Model 1 is given by:

$$\Delta LP_i = \sum_{m \in M} \eta_1^m I\left(\text{PRCS}, \text{ORGZ}, \text{PRDT}, \text{MRKT}\right) + \eta_2 \begin{pmatrix} CAP_i \\ AGE_i \\ XPWO_i \\ XPUS_i \\ C\_INDEX_i \\ GVC_i \\ X_i^{2007-09} \end{pmatrix} + \mu_i \qquad (4)$$

Labour productivity growth (ΔLP) is defined as the growth rate of the sales to employment ratio between 2007 and 2008 (data for 2009 were not timely available). The capital-labour ratio *CAP* is defined similarly. Exports to the U.S. (*XPUS*) and to the rest of the world (*XPWO*) are averaged from 2007–2008. Additional right-hand side variables include the age of the enterprise, an indicator of the intensity of competition (*C_INDEX*) and an indicator of the presence of business activities abroad (*GVC*).

The set M contains the probabilities of being any one of the 16 profiles of innovators. Using the binary algebra notation, these probabilities are defined as: **I**(0000), **I**(0001), **I**(0010), …, **I**(1110), **I**(1111). Each number corresponds to a type of innovation—the order is PRCS, ORGZ, PRDT and MRKT—and a zero means that this type of innovation has not been introduced. For example, the probability that an enterprise is a PRCS innovator only is represented by **I**(1000). Likewise, **I**(0110) represents the probability that an enterprise is a ORGZ–PRDT innovator, while **I**(1001) denotes the probability that an enterprise is a PRCS–MRKT innovator.

All 16 probabilities are estimated for each enterprise. It is thus assumed that an enterprise has a positive probability of belonging to any one of the innovator profile categories, which is similar to the assumption made on R&D expenditures. These probabilities are computed from the estimated parameters of Equations (2) (see Cappellari and Jenkins, 2006). As they sum to 1 for each enterprise, no constant is included in Equation (4).

Model 2: Level of innovation
For Model 2, the productivity equation becomes:

$$\Delta LP_i = \sum_{m' \in M'} \eta_1^{m'} \,\text{INT}\left(\text{PRCS}, \text{ORGZ}, \text{PRDT}, \text{MRKT}\right) + \eta_2 \begin{pmatrix} CAP_i \\ AGE_i \\ XPWO_i \\ XPUS_i \\ C\_INDEX_i \\ GVC_i \\ X_i^{2007-09} \end{pmatrix} + \mu_i \qquad (5)$$

Using a notation similar to Model 1, the set M′ contains 15 elements representing the predicted levels of innovation and interaction terms among them. Predictions are taken from Equation (3). For example, the terms **INT**(1000) and **INT**(0001) represent, repectively, the predicted expenditures on PRCS and MRKT innovations while **INT**(1001) is the interaction term between PRCS and MRKT expenditures. Applying the same logic, **INT**(1110) is the interaction term between the PRCS, ORGZ and PRDT levels of innovation. Consistent with Model 1, the level of each type of innovation is predicted for each enterprise. The term **INT**(0000) is not included in Equation (5) because it equals zero for all enterprises. A constant, however, is included. All other variables are the same as in Equation (4).

[1] The procedure proposed by Cameron and Trivedi (2009) (p. 540) is used to avoid losing observations when taking the log for non-R&D performers. The method essentially consists in using a threshold for the Tobit just below the first order statistics of the R&D variable.

[2] The **mvprobit** function implements the Geweke, Hajivassiliou and Keane algorithm and 200 Halton draws have been used.

4. Data

All variables come from Statistics Canada administrative databases or surveys, except for patent data that are extracted from the Canadian Intellectual Property Office database (CIPO). All variables are expressed at the enterprise level. Variables expressed in Canadian dollars have been deflated using the Statistics Canada Canadian Productivity Account price index (KLEMS).

Innovation-Related Variables
All innovative outputs variables come from the Survey of Innovation and Business Strategy 2009 (SIBS). As mentioned in Section 2, the dependent variables in Model 1 are binary variables indicating whether innovation has been introduced and continuous variables on amount spent on innovation (percentage of workers affected for ORGZ) for Model 2.

The traditional CDM framework uses R&D expenditures as the main input to innovation. Enterprise-level R&D expenditures come from the R&D in Canadian Industry (RDCI) database. RDCI is essentially a census of all R&D performers in Canada so a missing record is assumed to be a zero. Adoption of advanced technologies is another input to innovation included in the analysis. New technologies improve the way business activities are conducted, but also indirectly increase enterprises' capacity to absorb new knowledge through higher skills requirements (for a review of the Cohen and Levinthal absorptive capacity concept, see Volberda et al., 2009). This indirect effect is of relevance for innovation because new ideas may lead to more innovation. The Survey of Advanced Technologies 2007 (SAT) provides the number of advanced technologies used by the enterprise, which reflects its level of technological sophistication. The training variable is also taken from the SAT.

Past innovation-related activities can play a critical role for current innovation activities especially when complementarity between innovation types is present (see for example Le Bas and Poussing, 2012; Peters, 2009). Persistence of innovation activities—and as a matter of fact of R&D activities—can arise because of the fixed costs incurred by the enterprise that decided to innovate. Past decisions (binary variables) about PRCS, ORGZ, PRDT and MRKT innovations cover the 2005–2007 period and come from the SAT.

The last input considered is the number of Canadian patents owned by the enterprise in 2006. These data come from the Canadian Intellectual Property Office (CIPO) database. Although it is assumed that a missing value is a zero, this is an oversimplification as a missing record can simply mean that the CIPO record could not be matched with Statistics Canada databases. More importantly, CIPO data do not capture patents granted abroad.

In some recent papers, an information and communication technology (ICT) investments equation has been added (Polder et al., 2010; van Leeuwen and Farooqui, 2008; Hall et al., 2011). This makes sense as ICT is often considered to be a general purpose technology and as such has a potentially important role in innovation (Bresnahan et al., 2002; Crespi et al., 2007; Zandt et al., 2011). An ICT index can be constructed using the Survey of Electronic Commerce and Technology (SECT) data, but it was not included in the regressions because the sample size would had been too small.

Productivity Equation Variables
Sales and capital (the sum of tangible and intangible assets) come from the General Index of Financial Information (GIFI) database. The employment variable, the individual labour unit (ILU), is taken from the Longitudinal Employment Analysis Program (LEAP). The distinction between U.S. and non-U.S. exports (from the Exporter Register) is made to capture the complexity of the enterprise export strategy. It is thus assumed that exporting to the United States is easier.

The SIBS has several indicators of competition intensity and an index was constructed using four of them. Details on the index can be found in Appendix A. The global value chain (GVC) indicator is a binary variable from the SIBS indicating whether the enterprise conducted any business activities outside of Canada between 2007 and

2009. The age variable is computed using the date at which the enterprise was captured in the Business Register (BR), which may differ from the actual birth date, but it can still be considered a good approximation of the real age of the embryo.

Control Variables

Enterprise size was defined using ILU as follows: small (20–49 employees), medium (50–99), large (100–249) and extra large (250+). The country of control, multi-establishment status and provincial binary variables were taken from the BR. Three industrial sector indicators have been built based on average R&D expenditures of 3-digit NAICS industries in 2004: low-R&D (less than $250K), mid-R&D ($250K–$1M) and high-R&D ($1M+) industries.

Sample Size

The main challenge of combining data from surveys with different sampling design is the reduction of the sample size. For this project, combining the SIBS and the SAT is critical because all innovation variables are taken from these data sets. Since the SAT covers exclusively the manufacturing sector and the SIBS coverage is biased toward it, there is a reasonable number of common records between these two samples. However, inclusion of an ICT index from the SECT, which has a large sample but covers all the economy, is difficult because it has many fewer common records with the SIBS and SAT (see Table 1). Given the large number of parameters to estimate, it was decided not to pursue research with the ICT variable despite the fact that numerical convergence was achieved for these specifications.

Table 1: Sample size

	Model 1	Model 2
Inputs: only past innovation	1373 (Specification I)	1370 (Specification II)
Inputs: all except ICT	1296 (Specification III)	1293 (Specification IV)
Inputs: all	610 (Not reported)	607 (Not reported)

There is a negligeable loss of observations due to the use of variables coming from administrative sources. The last restriction imposed on the sample is removing extreme values for R&D expenditures and expenditures on PRDT[3]. For each model presented in Section 3, two specifications are estimated. The first one uses only past innovation as input to innovation and the second uses all the inputs except ICT. Table 1 shows the final sample size for each specification. For comparison purposes, the sample if the ICT index variable would had been included is also shown. Some descriptive statistics of the main variables are presented in Appendix B.

