Differential effects of training on innovation

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Evidence shows that training can increase product innovation. Yet few studies can differentiate between "new" and "improved" technical innovation due to an omission in survey design. Our objective is to determine whether training impacts product and process innovation differently, especially in terms of new versus improved innovations. We use a national, establishment level, mandatory survey, designed specifically as longitudinal to investigate the impact of training on new versus improved product and process innovations. We use a 2SLS approach to correct for endogeneity of training in the innovation production function. We find that training has no effect on new products, while it augments improved products. Training has a positive and significant effect on new and improved process innovations. A question that comes to mind is: "Can we specifically train for new product innovation?" While there are highly cited papers in strategic management, we conclude after scanning the economics literature that a widely accepted theory of new product innovation does not exist. Perhaps, it is possible to train for new product innovation, while remaining cognizant of our inability to predict the recombinant knowledge required for newness. As Polanyi (1958) surmised: "…invention must be acknowledged to be unpredictable, a quality which is assessed by the intensity of the surprise it might reasonably have aroused".

Keywords: employee training; training for innovation; new and improved process; new and improved product; human resource management; incentive schemes

Subject classification codes: O31, M52, M53

Introduction

The Conference Board of Canada ("Conference Board of Canada: Innovation Report" 2018) recently lamented that Canada gets a "C" on innovation. The report laments that government should invest in *skills training for innovation*. The Canadian government has the laudable goal of creating an innovation economy, which means new products and new processes need to be invented. It is unknown what proportion of current on-the-job training and corporate training is directed to enhancing innovation.

Training transmits codified knowledge and tacit knowledge (Polanyi 1958; Dewey 2011; Nonaka and Takeuchi 1995). In fact, Polanyi stated that all knowledge has a tacit component. Tacit knowledge can be transmitted through words, but sometimes tacitness becomes a major component of the knowledge and it can only be partially transmitted through words (Polanyi 1958). If we conceive of software training for instance, trainees can be exposed to the theory behind the software's command structure, but to truly learn how to use software, trainees must actually be shown it, and then use it in the classroom (mimicry). However, the typical transmission of knowledge in innovation literature has been external sources and R&D (Freeman 1994; Marsili and Salter 2005). While some evidence shows that training can increase product innovation (Caloghirou et al. 2018), there are few studies that differentiate between "new" and "improved" technical innovations. Thus, our objective is to determine whether training impacts product and process innovation differently, especially in terms of new versus improved innovations. We use a national, establishment level, mandatory survey, designed specifically as longitudinal to investigate the impact of training on new versus improved product and process innovations.

Conceptual background and related literature

New human capital theory (late 1990s and early 2000s) pioneered by (Acemoglu 1997) postulates that training and innovation are complements (here "innovation" means process innovation, in the form of a new machine with capital embodied technological change). If more firms were engaged in process innovation, workers would expect higher future wages, and would thus be willing to invest more in their present self-paid training. We are unable to find theoretical literature specifically discussing new product innovations and training. Some strategy research views product innovation as a direct outcome of knowledge mobilization in the firm (Eisenhardt and Martin 2000; Helfat and Raubitschek 2000). There is a perception that increases in human capital will result in a greater innovation capacity and therefore a greater number of innovations (Subramaniam and Youndt 2005). This is particularly important as knowledge accumulation has been determined to be a leading characteristic for innovative activity (Nelson and Winter 1982). Beyond Nelson & Winter (1982) evolutionary economists have modeled training and innovation. For brevity we omit the research here, however, we mention Ballot & Taymaz (1997) and Borrás & Edquist (2015) as two good examples.

Laplagne & Bensted (1999) conducted one of the earlier studies on training and innovation. They used the Australian Workplace Industrial Relations Surveys, which are similar to the data we use in this study. The survey contained questions pertaining to four process innovations (introduction of major new office technology; major new plant, machinery or equipment; major reorganization of workplace structure; major change in how workers do their work). Unfortunately, product innovation was omitted. They found that the timing effects of training on innovation depended on the type of innovation. They also found that both innovation and training were more prevalent in firms experiencing a high level of labor productivity growth. Freel (2005) had data from a 2001 survey called the Survey of Enterprise in Northern Britain. The author's dependent variables were coded as differences between innovation categories (none, incremental, new) and the signs were reversed for estimation. Rather than detail the results as positive or negative, we simply state if the result was significant. "Significance" implies that the hypothesized direction is correct, for example, when we say "training was significant for no product versus new" indicates that new product innovating firms had greater training than no product innovation firms. The data contained two measures for training: a binary variable equal to one if training expenditure exceeds one percent of sales turnover; a proportion variable for staff who received training. The binary training variable did not perform well in the logit regressions and we omit them here. We will simply refer to the proportion training variable as "training" in what follows. For manufacturing (sample size=378) training was significant and for no product innovation versus new product innovation, and incremental product versus new product. For processes, training was significant for no process innovation versus new, and incremental process innovation versus new. For the service sector (sample size=348) training was significant for no product innovation versus new; and incremental process innovation versus none. Reichstein & Salter (2006) used a sample of 2,885 firms from the 2001 UK Community Innovation Survey. All firms in the study were from the manufacturing sector and the survey itself was voluntary with a 42% response rate. The dependent variables were radical and incremental process innovation. Training was insignificant across the four regressions they performed. Thornhill (2006) conducted a study using Canada's Workplace and Employee Survey to investigate the effect of training on innovation. However, only product innovation was investigated. Two waves (1999 and 2000) of WES were used with a restricted sample of 845 firms. In a single equation framework, training was correlated with innovation at a 10% level of significance.

Arvanitis et al. (2016) use pooled data from ETH Zurich spanning 2005 (38.7%), 2008 (33.8%), 2011 (35.9%) for N=4,451. They attempted to create a panel from the data, however, less than 50% of firms were matched between two years. The data are therefore highly unbalanced and consequently fixed effects estimators were ruled out. The training variable is defined as the proportion of employees involved with continuous training. They admit that due to the nature of their data they cannot control for individual effects and thus their estimates may suffer from endogeneity. Like this paper, they include human resource management practices and incentive pay as independent variables. Yet, they cannot infer causality since they do not instrument for training, human resource practices or incentive pay. Their dependent variables are innovation (either a product and/or process) and percent of sales composed of new or improved products. In the case of innovation, the training variable was insignificant, while for percent of sales derived from innovative products was significant. A recent paper in this journal by Caloghirou et al. (2018) states that training increases absorptive capacity and consequently it is necessary for successful product and process innovation. The authors use a two-period survey of 524 Greek manufacturing firms. They use single equation probit models to investigate whether a binary variable for training is correlated with product innovation. Using various interaction terms they find that training has a positive and significant effect on product innovation. Regrettably, their data do not disaggregate product innovation into improved versus new.

Here we discuss innovation and the effects of human resources practices and incentive schemes. In particular, their impact should effect the types of technical innovations that the firm is able to produce (Gupta and Singhal 1993; Beugelsdijk 2008; Shipton et al. 2006; Lau and Ngo 2004). The underlying concepts are that the firm's human resource and incentive systems encourage innovation by reducing employee turnover, enhancing product quality, increasing profitability and sales growth (Rauch and Hatak 2016; Arvanitis, Seliger, and Stucki 2016). The HR and organizational practices used by (Arvanitis, Seliger, and Stucki 2016) closely resemble ours. Namely their HR variables include functional flexibility, team work, job rotation, while their incentive variables include individual performance pay, group performance pay and firm performance pay. Furthermore, Laursen & Foss (2003) found that human resource practices were an indicator of innovation. Therrien & Léonard (2003) found evidence for complementarities between various human resource practices to support first-to-market innovations as those workplaces with coherent human resource systems had significantly more innovations than those with few or no high powered human resource practices. The only inference we can make from this work is that workplace HR practices should be endogenous in the firm in concert with training. Without accounting for endogeneity, simultaneous causality bias is likely problematic.

According to (Brettel et al. 2011; Tidd and Bessant 2018) new product development requires integration between R&D, marketing and production. The implication is that new product innovation requires the ability to generate *new* knowledge by recombining and reorganizing existing knowledge (Koestler 2014). One could reasonably infer that generating new knowledge is hard. If that is the case, which is harder to create—a new process innovation or a new product innovation? Clearly, the answer is "It depends…" Other than that, we suppose that this is an empirical matter.