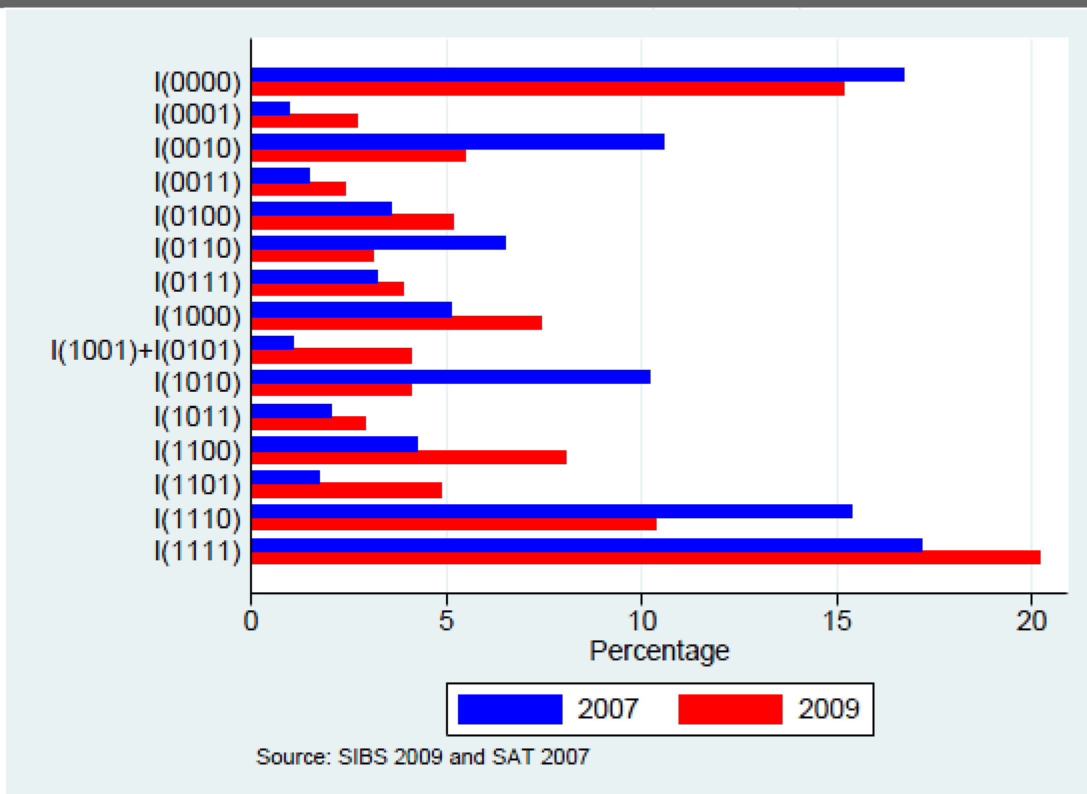
[3] For Model 1: $logRD$ < 10, with R&D being expressed in thousand of dollars; for Model 2: $logRD$ < 10 and INT^{PRDT} < 100, with expenditures on PRDT innovation expressed in $M.

5. Results

5.1 The Complexity of Innovation

Before analyzing the results, some descriptive statistics are presented to illustrate the complexity of innovation strategies in Canada. Figure 1 shows the incidence (unweighted) of the 16 mutually exclusive innovator profiles as defined in Section 3.3 for the sample used in the paper.

Figure 1: Incidence of innovator profiles by year*
– Unweighted percentages (N = 1370) –



* I(process; organizational; product; marketing)

Source: SIBS 2009 and SAT 2007

The complexity of innovation strategies did not change much between the two periods. The most two frequent innovator profiles in both periods were innovators introducing all four types (I(1111)) and non-innovators (I(0000)). Around 20% of enterprises followed a simple innovation strategy (only one type of innovation), about the same percentage implemented a two-type strategy and over 40% pursued a complex strategy (at least three types of innovation). This result suggests that a majority of enterprises in Canada are combining different types of innovation since at least 2005.

A closer look at the figure also suggests that the prevalence of PRDT has somewhat declined for this sample. From the 2005–2007 to 2007–2009 period, the percentage of enterprises that introduced PRDT (the sum of all strategy with PRDT) had decreased by 14 percentage points (pp) from 67% to 53%. In contrast, the percentage of MRKT innovators had increased by 13 pp over the same period (from 28% to 41%). The percentages of PRCS and ORGZ innovators had also increased slightly, by 3 pp and 5 pp respectively. These numbers should however be interpreted with caution because no sampling weights have been used.

Looking at the inputs to innovation, Table 2 clearly shows that performing R&D is not a necessary condition for innovating. The last line shows that 52% of all innovators from 2007–2009, no matter the type of innovation introduced, did not perform R&D over the 2005–2007 period. Even when considering the final sample used in this paper, which is more technology-oriented, a significant proportion of enterprises (35%) still did not perform R&D. This result should however be qualified as it is possible that the R&D performed from 2005–2007 yielded innovations after 2009. In addition, these statistics are not weighted and thus are not representative of the population of enterprises innovating in Canada.

Table 2: Percentage of enterprises by R&D and innovation status
– Unweighted percentages –

		Total SIBS sample [3]		Sample used in the paper [4]	
		Performed R&D in 2005–07		Performed R&D in 2005–07	
		No	Yes	No	Yes
Innovator in 2007–09	No	79.1%	20.9%	63.5%	36.5%
	Yes	52.1%	47.9%	35.4%	64.6%

3 N = 4227.

4 N = 1370.

Sources: SIBS 2009 and RDCI 2005–2007.

The last evidence on the complexity is given by the correlations between innovation inputs and outputs. Panel A of Table 3 shows that R&D expenditures are positively correlated with binary indicators of innovation (in Red), but it is not the only input. For example, many past innovation indicators are as much correlated to their current counterparts as R&D is (in Blue). Panel B shows similar relationships for expenditures on innovation (in Red and Orange). Table 9 in Appendix B also shows that most inputs to innovation are correlated with each other, in particular past innovation.

Table 3: Correlations between innovation inputs and outputs
– Unweighted (N = 1370) –

	A – Innovation incidence				B – Level of innovation			
	I^{PRCS}	I^{ORGZ}	I^{PRDT}	I^{MRKT}	INT^{PRCS}	INT^{ORGZ}	INT^{PRDT}	INT^{MRKT}
J^{PRCS}	0.25	0.18	0.15	0.08	0.10	0.10	0.10	0.07
J^{ORGZ}	0.16	0.20	0.17	0.11	0.12	0.14	0.09	0.07
J^{PRDT}	0.16	0.14	0.25	0.14	0.05	0.10	0.09	0.06
J^{MRKT}	0.11	0.12	0.18	0.17	0.09	0.10	0.08	0.10
$\ln \widehat{RD}$	0.22	0.15	0.23	0.08	0.15	0.05	0.23	0.12
ADVTECH	0.19	0.17	0.10	0.07	0.20	0.08	0.15	0.12
TRAINING	0.11	0.12	0.07	0.09	0.08	0.09	0.09	0.06
PATENTS	0.03	0.03	-0.03	0.03	0.00	-0.01	0.00	0.00

Note: I^X and J^X are binary variables indicating whether an enterprise has innovated in 2007–2009 and 2005–2007 respectively. INT^X represent the expenditures on innovation. See Appendix A for the details.
Source: SIBS 2009, RDCI 2005–2007, SAT 2007 and CIPO 2000–2006.

To sum up, it seems that business innovation in Canada is a complex process that depends upon the combination of several activities. Results from the CDM presented in the remaining of this section attempt to disentangle the effects of these various inputs and to identify their relationships with productivity.

5.2 R&D Equation Results

Table 11 in Appendix C presents the results for the R&D equation. Only results for Model 2 are presented to preserve confidentiality as the R&D equation of Model 1 is the same as for Model 2 but with only three less observations. The average of positive R&D expenditures over 2004-07 is about $308K as shown in Table 8 of Appendix B. The non-parametric density of R&D expenditures is presented in Figure 2.

The results are fairly standard. The estimated parameter of past R&D expenditures is significant and positive along with the one for ADV T ECH . The latter means that the technological sophistication (number of technologies used) is positively correlated with R&D. Larger enterprises and enterprises in high average R&D industries (not shown) are also more likely to spend more on R&D activities, a result consistent with other Canadian studies (see for example Baldwin et al., 2000).

5.3 Innovation Outputs Equations Results

Table 4 summarizes the results for the innovation outputs equation using the two empirical models presented in Section 3. Tables 12 and 13 in Appendix C show the whole set of estimated parameters. The most striking feature is that past innovation is strongly related to current innovation no matter the specification or model considered. Adding the other inputs (Specifications II and IV) usually does not change greatly the results much although some parameters become non-statistically significant.

Two main conclusions can be drawn from these results. First, there is evidence of path dependence in the innovation process as shown by the diagonal elements of the past-current innovation matrix in Table 4 (in bold). Since all these elements are positive and significant, it means that once an enterprise has introduced one type of innovation, it is likely that some other innovations of the same type will follow. The presence of sunk costs may contribute to explain this path dependance pattern. This finding is also robust as the relationship holds for all estimated specifications—both for the incidence and level of innovation.

Table 4: Summary of innovation outputs equations results

Incidence of innovation – Model 1, Equation (2)									
		Specification I				Specification II			
Variable		PRCS	ORGZ	PRDT	MRKT	PRCS	ORGZ	PRDT	MRKT
J^{PRCS}		+	+			+	+		
J^{ORGZ}		+	+	+			+	+	
J^{PRDT}		+	+	+	+			+	+
J^{MRKT}				+	+			+	+
$\ln \widehat{RD}$		n/a	n/a	n/a	n/a				
ADVTECH		n/a	n/a	n/a	n/a	+			
TRAINING		n/a	n/a	n/a	n/a				+
PATENTS		n/a	n/a	n/a	n/a				
Size	Medium								
	Large	+							
	X-large	+							

+ indicates a significant and positive estimated parameter at least a 0.10 level.
n/a means that the variable is not included in the regression.

Level of innovation – Model 2, Equation (3)								
	Specification III				Specification IV			
Variable	PRCS	ORGZ	PRDT	MRKT	PRCS	ORGZ	PRDT	MRKT
J^{PRCS}	+	+			+			
J^{ORGZ}	+	+			+	+		
J^{PRDT}		+	+	+		+	+	+
J^{MRKT}			+	+			+	+
$\ln \widehat{RD}$	n/a	n/a	n/a	n/a				
ADVTECH	n/a	n/a	n/a	n/a	+			
TRAINING	n/a	n/a	n/a	n/a				
PATENTS	n/a	n/a	n/a	n/a				
Size: Medium	+							
Size: Large	+		+		+			
Size: X-large	+		+	+	+			

+ indicates a significant and positive estimated parameter at least a 0.10 level.
n/a means that the variable is not included in the regression.

Second, past (2005–2007) PRCS and ORGZ are linked to current (2007–2009) PRCS and ORGZ, while past PRDT and MRKT are linked to current PRDT and MRKT. This can be seen by the shaded areas in Table 4. In addition, a weaker dynamic link is found between ORGZ and PRDT. Following Martinez-Ros (1999), these results support the presence of complementarity among innovation types because the significant estimated parameters are all positive. This result is reinforced by the fact that most relationships are also reciprocal (the off main diagonal elements in each shaded area). For example, the past PRDT is positively correlated with current MRKT and at the same time past MRKT is positively associated with current PRDT in all four specifications. This suggest that in contrast to the traditional technological (PRCS and PRDT) versus non-technological (ORGZ and MRKT) dichotomy of innovation, a PRCS-ORGZ and PRDT-MRKT classification is more appropriate, at least to describe the dynamic relationships among innovation types.

More evidence for complementarity is given by the estimated correlations of the multivariate Probit from Model 1. They are all positive and statistically significant as reported at the bottom of Table 12. This means that introducing any type of innovation increases the likelihood of introducing another type of innovation during the same period. Note however the difference with the results reported in the previous paragraph as the correlations from the Probit point to complementarity among innovation types from 2007–2009, not between 2005–2007 and 2007–2009. All these findings are consistent with what is found in the empirical literature (see for example Rouvinen, 2002; Schmidt and Rammer, 2007). It is also consistent, to a lesser extent, with the simple correlations between innovation types reported in Table 3 and in Panel A of Table 10 of Appendix B.

In contrast to what Polder et al. (2010) and Hall et al. (2011) have found, R&D is not a significant input to innovation. The presence of past innovation is a likely suspect for the non-significant R&D results because the latter may already be embedded in the former. Indeed, adding past innovation, but without the other control variables, makes the R&D estimates non-significant. However, the addition of the other control variables, in particular firm size, also make the R&D estimated coefficient non-significant. This is not surprising considering the strong relationship between firm size and R&D expenditures (Table 11). Consequently, including both past innovation and firm size variables are probably causing the non-significant results for R&D.

Few other inputs to innovation are significant in Specification II. Only the number of advanced technologies used is related to PRCS and training associated with advanced technologies seems to explain MRKT, although the meaning of the last relationship is obscure and it is not significant in Specification IV. Enterprise size is positively related with PRCS and to a lesser extent to PRDT. This relationship is however weaker when additional inputs are added (Specifications II and IV) and only holds for PRCS.

5.4 Productivity Equation Results

Table 5 summarizes the results for the productivity equation (see also Table 14 of Appendix C). In contrast to the results of the second stage, there is a striking difference in the number of significant estimated parameters for Specifications I and II, but no clear pattern emerges from these results, as half are positive (Specification I). Indeed, Table 14 shows that PRCS-PRDT-MRKT, MRKT and ORGZ-PRDT-MRKT are the combinations increasing labour productivity growth the most. In contrast, PRCS-MRKT, PRDT-MRKT and PRDT-PRCS are the combinations with the largest negative sign. However, the estimates are not robust to the inclusion of the other inputs to innovation (Specification II) and should therefore be interpreted with caution.

Table 5: Summary of productivity equation results*

Incidence – Model 1, Equation (4)			Level – Model 2, Equation (5)		
Variables	Specification I	Specification II	Variables	Specification III	Specification IV
I(0000)					
I(0001)	+		**INT**(0001)		
I(0010)			**INT**(0010)		–
I(0011)	–		**INT**(0011)		
I(0100)			**INT**(0100)		
I(0101)			**INT**(0101)		
I(0110)			**INT**(0110)	+	
I(0111)	+		**INT**(0111)		
I(1000)	+		**INT**(1000)	+	+
I(1001)	–		**INT**(1001)		
I(1010)	–		**INT**(1010)		
I(1011)	+	+	**INT**(1011)		
I(1100)	–		**INT**(1100)	–	–
I(1101)			**INT**(1101)		
I(1110)	+		**INT**(1110)		
I(1111)	–		**INT**(1111)		

* I(process; organizational; product; marketing)

+ indicates a significant and positive estimated parameter at a level of at most 0.10.

– indicates a significant and negative estimated parameter at a level of at most 0.10.

Fewer parameters are significant in Specification II. The results from this specification are nevertheless in line with the results of Hall et al. (2011) as they find few significant relationships between innovation and productivity. The present results are however different from the results in Polder et al. (2010) as they find that all the combinations with a positive and significant sign involve ORGZ.

Turning to Model 2, results seem more robust to the inclusion of the other inputs to innovation, but few estimated parameters are statistically different from zero. Marginal effects for the four types of innovation are reported in Table 6. No marginal effects are significantly different from zero, but the ones for PRCS innovation are close to be at a 0.10 level. This differs from what is usually found in the literature where the estimated parameter for PRCS is negative or not significant (see especially OECD, 2009). A similar non-standard result is also found for PRDT as it does not have the usual positive sign and is insignificant.

Table 6: Model 2 – Marginal effects of innovation on productivity

	Specification III		Specification IV	
Variable	Average [5]	T-stat	Average [5]	T-stat
$\mathbf{INT}^{PRCS}$	0.2487	1.61	0.2123	1.6
$\mathbf{INT}^{ORGZ}$	-0.0076	-0.53	-0.0008	-0.06
$\mathbf{INT}^{PRDT}$	-0.0551	-0.79	-0.0125	-0.21
$\mathbf{INT}^{MRKT}$	0.2405	0.34	-0.0581	-0.12

[5] Average of enterprises marginal effects.