Data

Before discussing the data in detail we should discuss innovation nomenclature. Freeman's (1994) terminology for new innovation is 'radical' or 'major', and improved is 'incremental' or 'minor'. A foremost contribution of the analysis here hinges on the disaggregation of 'innovation' into two constituent parts. As Freeman (1994) says:

> The difficulties of definition are considerable even for this simple dichotomy, but nevertheless it is an important one because the two types of innovation embody a very different mix of knowledge inputs and have different consequences for the economy and the firms which make them.

Freeman also elaborates that new innovations get the preponderance of attention in the media, journals, manuals and textbooks. Thus, before innovation surveys became the norm, innovation data was biased towards new products and new processes. Since the advent of innovation surveys, incremental innovations have been explicitly accounted for.

We use the Workplace and Employee Survey (WES) conducted by Canada's national statistical agency. We use the terms "firm" and "workplace" loosely to indicate an "establishment". As defined by Statistics Canada, an establishment represents the lowest statistical unit of observation with its own records for output, employment and financial statements. Randomized stratified sampling from the Business Register (a continuously updated registry of *every* company in Canada) was used with the specific purpose to track the same firms over many years (Krebs et al. 1999). We have a balanced panel of 3,977 firms from 1999-2006 yielding a sample size of 31,820 observations. We also have an unbalanced panel with a sample size of 49,590. The survey asks questions related to employment, separations, unionization, human resource management practices, implementation of new equipment and innovation (Statistics Canada 2012). The respondent is either the manager or CEO of the workplace. Over 6,000 were surveyed every year, while random sampling was stratified by industry, region and size. Because the survey was *mandatory*, response rates were consistently above 80%. Data on missing firms was not for systematic reasons, but because firms went bankrupt or were acquired; meaning the missing firms were missing at random. If on the other hand, the survey design deliberately dropped firms over time, that would introduce bias (Woolridge 2010). For sample statistics, variable construction and industry coverage please see the Appendix.

The key variable for this analysis is the workplace's expenditure on training. The survey asks whether classroom job-related training took place within the past year and then gives the respondent a list of 13 possible items to check.[1] Later in the survey the respondent is asked whether the firm implemented a major new software application and/or hardware installation within the past year, and/or if the firm implemented computer-controlled or computer-assisted technology within the past year and/or if the firm had any major implementations of other technologies or machinery within the past year. The three questions qualify as new process innovations. Respondents are also asked to quantify the number of days and/or hours in which classroom

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[1]The respondent can check multiple items: orientation for new employees, managerial-supervisory training, professional training, apprenticeship training, sales and marketing training, computer hardware, computer software, other office and non-office equipment, group decision-making or problem-solving, team-building-leadership-communication, occupational health and safety-environmental protection, literacy or numeracy, other training-specify".

training took place. The respondent is then asked to estimate the workplace's total training expenditure over the past year. Table 1 shows the average variable cost of training from 1999-2006. Table 1 also shows the 50th, 75th, 90th and 99th percentile of the average variable cost. The mean expenditure for the balanced and unbalanced panel is $353/employee and $334/employee respectively. If non-training workplaces are omitted the mean increases to $569/employee for the balanced panel and $585/employee in the unbalanced panel. Workplaces in the 99th percentile have training expenditures in excess of $3,000/employee.

Table 1. Average training expenditure, AVC = $/employee (1999-2006)*

	Balanced Panel			Unbalanced Panel	
	All firms	Only firms that train		All firms	Only firms that train
	(N=31,820)	(N=19,720)		(N=49,590)	(N=28,320)
Mean	353	569		334	585
50th percentile	91	299		60	305
75th percentile	400	665		371	675
90th percentile	963	1,339		914	1,367
99th percentile	3,253	3,986		3,333	4,167

*Population weighted.