The estimated elasticity of the capital-labour ratio growth on labour productivity growth is about 0.07 in all specifications (see Table 14). Aside from the innovation indicators, there are few other variables that are significantly different from zero. A notable exception is age, which it is inversely related to the labour productivity growth. The export to non-U.S. countries parameters are also significant for Model 2 and are positively related to productivity, although they are close to zero. This suggests that exporting to non-U.S. markets is more demanding than exporting to the United States and that only the most efficient enterprises are able to compete in global markets.

5.5 Complementarity Between Innovation and Productivity

As mentioned in Section 5.3, the results are consistent with other studies in the literature about the complementarity between innovation types. This concept is however not equivalent to the one being formally tested for example by Polder et al. (2010) and Hall et al. (2011). The former measures the correlation between the incidence of innovation, while the latter measures the impact of combining different types of innovation on labour productivity growth.

Testing for complementarity of innovation and productivity within a CDM framework can be done using the test described by Mohnen and Röller (2005) (see for example Hall et al., 2011; Polder et al., 2010). Unfortunately, it is not possible to apply this method in the present case because the Wald statistics (Kodde and Palm, 1986) for this test require an optimization under inequality constraints that leads to multiple solutions. Instead, the method proposed by Carree et al. (2010) is used for both Models 1 and 2.

This technique is simpler because it directly imposes conditions for complementarity/substitution in Equations (4) or (5) by adding and substracting the relevent I (INT) variables. The tests on complementarity/substitution can then be performed on the estimated parameters of the transformed model. The test stills a pair-wise comparison test and both complementarity and substitution must be tested as rejecting one does not imply the other. Details of the tests are given in Appendix D.

Table 7 shows the results of the tests. Although few complementarity/substitution relationships are found, more are found for Model 2 than for Model 1. This suggests that the "effort" or "intensity" of innovation measured by the amount spent on innovation is better captured by Model 2. For both Specifications III and IV, substitution between PRCS and ORGZ is not rejected. Introducing both types of innovation at the same time reduces labour productivity growth compared to when only one is introduced at the time. This result is consistent with the presence of a disruptive effect as mentioned in Section 2: in the short run, enterprises have limited resources and introducing both types at the same time may actually reduce the efficiency of the production process.

Table 7: Test results for complementarity and substitution

Combination tested	Incidence – Model 1		Level – Model 2	
	Spec. I	Spec. II	Spec. III	Spec. IV
PRCS-ORGZ			SUBS	SUBS
PRCS-PRDT				
PRCS-MRKT	SUBS			
ORGZ-PRDT			COMP	
ORGZ-MRKT				
PRDT-MRKT				

SUBS: Substitution is not rejected.
COMP: Complementarity is not rejected.

There is complementarity between ORGZ and PRDT for Specification III. It would be interesting to assess the causality of this relationship, but a plausible story is that PRDT requires ORGZ to positively affect labour productivity growth. This suggests that in the short term, enterprises would be better off by working both on their cost and revenue functions rather than working only on their cost function.

This explanation is however not consistent with the PRCS-MRKT (Model 1) or the PRCS-ORGZ (Model 2) substitution relationships. In these case, trying to increase revenue while reducing cost seems to slow down labour productivity growth. The complementarity between ORGZ-PRDT and the substitution relationship between PRCS-MRKT should however be considered as less robust than the PRCS-ORGZ substitution as they are sensitive to the choice of the empirical specification.

Results presented in Table 7 are consistent with Hall et al. (2011) as they failed to find any significant complementarity relationships between innovation and productivity. In contrast, Polder et al. (2010) reported complementarity between i) PRDT-PRCS and ii) PRCS-ORGZ and productivity. These differences can be due to the timing problem for the measurement of labour productivity growth and innovation referred in the next section, but it cannot be a priori ruled out that the relationship between PRCS and ORGZ innovation is different in Canada compared to the Netherlands.

Although few significant relationships are found in this analysis, it is interesting to note that there are no robust results between the incidence (Model 1) and level (Model 2) analyses. This emphasizes the difference between both types of indicators and suggests that the results may depend on how innovation is measured.

5.6 Caveats

The main caveat of the analysis concerns the timing in measuring the different variables used. At least two examples of this issue are worth mentioning.

First, left and right-hand side variables in the productivity equation are both measured over the same period: innovation indicators cover the 2007–2009 period while the labour productivity growth is measured over the 2007–2008 period. It would have made more sense that productivity be measured after 2009, but the data were not readily available. Consequently, this means that the estimated relationships should not be interpreted in terms of impacts or causality, but as correlations.

Second, inputs and outputs to innovation used in the estimation of the knowledge-generating equation (second stage of the CDM) have one year in common. Inputs are measured from 2005–2007 and outputs from 2007–2009. This common year may introduce a bias in the estimated relationships between past and current innovation, if a sufficient number of enterprises had innovated in 2007 only. An artificial correlation may arise because 2007 innovation would be counted both as an input and an output. Unfortunately, as the data are collected for these periods and not on a yearly basis, it is difficult to assess the potential impact of this issue on the conclusions.

Another problem comes from the different treatment of the inputs to innovation. Only R&D is endogenized in the first stage. The number of advanced technologies used and past innovation, which were found to be significant determinants of innovation, could also be endogenous. But as mentioned in Section 3.2, there is no data currently available to estimate a first stage regression for all the inputs considered.

Despite the above limitations, the current analysis provides useful insight to better understand how businesses conduct their innovation-related activities in Canada. Moreover, the methodology used compares well to most recent papers using the CDM model that test for complementarity.

6. Conclusion

Several pieces of evidence of the complexity of innovation in Canada have been provided using a rich business micro-data environment. The main results from a Crépon-Duguet-Mairesse (CDM) model can be summarized as follows: i) innovation is a complex process involving many different business activities; ii) past innovation is the most significant input to explain current business innovation suggesting the presence of persistance in innovation activities; iii) a process/organizational and product/marketing classification seems to better describe the dynamic relationships among innovation types compared to the traditional technological versus non-technological classification; iv) the marginal effect of process innovation on labour productivity growth is positive; v) the few examples of complementarity/substitution of innovation with labour productivity found involve either process or organizational innovation.

The results of this analysis raises some interesting policy questions. A literal interpretation would suggest that non-R&D investments should be supported in the same way as R&D activities because the former are also significant inputs to innovation. In other terms, should other activities such as adoption of advanced technologies, implementation of better management practices or training of employees and managers be supported to the same extent as R&D?

However, a rationale for government intervention needs to be articulated before supporting these non-R&D or non-technological activities. The main argument to support R&D is the presence of spillovers that benefit other enterprises and prevent the innovator or R&D performer to capture all the returns on its initial investment. On the one hand, if this inequal treatment of non-R&D activities is an impediment to innovation, and that increasing innovation is one of the stated goals of the government, there is some sense in widening the current policy. On the other hand though, if the benefits of non-R&D activities are mainly private, it is harder to make a case for stronger support. Finding the right balance is a challenge but empirical economic research can provide some useful insights.

Another interesting follow-up paper would be to further investigate the link between innovation and R&D investments. R&D is considered to be an important input to innovation, but the present analysis failed to capture this relationship. This is in contrast to other papers such as Polder et al. (2010) and Hall et al. (2011) where R&D plays a significant role in the innovation process. A first explanation might be the inclusion of past innovation that makes R&D non-significant. Another explanation may relate to the timing of the investments. It can take many years for R&D investments to bear fruit, especially if product innovation is considered because of the lengthy development and commercialization periods. This means that the period used in this paper is too short and that R&D performed in 2000 would be more relevant innovation from 2007–2009 than R&D performed from 2005–2007. A last explanation may relate to the channels through which R&D flows into Canada. For instance, the role of multinational enterprises should be more closely investigated. Finally, combined with continuing micro-data development initiatives, this type of project could contribute to the development of better evidence-based policy for innovation in Canada.

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Appendix A – Variables Used and Data Sources

Data sources

Statistics Canada administrative databases	
Name	Years
Business Register (BR)	2004–09
General Index of Financial Information (GIFI)	2007–08
Longitudinal Employment Analysis Program (LEAP)	2004–08
Exporter Register	2007–08
Research and Development in Canadian Industry (RDCI)	2004–07

Statistics Canada surveys	
Name	Years
Survey of Innovation and Business Strategy (SIBS)	2009
Survey of Advanced Technology (SAT)	2007
Survey of Electronic Commerce and Technology (SECT)	2004–07

Other administrative databases	
Name	Years
Canadian Intellectual Property Office (CIPO)	2000–06

Variables used and definitions

All dollar variables are expressed in Canadian dollars and have been deflated using Canadian Productivity Account price index (KLEMS) produced by Statistics Canada.

R&D – Equation (1)		
Variable	Description	Source
ln *RD*	Average R&D expenditures in thousands of dollars (2005–07) in log	RDCI
RD^{2004}	R&D expenditure in $1000 (2004)	RDCI
ADVTECH	Number of advanced technologies used as of 2007	SAT

Inputs to innovation – Equations (2) and (3)		
Variable	Description	Source
J^{PRCS}	= 1 if introduced PRCS innovation in 2005–07	SAT
J^{ORGZ}	= 1 if introduced ORGZ innovation in 2005–07	SAT
J^{PRDT}	= 1 if introduced PRDT innovation in 2005–07	SAT
J^{MRKT}	= 1 if introduced MRKT innovation in 2005–07	SAT
$\ln \widehat{RD}$	Predicted value of ln *RD*	Eq. (1)
ADVTECH	As above	SAT
TRAINING	= 1 if employees were trained to use adv. tech.	SAT
PATENTS	Number of patents owned in 2006	CIPO

Outputs to innovation – Equations (2) and (3)		
Variable	Description	Source
I^{PRCS}	= 1 if introduced PRCS innovation in 2007–09	SIBS
I^{ORGZ}	= 1 if introduced ORGZ innovation in 2007–09	SIBS
I^{PRDT}	= 1 if introduced PRDT innovation in 2007–09	SIBS
I^{MRKT}	= 1 if introduced MRKT innovation in 2007–09	SIBS
INT^{PRCS}	Expenditures on PRCS innovation in 2007–09	SIBS
INT^{ORGZ}	% of workers affected by ORGZ innovation in 2007–09	SIBS
INT^{PRDT}	Expenditures on PRDT innovation in 2007–09	SIBS
INT^{MRKT}	Expenditures on MRKT innovation in 2007–09	SIBS

Productivity – Equation (4)		
Variable	Description	Source
ΔLP	Labour productivity (sales/employment) growth (2007–08)	GIFI, LEAP
I (0000)	Probability of being non-innovator	Eq. (2)
I (0001)	Probability of being MRKT innovator	Eq. (2)
I (0010)	Probability of being PRDT innovator	Eq. (2)
I (0011)	Probability of being PRDT and MRKT innovator	Eq. (2)
I (0100)	Probability of being ORGZ innovator	Eq. (2)
I (0101)	Probability of being ORGZ and MRKT innovator	Eq. (2)
I (0110)	Probability of being ORGZ and PRDT innovator	Eq. (2)
I (0111)	Probability of being ORGZ, PRDT and MRKT innovator	Eq. (2)
I (1000)	Probability of being PRCS innovator	Eq. (2)
I (1001)	Probability of being PRCS and MRKT innovator	Eq. (2)
I (1001)	Probability of being PRCS and PRDT innovator	Eq. (2)
I (1010)	Probability of being PRCS, PRDT and MRKT innovator	Eq. (2)
I (1011)	Probability of being PRCS and ORGZ innovator	Eq. (2)
I (1100)	Probability of being PRCS, ORGZ and MRKT innovator	Eq. (2)
I (1110)	Probability of being PRCS, ORGZ and PRDT innovator	Eq. (2)
I (1111)	Probability of being PRCS, ORGZ, PRDT and MRKT innovator	Eq. (2)

Productivity – Equation (5)		
Variable	Description	Source
Δ*LP*	Labour productivity (sales/employment) growth (2007–08)	GIFI, LEAP
INT (0001)	Predicted expenditures on MRKT innovation	Eq. (3)
INT (0010)	Predicted expenditures on PRDT innovation	Eq. (3)
INT (0011)	Interaction of predicted amounts: PRDT and MRKT	Eq. (3)
INT (0100)	Predicted % of workers affected by ORGZ innovation	Eq. (3)
INT (0101)	Interaction of predicted amounts: ORGZ and MRKT	Eq. (3)
INT (0110)	Interaction of predicted amounts: ORGZ and PRDT	Eq. (3)
INT (0111)	Interaction of predicted amounts: ORGZ, PRDT and MRKT	Eq. (3)
INT (1000)	Predicted expenditures on PRCS innovation	Eq. (3)
INT (1001)	Interaction of predicted amounts: PRCS and MRKT	Eq. (3)
INT (1010)	Interaction of predicted amounts: PRCS and PRDT	Eq. (3)
INT (1011)	Interaction of predicted amounts: PRCS, PRDT and MRKT	Eq. (3)
INT (1100)	Interaction of predicted amounts: PRCS and ORGZ	Eq. (3)
INT (1101)	Interaction of predicted amounts: PRCS, ORGZ and MRKT	Eq. (3)
INT (1110)	Interaction of predicted amounts: PRCS, ORGZ and PRDT	Eq. (3)
INT (1111)	Interaction of predicted amounts: PRCS, ORGZ, PRDT and MRKT	Eq. (3)

Control variables		
Variable	Description	Source
CAP	Capital/labour ratio (tangible+intangible assets) growth (2007–08)	GIFI, LEAP
AGE	Age of the enterprise in 2009	BR
XPWO	Average exports to the world, excluding U.S. (2007–08)	ER
XPUS	Average exports to U.S. (2007–08)	ER
C_INDEX	Index of competition intensity in 2009	SIBS
GVC	= 1 if had activities outside of Canada in 2007–09	SIBS
Enterprise size	Small: 20–49 employees; medium: 50–99; large: 100-249; x-large: 250+. Reference category: small.	LEAP
Country	= 1 if country of control is Canada	BR
Multiest	= 1 if a multi-establishment enterprise	BR
Province	Four binary variables for Québec, Ontario, British Columbia and Alberta. Reference category: all other provinces	BR
Industry	High, mid and low R&D industries (based on 2004 average R&D in industry). Reference category: low R&D.	RDCI

Industrial groups variable

The three industrial groups are based on the average R&D expenditures in each 3-digit NAICS, meaning that the classification is defined by the data only. Incidentally, it happens to be close to an OECD-type high/low technology classification. The following table lists the NAICS within each class.

Low-RD: Average industry R&D < $250K	
113	Forestry and Logging
314	Textile Product Mills
315	Clothing Manufacturing
316	Leather and Allied Product Manufacturing
332	Fabricated Metal Product Manufacturing
337	Furniture and Related Product Manufacturing
444	Building Material and Garden Equipment and Supplies Dealers
445	Food and Beverage Stores
483	Water Transportation
523	Securities, Commodity Contracts, and Other Financial Investment and Related Activities
812	Personal and Laundry Services

Mid-RD: Average industry $250K < R&D < $1M	
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
323	Printing and Related Support Activities
326	Plastics and Rubber Products Manufacturing
327	Non-Metallic Mineral Product Manufacturing
335	Electrical Equipment, Appliance and Component Manufacturing
339	Miscellaneous Manufacturing

High-RD: Average industry R&D > $1M	
211	Oil and Gas Extraction
212	Mining (except Oil and Gas)
213	Support Activities for Mining and Oil and Gas Extraction
321	Wood Product Manufacturing
322	Paper Manufacturing
324	Petroleum and Coal Products Manufacturing
325	Chemical Manufacturing
331	Primary Metal Manufacturing
333	Machinery Manufacturing
334	Computer and Electronic Product Manufacturing
336	Transportation Equipment Manufacturing
511	Publishing Industries (except Internet)
541	Professional, Scientific and Technical Services
551	Management of Companies and Enterprises

Competition intensity index

The main market for an enterprise main product (highest selling product) is the geographical area from which the highest share of revenue associated with its main product is derived. The main market can be local, province, Canada, the United States, Europe, Asia or rest of the world. For example, if 50% of an enterprise's main product revenue come from Canada, 25% from the United States and 25% from the rest of the world, the main market for this enterprise is Canada.

The competition index is constructed using four questions from the SIBS relating to an enterprise main product or main market: A) the number of products competing against its main product in its main market; B) the number of competitors in its main market; C) the presence of multinational enterprises in its main market; and D) entry of new competitors in its main market. The following table shows how the four components are computed. Each component is normalized (between 0 and 1), which means that they are given the same weight in the global index.