Innovation: Oslo Manual and WES definitions

The WES was first conducted in 1999 and at that time the Oslo Manual was in its second edition (OECD/Eurostat 1997). The contribution of this paper hinges on the manual's definitions and how these were implemented in WES. The manual defines new products as: "A technologically new product is a product whose technological characteristics or intended uses differ significantly from those of previously produced products" (paragraph 136) and improved products as: "A technologically improved product is an existing product whose performance has been significantly enhanced or upgraded" (paragraph 138). The manual's declarative sentence for process innovation is: "Technological process innovation is the adoption of technologically new or significantly improved production methods, including methods of product delivery" (paragraph 141). This definition encompasses both new process and improved product innovation as is further demonstrated in Figure 3 (p.36) of the manual. The designers of WES chose to ask whether the firm introduced "new products or services" (new products or services differ significantly in character or intended use from previously produced goods or services), "improved products or services" (improved products or services are those whose performance has been significantly enhanced or upgraded), "new processes" (new processes include the adoption of new methods of good production or service delivery), and "improved processes" (improved processes are those whose performance has been significantly enhance or upgraded). To further clarify the nature of the innovation respondents were then asked to name the "most important innovation" in terms of its implementation cost. While 38.5% of firms reported a product innovation, 27.7% reported a new product and 32.9% reported an improved product. Process innovation occurred 27.1% of the time, while new process innovation was reported to be 19.4% and improved process innovation was reported as 24.8%. These figures are for the balanced panel; for a comparison to the unbalanced panel please see Table A1.

Method and model

The premise of our paper is that training has a direct (enhancing the thought process of employees, who apply knowledge and create new ideas) and indirect effect (by creating a learning organization) on innovation. The direct effect augments labor by increasing the marginal product of innovation in the same way that Harrod-neutral technological change increases the marginal product of labor.

Although firms train and attempt to innovate for a variety of reasons, one would expect that they are endogenous. Let us assume that: $y = X\beta + \epsilon$, and the estimate of the vector of coefficients is found via OLS: $\beta = \frac{\sigma_{XY}}{\sigma_X^2}$. There is evidence of endogeneity when the covariance between *X* and the error term does not equal zero ($\sigma_{X\epsilon} \neq 0$). In our case *y* is innovation, while *X* is the average variable cost in dollars per employee of training. Endogeneity is indeed borne out by the data in via the Durbin-Wu-Hausman test (Nakamura and Nakamura 1985). Two solutions present themselves: one can implement an instrumental variable (IV) estimator or one can implement a two-stage lease squares approach (2SLS). With IV we have: $\beta_{IV} = \frac{\sigma_{ZY}}{\sigma_{ZX}}$ where *Z* is the instrument, while with 2SLS we have: $\beta_{2SLS} = \frac{\sigma_{X^*Y}}{\sigma_{X^*X}}$ where X^* represents the predicted values from the first stage. The designers of national surveys rarely foresee the need to include possible policy instruments in their sample frame. Thus it is very difficult to find suitable instruments for the data we use in this study. Our only recourse is to implement a 2SLS estimation approach.

Below the structure of the econometric model is shown. Let *T* represent the intensity of current training activity ($/employee), *H* is the sum of six human resource practices (employee suggestion program, flexible job design, information sharing, problem-solving teams, joint labor management committees, self-directed work groups), *N* is the sum of incentive programs (individual incentive systems, group incentive systems, profit-sharing, merit pay/skill-based pay, employee stock plan), *I* is dichotomous for these forms of innovation: any product, any process, new product, improved product, new process, improved process. The *Z*, *W* and *X* matrices contain firm-level variables.

The control variables are somewhat standard fair within innovation literature (Cohen 2010). They include: threat of competitors, proportion of computer users, proportion of non-permanent/part-time workers, total separations, proportion of professional-technical workers, adoption of new technology, union membership, an organizational change index[2] and wages (see Table A2 for definitions).

Equation (1) is estimated with a random effects Tobit Type I estimator instead of Tobit Type III (Heckman) since all firms in the sample are queried as to whether they offer training programs. Furthermore, if firms train, Statistics Canada requires the firm to report its total expenditure on training. Equations (2) and (3) are estimated with a panel Poisson estimator. Equation (4) is estimated with a fixed effect logit estimator that accounts for unobserved heterogeneity. Error terms are corrected for heteroskedasticity and are bootstrapped. The terms $T*$, $H*$ and $N*$ are the predicted values from (1), (2) and (3). The predicted values serve as instruments in the innovation equation (4), where the fixed effect μ represents unobservable heterogeneity.

$$T(Z) \qquad \rightarrow T^{*}(Z) + \epsilon_T \tag{1}$$

$$H(W) \qquad \rightarrow H^{*}(W) + \epsilon_H \tag{2}$$

$$N(W) \qquad \rightarrow N^{*}(W) + \epsilon_N \tag{3}$$

[2]Organizational innovation has a strong linkage to technical innovation (Freeman 1994).

$$I(T^{*}, H^{*}, N^{*} \mid X) + \mu + \epsilon_{I} \tag{4}$$

The hypotheses from the model are that training, human resource practices and incentives should increase process and product innovation. The model cannot accommodate hypotheses pertaining to the expected effect of training on “new” versus “improved” innovations. Other than we expect that a new innovation is harder to achieve, the relevance of training to “new” versus “improved” is dependent on the proximity of the training to the required antecedent knowledge and the ensuing discovery. We cannot predict this in advance due to the stochastic nature of new inventions in terms of their recombination of knowledge.