Question	Score
Number of product (#N) competing against the enterprise main product in its main market.	$A = \frac{\#N - \min \#N}{\max \#N - \min \#N}$
Number of competitor (#C) in the main market for the enterprise main product.	$B = \begin{cases} 0 \text{ if } \#C = 1 \\ 1/6 \text{ if } \#C = 2 \\ 2/6 \text{ if } \#C = 3 \\ 3/6 \text{ if } \#C \in [4-5] \\ 4/6 \text{ if } \#C \in [6-10] \\ 5/6 \text{ if } \#C \in [11-20] \\ 1 \text{ if } \#C > 20 \end{cases}$
A multinational enterprise (MNE) is present in the main market for the enterprise main product.	$C = \begin{cases} 1 \text{ if MNE is present} \\ 0 \text{ otherwise} \end{cases}$
New competitors enters the main market for the enterprise main product.	$D = \begin{cases} 1 \text{ if new competitors entered} \\ 0 \text{ otherwise} \end{cases}$

For B, the implicit assumption is that more competitors results in more competition.This can be challenged on the basis that passed a certain number, adding another competitor does not affect the competition intensity in the market (see for example Bresnahan and Reiss, 1991). However, because the respondents considered these enterprises as competitors in their main market for their main product, it is reasonable to assume that the addition of these competitors has some impact.

The global index for an enterprise is $\text{C\_}INDEX = 1/4\ (A + B + C + D)$.

Appendix B – Descriptive Statistics

Table 8: Descriptive Statistics
– Unweighted –

	Variable	N	Mean	S.d.
Dependent variables				
INT^{PRCS} [6]		748	0.9545	2.8547
INT^{PRDT} [6]		670	1.3896	4.0163
INT^{MRKT} [6]		503	0.4084	2.0288
INT^{ORGZ}		1370	27.3869	36.2974
ln *RD* [6]		827	5.7311	1.5325
Inputs				
ADV TEDH		1293	3.7718	1.5459
TRAINING		1293	0.2792	5.5505
PATENTS		1293	0.7022	0.4574
Control variables				
CAP		1289	0.0567	0.3959
AGE		1370	17.4416	7.2638
XPWO [6]		824	15.6755	75.9952
XPUS [6]		1074	40.1552	207.091
C_INDEX		1370	0.533	0.2203
GVC		1370	0.592	0.4916
Country (2007)		1370	0.7956	0.4034
Multiest (2007)		1370	0.3474	0.4763
Size	Medium (2007)	1370	0.2693	0.4438
	Large (2007)	1370	0.1518	0.359
	X-large (2007)	1370	0.1445	0.3518
Prov.	ON (2007)	1370	0.4314	0.4955
	QC (2007)	1370	0.2562	0.4367
	AB (2007)	1370	0.0876	0.2828
	BC (2007)	1370	0.0934	0.2911
Ind.	High_rd (2007)	1370	0.5073	0.5001
	Mid_rd (2007)	1370	0.319	0.4663

[6] Mean for positive values.

Sources: SIBS 2009, SAT 2007, RDCI 2004–2007, BR 2007–2009, LEAP 2007–2008, Export Register 2007–2008 and CIPO 2000–2006.

Table 9: Correlations between innovation inputs (2005–2007)
– Unweighted (N = 1370) –

Past innovation				
	J^{PRCS}	J^{ORGZ}	J^{PRDT}	J^{MRKT}
J^{PRCS}	1.00			
J^{ORGZ}	0.36	1.00		
J^{PRDT}	0.32	0.30	1.00	
J^{MRKT}	0.25	0.38	0.26	1.00
Other inputs				
	ln *RD*	ADVTECH	TRAINING	PATENTS
ln *RD*	1.00			
ADVTECH	0.32	1.00		
TRAINING	0.18	0.45	1.00	
PATENTS	0.07	0.03	0.02	1.00

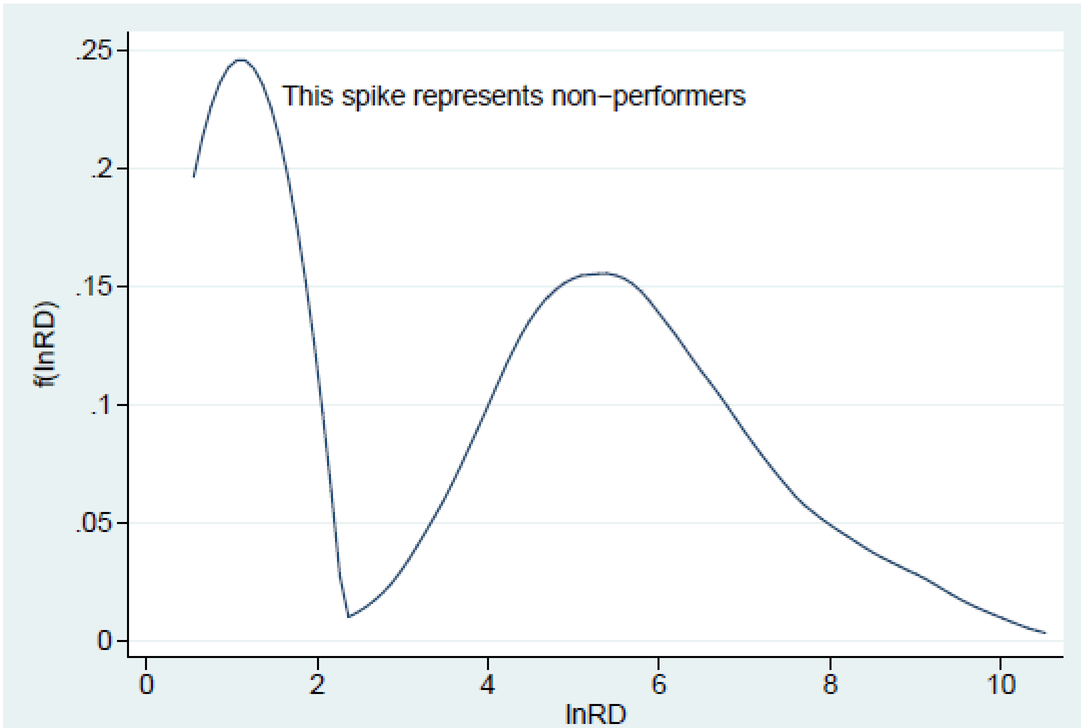
Sources: SAT 2007, RDCI 2005–2007 and CIPO 2000–2006.

Table 10: Correlations between innovation types (2007–2009)
– Unweighted (N = 1370) –

A – Innovation incidence				
	J^{PRCS}	J^{ORGZ}	J^{PRDT}	J^{MRKT}
J^{PRCS}	1.00			
J^{ORGZ}	0.37	1.00		
J^{PRDT}	0.26	0.29	1.00	
J^{MRKT}	0.21	0.31	0.32	1.00
B – Level of innovation				
	INT^{PRCS}	INT^{ORGZ}	INT^{PRDT}	INT^{MRKT}
INT^{PRCS}	1.00			
INT^{ORGZ}	0.08	1.00		
INT^{PRDT}	0.27	0.12	1.00	
INT^{MRKT}	0.03	0.05	0.19	1.00

Source: SIBS 2009.

Figure 2: Non-parametric density of R&D expenditures (lnRD)
- Unweighted (N = 827) –



Source: RDCI 2005−07

Appendix C – Results

Table 11: R&D equation results for Model 2 (Specification IV)
– Dep. var.: log(RD) in 2005–2007 –

Variable		Parameter	T-stat
RD^{2004}		0.0004	8.42
ADVTECH		0.4404	6.35
Size	Medium	0.7625	3.16
	Large	1.1771	3.72
	X-large	2.5329	6.81

N = 1293. Highlighted parameters are statistically significant at 0.10 level or less.