Econometric results

Table 2 contains the variable cost training equation. All estimated coefficients are significant and of the expected sign. Table 3 contains the human resource management and incentive equations. Wage is negative in HRM and insignificant in incentives. Organizational change has a positive correlation with HRM and incentives. The proportion of professional and technical workers has no effect. Tables 4 to 6 are the main tables of interest that detail the effects of training on product and process innovation, and on new versus improved products and processes. Incentives has a positive impact on innovation in all cases, HRM practices have a varied impact. In Table 4 training has a positive impact on aggregate product and process innovation. Table 5 shows disaggregated innovation results (new vs improved). Training has a positive impact on improved products but is insignificant for new products. In contrast, HRM practices and incentives are positive and significant for new products. Table 6 shows the impact of training on new processes and improved processes is positive and significant.

Tables 7 and 8 show the marginal effects at representative values. Note that in some instances confidence intervals intersect; such cases are identified by a dark border. In Table 7 probabilities of product innovation increase based on expenditure per employee. From $2000-$3000 per employee the probability of product innovation is within a 95% confidence interval of 0.78 to 1.00 (based on balanced and unbalanced panels). From $2000 to $3000 per employee we see that the probability of process innovation is between 0.88 and 1.00. Table 8 tells a slightly different story because training has no effect on new product innovation. Training affects the probability of an improved product with a 95% confidence interval of 0.81 and 1.00 when expenditure ranges from $2000-$3000 per employee. New and improved processes are impacted by training as well, however, the confidence interval is much larger for new processes (0.59-1.00 for balanced, and 0.83-1.00 for unbalanced) than for improved processes (0.91-1.00 for balanced, and 0.93-1.00 for unbalanced). The disparity between the confidence intervals indicates that "new" process is appreciably more difficult than "improved" process. Furthermore, if we compare improved products (CI is 0.81-1.00) to improved processes (CI is 0.91-1.00) we see that process innovation has a lower range of probabilities. This indicates that improved process innovation is "easier" than improved product innovation.

To put these results into perspective we compare our results to recent findings. Caloghirou et al., (2018) do not provide marginal effects for their probit regressions. We tried to calculate a marginal effect for training on product innovation where $\Pr(Y_i = 1|\, train = 1) - \Pr(Y_i = 1|train = 0)$. Using their regression results $\Phi(\beta_1 x_1 + \cdots \beta_n x_n + \beta_T * 1) - \Phi(\beta_1 x_1 + \cdots \beta_n x_n + \beta_T * 0) =$

0.021.[3] Gonzalez (2016) estimate similar probit regressions, but for product and process innovation. Training without an interaction variable has no effect on process innovation, and a positive and significant effect on product innovation (AME=0.027). When training and R&D are interacted there is a significant effect on both product (AME=0.139) and process (not stated) innovation.

[3] To obtain this result we used the mean value of all independent variables, except we used the median values for firm size. It seems as though the coefficients on size in Table 5 were miscoded as the z-values from $AME = \Phi(\beta_1 x_1 + \cdots \beta_n x_n + \beta_T * 1) - \Phi(\beta_1 x_1 + \cdots \beta_n x_n + \beta_T * 0)$ only make sense when the coefficient is divided by 100.