Table 12: Model 1 – Incidence of innovation: Estimated parameters

– Dep. var.: Binary indicators of innovation (2007–2009) –

		Specification I				Specification II			
Variable		PRCS	ORGZ	PRDT	MRKT	PRCS	ORGZ	PRDT	MRKT
J^{PRCS}		**0.4907** **(6.46)**	**0.2648** **(3.56)**	0.0757 (0.92)	0.0450 (0.61)	**0.4114** **(5.02)**	**0.1793** **(2.11)**	0.0654 (0.75)	0.0112 (0.14)
J^{ORGZ}		**0.1561** **(1.88)**	**0.2860** **(3.6)**	**0.1691** **(2.09)**	0.0696 (0.87)	0.0840 (0.97)	**0.2433** **(2.75)**	**0.1699** **(1.89)**	0.0237 (0.25)
J^{PRDT}		**0.1523** **(1.95)**	**0.1375** **(1.74)**	**0.5122** **(6.51)**	**0.2460** **(3.29)**	0.0822 (0.89)	0.1049 (1.16)	**0.5364** **(6.35)**	**0.2199** **(2.54)**
J^{MRKT}		0.0959 (1.09)	0.1089 (1.24)	**0.3092** **(3.63)**	**0.3988** **(4.44)**	0.1023 (1.12)	0.0836 (0.91)	**0.3011** **(3.22)**	**0.3857** **(4.51)**
$\ln \widehat{RD}$		—	—	—	—	0.0129 (0.26)	0.0896 (1.53)	0.0165 (0.31)	0.0176 (0.4)
ADVTECH		—	—	—	—	**0.1113** **(2.98)**	0.0462 (1.29)	0.0070 (0.21)	0.0174 (0.56)
TRAINING		—	—	—	—	-0.0186 (-0.21)	0.0156 (0.16)	-0.1121 (-1.34)	**0.1465** **(1.69)**
PATENTS		—	—	—	—	0.0132 (0.17)	0.0062 (0.11)	-0.0129 (-0.21)	0.0110 (0.19)
Size	Medium	0.1343 (1.47)	0.1051 (1.21)	0.0276 (0.3)	0.0675 (0.75)	0.0322 (0.33)	-0.0287 (-0.31)	-0.0023 (-0.02)	0.0032 (0.04)
	Large	**0.3336** **(2.6)**	0.0604 (0.49)	-0.0616 (-0.52)	0.1292 (1.2)	0.2092 (1.54)	-0.1023 (-0.76)	-0.0849 (-0.61)	0.0672 (0.5)
	X-large	**0.2584** **(2.05)**	0.1481 (1.1)	0.0345 (0.29)	0.0087 (0.06)	0.0391 (0.2)	-0.2037 (-0.99)	-0.0015 (-0.01)	-0.1150 (-0.62)
Corr.	$\rho 21$	**0.5122 (14.20)**				**0.4996 (12.42)**			
	$\rho 31$	**0.3533 (8.57)**				**0.3581 (8.08)**			
	$\rho 41$	**0.3090 (7.01)**				**0.3224 (7.16)**			
	$\rho 32$	**0.3818 (9.23)**				**0.3826 (9.45)**			
	$\rho 42$	**0.4783 (12.47)**				**0.4853 (13.16)**			
	$\rho 43$	**0.4586 (11.41)**				**0.4758 (12.44)**			

N = 1373 (Specification I) – N = 1296 (Specification II)

T-stat are in parenthesis. Highlighted parameters are statistically significant at 0.10 level or less.

Table 13: Model 2 – Level of innovation: Estimated parameters
– Dep. var.: Continuous indicators of innovation (2007–2009) –

		Specification III				Specification IV			
Variable		PRCS	ORGZ	PRDT	MRKT	PRCS	ORGZ	PRDT	MRKT
J^{PRCS}		**0.6550** **(3.57)**	**10.0571** **(1.98)**	0.3101 (1.08)	0.0660 (0.52)	**0.4239** **(2.25)**	4.9454 (0.98)	0.1968 (0.69)	0.0086 (0.06)
J^{ORGZ}		**0.5353** **(2.47)**	**14.8486** **(2.96)**	0.4730 (1.34)	0.1300 (1.09)	**0.3789** **(2.08)**	**11.4116** **(2.09)**	0.4452 (1.20)	0.0628 (0.47)
J^{PRDT}		0.0305 (0.15)	**12.6573** **(2.49)**	**1.4307** **(4.15)**	**0.4357** **(2.52)**	-0.1328 (-0.60)	**9.2308** **(1.71)**	**1.4135** **(3.91)**	**0.4169** **(2.38)**
J^{MRKT}		0.2606 (1.19)	8.1726 (1.56)	**0.7262** **(2.06)**	**0.7683** **(3.10)**	0.2765 (1.38)	7.4661 (1.44)	**0.7180** **(2.03)**	**0.7695** **(2.96)**
$\ln \widehat{RD}$		—	—	—	—	0.2600 (1.26)	1.8574 (0.95)	0.4013 (1.36)	-0.0043 (-0.05)
ADVTECH		—	—	—	—	**0.2611** **(2.48)**	2.2757 (1.13)	0.0594 (0.37)	0.0980 (1.53)
TRAINING		—	—	—	—	-0.1405 (-0.81)	7.9379 (1.34)	-0.3372 (-1.31)	0.0320 (0.23)
PATENTS		—	—	—	—	-0.1220 (-0.45)	-0.1095 (-0.03)	-0.0421 (-0.14)	0.0025 (0.02)
Size	Medium	**0.4827** **(2.80)**	2.2349 (0.40)	0.4961 (1.59)	0.1756 (1.33)	0.1022 (0.52)	-4.7076 (-0.80)	0.1864 (0.55)	0.1095 (0.74)
	Large	**1.3609** **(3.76)**	-3.8552 (-0.52)	**0.9750** **(2.23)**	0.1786 (0.96)	**0.8167** **(2.25)**	-11.1511 (-1.43)	0.4776 (0.88)	0.0997 (0.47)
	X-large	**2.2981** **(5.25)**	0.1675 (0.02)	**2.3445** **(3.72)**	**0.8300** **(2.29)**	**1.1898** **(1.94)**	-12.2387 (-1.25)	1.1298 (1.39)	0.6866 (1.59)
Corr. (σ)		**2.9312** **(6.60)**	**72.6835** **(26.89)**	**4.2221** **(6.93)**	**2.0937** **(4.30)**	**2.9293** **(6.80)**	**72.0862** **(26.81)**	**4.2544** **(7.00)**	**2.1259** **(4.46)**

N = 1370 (Specification III) – N = 1293 (Specification IV)
T-stat are in parenthesis. Highlighted parameters are statistically significant at 0.10 level or less.

Table 14: Productivity: Estimated Parameters
– Dep. var.: Labour productivity growth (2007–2008) –

		Specification III				Specification IV			
Variable		PRCS	ORGZ	PRDT	MRKT	PRCS	ORGZ	PRDT	MRKT
CAP		**0.0729**	**(2.93)**	**0.0713**	**(2.94)**	**0.0745**	**(3.18)**	**0.0725**	**(2.79)**
I (0000)		-1.2772	(-1.61)	-0.5485	(-0.89)	—	—	—	—
I (0001)		**10.5108**	**(1.76)**	1.8520	(0.43)	—	—	—	—
I (0010)		5.0159	(1.48)	1.3552	(0.54)	—	—	—	—
I (0011)		**-17.0447**	**(-2.66)**	-6.7410	(-1.39)	—	—	—	—
I (0100)		2.8024	(0.86)	-0.3334	(-0.17)	—	—	—	—
I (0101)		-6.6510	(-0.84)	2.8573	(0.62)	—	—	—	—
I (0110)		-8.0044	(-1.51)	-1.6830	(-0.49)	—	—	—	—
I (0111)		**8.7099**	**(2.18)**	2.6679	(0.96)	—	—	—	—
I (1000)		**5.5607**	**(2.30)**	2.7131	(1.61)	—	—	—	—
I (1001)		**-22.5794**	**(-2.14)**	-5.5246	(-0.95)	—	—	—	—
I (1010)		**-9.5251**	**(-2.37)**	-3.8990	(-1.39)	—	—	—	—
I (1011)		**16.5474**	**(2.97)**	**6.0653**	**(1.81)**	—	—	—	—
I (1100)		**-3.8658**	**(-1.67)**	-1.0919	(-0.86)	—	—	—	—
I (1101)		5.0303	(1.39)	0.0942	(0.06)	—	—	—	—
I (1110)		**3.7129**	**(2.16)**	1.3258	(1.21)	—	—	—	—
I (1111)		**-1.8949**	**(-2.57)**	-0.6057	(-1.40)	—	—	—	—
INT (0001)		—	—	—	—	-0.4965	(-0.61)	0.1628	-0.22
INT (0010)		—	—	—	—	**-0.3539**	**(-1.65)**	-0.2363	(-1.11)
INT (0011)		—	—	—	—	0.5819	(0.78)	-0.1318	(-0.20)
INT (0100)		—	—	—	—	0.0003	(0.03)	0.0035	(0.39)
INT (0101)		—	—	—	—	0.0333	(1.27)	0.0054	(0.24)
INT (0110)		—	—	—	—	**0.0127**	**(1.88)**	0.0100	(1.50)
INT (0111)		—	—	—	—	-0.0289	(-1.34)	-0.0047	(-0.26)
INT (1000)		—	—	—	—	**0.7857**	**(2.20)**	**0.7460**	**(2.30)**
INT (1001)		—	—	—	—	-0.6397	(-0.81)	-0.7712	(-1.24)
INT (1010)		—	—	—	—	-0.1685	(-0.74)	-0.0885	(-0.45)
INT (1011)		—	—	—	—	0.0724	(0.16)	0.2666	(0.81)
INT (1100)		—	—	—	—	**-0.0255**	**(-2.02)**	**-0.0218**	**(-2.10)**
INT (1101)		—	—	—	—	0.0122	(0.52)	0.0188	(1.03)
INT (1110)		—	—	—	—	0.0054	(0.80)	0.0017	(0.33)
INT (1111)		—	—	—	—	0.0018	(0.15)	-0.0046	(-0.54)
AGE		**-0.0018**	**(-1.95)**	**-0.0016**	**(-1.91)**	**-0.0017**	**(-1.82)**	-0.0015	(-1.56)
C_INDEX		-0.0148	(-0.51)	-0.0231	(-0.81)	-0.0119	(-0.42)	-0.0241	(-0.84)
XPWO		3.56E-07	(0.00)	3.41E-07	(0.00)	**0.0004**	**(2.51)**	**0.0004**	**(2.39)**
XPUS		-2.77E-08	(0.00)	-2.80E-08	(0.00)	-0.0001	(-0.92)	-0.0001	(-0.70)
GVC		-0.0063	(-0.53)	-0.0059	(-0.50)	-0.0113	(-0.96)	-0.0112	(-0.95)
Size	Medium	0.0230	(1.36)	**0.0265**	**(1.76)**	**0.0297**	**(1.77)**	**0.0316**	**(2.07)**
	Large	0.0141	(0.57)	0.0115	(0.51)	0.0426	(1.22)	0.0247	(0.93)
	X-large	0.0173	(0.69)	0.0115	(0.45)	0.0772	(1.47)	0.0416	(1.04)