Table 2. Stage 1, training expenditure (T/L), random effects Tobit estimation (1999-2006)		
	Balanced	Unalanced
	trn_exp	trn_exp
union	279.6***	404.2***
	(23.94)	(19.18)
ttl_sep	0.448***	0.212***
	(0.10)	(0.05)
cpu	329.2***	365.3***
	(22.28)	(17.21)
prof_tech	105.1***	170.9***
	(24.67)	(19.34)
tech	115.5***	160.4***
	(11.34)	(9.66)
wage	0.00379***	0.00324***
	-0.000193	-0.000135
_cons	-479.8***	-671.3***
	(21.82)	(15.74)
sigma_u		
_cons	762.4***	698.2***
	(11.16)	(6.99)
sigma_e		
_cons	740.2***	756.7***
	(4.02)	(3.45)
N	31820 (Rounded to base 10)	49590 (Rounded to base 10)
Loglikelihood	-167392.9	-244045.8
rho	0.515	0.46
Standard errors in parentheses		
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

Table 3. Stage 1, human resource management practices and incentive programs, conditional fixed effects Poisson regression (1999-2006)

	Balanced	Unbalanced		Balanced	Unbalanced
	HRM	HRM		Incentives	Incentives
non_perm	-0.0000516	-0.0000198		0.000521**	0.000442
	(0.0001)	(0.0000)		(0.0003)	(0.0003)
now_part	-0.000243***	-0.000173***		0.00406***	0.00367***
	(0.0001)	(0.0001)		(0.0007)	(0.0007)
cpu	0.0574	0.0346		0.275***	0.271***
	(0.0384)	(0.0288)		(0.0520)	(0.0610)
prof_tech	0.0469	0.0568*		-0.0116	-0.00173
	(0.0341)	(0.0319)		(0.0787)	(0.0530)
tech	0.0851***	0.0823***		-0.0589**	-0.0176
	(0.0127)	(0.0088)		(0.0262)	(0.0231)
wage	-0.00000187***	-0.00000156***		0.000000862	0.000000358
	(0.0000)	(0.0000)		(0.0000)	(0.0000)
sorg_chg	0.0999***	0.0924***		0.0253**	0.0492***
	(0.0068)	(0.0045)		(0.0116)	(0.0108)
union	0.00024	-0.0223		0.715***	0.673***
	(0.0393)	(0.0321)		(0.0723)	(0.0654)
N	22830 (Rounded to base 10)	30730 (Rounded to base 10)		23460 (Rounded to base 10)	33140 (Rounded to base 10)
Log likelihood	-27919.5	-35914.6		-19198	-26567.5

Bootstrapped standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Stage 2, product and process innovation, conditional fixed effects logistic regression (1999-2006)

	Balanced	Unbalanced		Balanced	Unbalanced
	New and/or Improved Product			New and/or Improved Process	
cpu	-0.459^{***}	-0.413^{***}		-0.710^{***}	-0.681^{***}
	(0.1580)	(0.1020)		(0.1360)	(0.1420)
prof_tech	-0.352^{***}	-0.519^{***}		-0.339^{***}	-0.609^{***}
	(0.0862)	(0.0683)		(0.0958)	(0.0865)
union	-0.345^{**}	-0.429^{***}		-0.599^{***}	-0.754^{***}
	(0.1400)	(0.1310)		(0.1140)	(0.1690)
competitor	0.126^{***}	0.126^{***}		0.0825^{***}	0.0869^{***}
	(0.0094)	(0.0074)		(0.0096)	(0.0091)
hrm_hat	4.699^{***}	4.954^{***}		5.190^{***}	5.524^{***}
	(0.1790)	(0.1770)		(0.2070)	(0.2140)
incen_hat	0.264^{***}	0.200^{***}		0.224^{***}	0.136^{*}
	(0.0723)	(0.0623)		(0.0792)	(0.0701)
tech	0.0969^{*}	-0.0134		0.184^{***}	0.047
	(0.0517)	(0.0607)		(0.0550)	(0.0699)
trn_hat	0.00114^{***}	0.00136^{***}		0.00166^{***}	0.00188^{***}
	(0.0003)	(0.0002)		(0.0003)	(0.0003)
N	26500 (Rounded to base 10)	36750 (Rounded to base 10)		25550 (Rounded to base 10)	35140 (Rounded to base 10)
Log likelihood	-10534.5	-14256.7		-9783.1	-13155.9

Bootstrapped standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Stage 2, new product, improved product conditional fixed effects logistic regression (1999-2006)