N = 1285 (Specification I) – N = 1209 (Specification II)
N = 1282 (Specification III) – N = 1206 (Specification IV)
T-stat are in parenthesis. Highlighted parameters are statistically significant at 0.10 level or less.

Appendix D – Details of the Carree et al. (2010) test

Testing for complementarity can be performed in a pair-wise fashion. Let's rewrite Equation (4) as follows (Equation (5) can be modified in the same way):

$$\Delta \mathrm{LP} = \begin{array}{c} \eta_1^{0001}\,\mathrm{I}\,(0001) + n_1^{0010}\,\mathrm{I}\,(0010) + \eta_1^{0011}\,\mathrm{I}\,(0011)\,\eta_1^{0100}\,\mathrm{I}(0100) + \\ \eta_1^{0101}\,\mathrm{I}\,(0101) + \eta_1^{0110}\,\mathrm{I}\,(0110) + \eta_1^{0111}\,(0111) + \eta_1^{1000}\,(1000) + \\ \eta_1^{1001}\,\mathrm{I}\,(1001) + \eta_1^{1010}\,\mathrm{I}\,(1010) + \eta_1^{1011}\,(1011) + \eta_1^{1100}\,\mathrm{I}\,(1100) + \\ \eta_1^{1101}\,\mathrm{I}\,(1101) + \eta_1^{1110} + \eta_1^{1111}\,\mathrm{I}\,(1111) + \eta_2 W + \mu \end{array} \qquad (6)$$

where W represents all the non-innovation variables. Complementarity between PRCS and ORGZ—factors in positions 1 and 2 respectively in I—requires

$$\begin{aligned} \eta_1^{1100} &> \text{0 and} \\ \eta_1^{1100} + \eta_1^{1110} &> \text{0 and} \\ \eta_1^{1100} + \eta_1^{1101} &> \text{0 and} \\ \eta_1^{1100} + \eta_1^{1110} + \eta_1^{1101} + \eta_1^{1111} &> 0 \end{aligned} \qquad (6.1)$$

Let's transform Equation (6) into:

$$\Delta \mathrm{LP} = \begin{array}{c} \eta_1^{0001}\,\mathrm{I}\,(0001) + \eta_1^{0010}\,\mathrm{I}\,(0010) + \eta_1^{0011}\,\mathrm{I}\,(0011) + \eta_1^{0100}\,\mathrm{I}\,(0100) + \\ \eta_1^{0100}\,\mathrm{I}\,(0100) + \eta_1^{0110}\,\mathrm{I}\,(0110) + \eta_1^{0111}\,\mathrm{I}\,(0111) + \eta_1^{1000}\,\mathrm{I}\,(1000) + \\ \eta_1^{1001}\,\mathrm{I}\,(1001) + \eta_1^{1010}\,\mathrm{I}\,(1001) + \eta_1^{1011}\,\mathrm{I}\,(1011) + \\ \eta_1^{1100}\,(\mathrm{I}\,(1100) + \mathrm{I}\,(1111) - \mathrm{I}\,(1110) - \mathrm{I}\,(1101)) + \\ \left(\eta_1^{1100} + \eta_1^{1101}\right)\,(\mathrm{I}\,(1101) - \mathrm{I}\,(1111)) + \\ \left(\eta_1^{1100} + \eta_1^{1110}\right)\,(\mathrm{I}\,(1110) - \mathrm{I}\,(1111)) + \\ \left(\eta_1^{1100} + \eta_1^{1110} + \eta_1^{1101} + \eta_1^{1111}\right)\mathrm{I}\,(1111) + \eta_2 W + \mu \end{array} \qquad (7)$$

The parameters highlighted in red in the transformed model correspond to the restrictions of the test. Let's define the t-statistics associated with these estimated coefficients as t_1, t_2, t_3 and t_4. Complementarity implies that

$$\begin{array}{c} t_1 > t_c \text{ and } t_2 > -t_d \text{ and } t_3 > -t_d \text{ and } t_4 > -t_d \\ \text{OR} \\ t_1 > t_d \text{ and } t_2 > -t_c \text{ and } t_3 > -t_d \text{ and } t_4 > -t_d \\ \text{OR} \\ t_1 > t_d \text{ and } t_2 > -t_d \text{ and } t_3 > -t_c \text{ and } t_4 > -t_d \\ \text{OR} \\ t_1 > t_d \text{ and } t_2 > -t_d \text{ and } t_3 > -t_d \text{ and } t_4 > -t_c \end{array}$$

where t_c and t_d are the critical values. As in the Carree et al. paper, for a two-sided 0.10 significance level, t_c = 2.24 and t_d = 1.65.

Rejecting complementarity does not mean there is a substitution relationship, so the latter is tested using the same transformation and the following conditions

$$
\begin{gathered}
t_1 < -t_c \text{ and } t_2 < t_d \text{ and } t_3 < t_d \text{ and } t_4 < t_d \\
\text{OR} \\
t_1 < t_d \text{ and } t_2 < -t_c \text{ and } t_3 < t_d \text{ and } t_4 < t_d \\
\text{OR} \\
t_1 < t_d \text{ and } t_2 < t_d \text{ and } t_3 < -t_c \text{ and } t_4 < t_d \\
\text{OR} \\
t_1 < t_d \text{ and } t_2 < t_d \text{ and } t_3 > t_d \text{ and } t_4 < -t_c
\end{gathered}
$$

The equivalence of this test to the Mohnen and Röller (2005) test can be seen by relating the hypotheses tested by the two techniques. As shown in the following tables for factors 1 and 2, the main idea of both techniques is to test for the relevant pair, holding the other factors constant. Conditions for other pairs and for substitution tests are derived in a similar fashion.

Assumptions for complementarity between factors 1 and 2 in	
Carree et al.	Mohnen and Röller
$\eta_1^{1100} > 0$	$\mathrm{I}(1100) - \mathrm{I}(0100) > \mathrm{I}(1000) - \mathrm{I}(0000)$
$\eta_1^{1100} + \eta_1^{1110} > 0$	$\mathrm{I}(1110) - \mathrm{I}(0110) > \mathrm{I}(1010) - \mathrm{I}(0010)$
$\eta_1^{1100} + \eta_1^{1101} > 0$	$\mathrm{I}(1101) - \mathrm{I}(0101) > \mathrm{I}(1001) - \mathrm{I}(0001)$
$\eta_1^{1100} + \eta_1^{1110} + \eta_1^{1101} + \eta_1^{1111} > 0$	$\mathrm{I}(1111) - \mathrm{I}(0111) > \mathrm{I}(1011) - \mathrm{I}(0011)$