	Balanced	Unbalanced		Balanced	Unbalanced
	New product			Improved product	
cpu	-0.00666	0.0499		-0.484***	-0.459***
	(0.1420)	(0.1340)		(0.1400)	(0.1350)
prof_tech	-0.268***	-0.309***		-0.177**	-0.394***
	(0.0984)	(0.1100)		(0.0852)	(0.0969)
union	-0.0665	0.0358		-0.467***	-0.540***
	(0.1430)	(0.1610)		(0.1030)	(0.1540)
competitor	0.116***	0.119***		0.121***	0.126***
	(0.0102)	(0.0081)		(0.0094)	(0.0089)
hrm_hat	3.523***	3.776***		4.532***	4.828***
	(0.2320)	(0.1780)		(0.1780)	(0.1720)
incen_hat	0.222***	0.173***		0.193***	0.135***
	(0.0841)	(0.0584)		(0.0696)	(0.0521)
tech	0.199***	0.177**		0.0668	-0.0546
	(0.0725)	(0.0690)		(0.0516)	(0.0601)
trn_hat	0.0000626	0.000219		0.00125***	0.00144***
	(0.0004)	(0.0003)		(0.0003)	(0.0003)
N	23720	32470 (Rounded to base 10)		26020 (Rounded to base 10)	35920 (Rounded to base 10)
Log likelihood	-9267	-12442.8		-10314.1	-13905.6

Bootstrapped standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Stage 2, new process, improved process conditional fixed effects logistic regression (1999-2006)

	Balanced	Unbalanced		Balanced	Unbalanced
	New process			Improved process	
cpu	-0.545***	-0.473***		-0.724***	-0.718***
	(0.1550)	(0.1270)		(0.1380)	(0.1090)
prof_tech	-0.289**	-0.499***		-0.323***	-0.605***
	(0.1130)	(0.0702)		(0.0995)	(0.0795)
union	-0.534***	-0.546***		-0.636***	-0.805***
	(0.1420)	(0.1480)		(0.1120)	(0.1120)
competitor	0.0780***	0.0834***		0.0763***	0.0830***
	(0.0103)	(0.0102)		(0.0086)	(0.0070)
hrm_hat	4.889***	5.160***		4.950***	5.276***
	(0.2220)	(0.1330)		(0.2270)	(0.1660)
incen_hat	0.237**	0.144**		0.252***	0.155**
	(0.0978)	(0.0713)		(0.0811)	(0.0691)
tech	0.210***	0.128**		0.120**	-0.0288
	(0.0615)	(0.0524)		(0.0500)	(0.0500)
trn_hat	0.00108***	0.00134***		0.00176***	0.00196***
	(0.0003)	(0.0002)		(0.0003)	(0.0002)
N	23140 (Rounded to base 10)	31610 (Rounded to base 10)		24940 (Rounded to base 10)	34220 (Rounded to base 10)
Log likelihood	-8677.1	-11625		-9567.3	-12871
Bootstrapped standard errors in parentheses					
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$					

Table 7. Probability of product/process innovation conditional on training expenditure (1999-2006 panel)*

Expenditure	Product				
$/employee	Balanced			Unbalanced	
0	0.45			0.43	
	[0.39	*0.51]*		*[0.38*	*0.47]*
500	*0.58*			*0.58*	
	[0.55	*0.61]*		*[0.56*	*0.61]*
1,000	0.70			0.72	
	[0.63	*0.77]*		*[0.67*	*0.78]*
2,000	0.87			0.91	
	[0.78	*0.97]*		*[0.84*	*0.97]*
3,000	0.95			0.97	
	[0.89	*1.00]*		*[0.94*	*1.00]*
Expenditure	Process				
$/employee	Balanced			Unbalanced	
0	0.40			0.37	
	[0.35	*0.45]*		*[0.31*	*0.43]*
500	*0.58*			*0.57*	
	[0.56	*0.61]*		*[0.55*	*0.59]*
1,000	0.75			0.76	
	[0.69	*0.81]*		*[0.71*	*0.81]*
2,000	0.93			0.95	
	[0.88	*0.99]*		*[0.91*	*0.99]*
3,000	0.99			0.99	
	[0.97	*1.00]*		*[0.98*	*1.00]*

* *[x   y]* indicates 95% confidence interval

Table 8. Probability of new/improved product/process innovation conditional on training expenditure (1999-2006 panel)*

Expenditure	New Product		Improved Product	
$/employee	Balanced	Unbalanced	Balanced	Unbalanced
0	.	.	0.45	0.42
			[0.39 0.50]	*[0.36 0.48]*
500	.	.	0.59	0.58
			[0.55 0.62]	*[0.56 0.60]*
1,000	.	.	0.72	0.73
			[0.65 0.79]	*[0.67 0.79]*
2,000	.	.	0.89	0.92
			[0.81 0.98]	*[0.85 0.98]*
3,000	.	.	0.97	0.98
			[0.92 1.00]	*[0.95 1.00]*
Expenditure	New Process		Improved Process	
$/employee	Balanced	Unbalanced	Balanced	Unbalanced
0	0.44	0.42	0.40	0.36
	[0.37 0.50]	*[0.37 0.47]*	*[0.35 0.44]*	*[0.32 0.40]*
500	0.56	0.57	0.59	0.57
	[0.53 0.59]	*[0.55 0.60]*	*[0.57 0.62]*	*[0.55 0.60]*
1,000	0.68	0.71	0.77	0.77
	[0.59 0.76]	*[0.65 0.77]*	*[0.72 0.82]*	*[0.72 0.81]*
2,000	0.85	0.90	0.95	0.96
	[0.73 0.98]	*[0.83 0.97]*	*[0.91 0.98]*	*[0.93 0.98]*
3,000	0.94	0.97	0.99	0.99
	[0.85 1.00]	*[0.93 1.00]*	*[0.98 1.00]*	*[0.99 1.00]*

* *[x, y]* indicates 95% confidence interval

Summary and conclusion

There is strong statistical inference indicating that training affects product and process innovation. Considering the balanced sample results the confidence interval for the probability of a product innovation *95%CI*[0.78, 1.00] is greater than for process innovation *95%CI*[0.88, 1.00]. The implication is that product innovation is more difficult than process innovation. When we further disaggregate innovation into new versus improved, we find that training has no effect on new products, while it augments improved products. Training has a positive and significant effect on new and improved process innovations.

Admittedly this paper uses a narrow but at least measurable proxy for training, namely expenditure per employee on job-related classroom training (on-the-job training, and coursework outside of working hours are omitted). Nevertheless, classroom training covers a broad array of scenarios--orientation for new employees, managerial-supervisory training, professional training, apprenticeship training, sales and marketing training, computer hardware, computer software, other office and non-office equipment, group decision-making or problem-solving, team-building-leadership-communication, occupational health and safety-environmental protection, literacy or numeracy, other training-specify, as well as classroom training for new process innovations (new software/hardware, capital embodied technological change in new machinery, any major implementation of other technologies or machinery).

Clearly, the aforementioned types of training are avenues for further research. At this stage, we cannot infer from the list that “group decision-making or problem-solving” and “team-building, leadership, communication” are directed exclusively at innovation, other than saying these courses probably facilitated process and product innovation. As (Freeman, 1994) says "…the vast majority of firms do not make radical innovations, but all can and should make incremental innovations…". A more nuanced question that comes to mind is: "Can we specifically train for new product innovation?" The technology and innovation management literature, popular books and media discuss new product development continuously. Tidd & Bessant (2018) discuss the stages of "high-involvement innovation" or HHI where training is a component of basic high involvement innovation tools, incremental and radical innovation...". There are highly cited papers in strategic management (Helfat and Raubitschek 2000; Helfat and Peteraf 2003; Eisenhardt and Martin 2000), however, we conclude after scanning the economics literature that a widely accepted theory of new product innovation does not exist. Although Stoneman et al. (2018) chronicle what we currently know. Perhaps, it is possible to train for new product innovation. We will need to wait for such data to test that hypothesis. Until then, it remains obvious that new product innovation is very hard. A reviewer astutely observed what Edison said: "Genius is one percent inspiration and ninety-nine percent perspiration" and then added their own observation "And the genius is not in the databases".

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Appendix

Table A1. Sample statistics, balanced and unbalanced panel, weighted (1999-2006)*

		Balanced (N=31,820)			*Unbalanced (N=49,590)*	
Variable		Mean	Std. Dev.		Mean	Std. Dev.
trn_exp**	Training expenditure per employee	174.58	500.88		169.45	602.91
prd	Product innovation (binary)	0.385	0.487		0.375	0.484
prc	Process innovation (binary)	0.271	0.444		0.259	0.438
pd_imp	Improved product (binary)	0.329	0.470		0.321	0.467
pd_new	New product (binary)	0.277	0.447		0.268	0.443
pc_imp	Improved process (binary)	0.248	0.432		0.235	0.424
pc_new	New process (binary)	0.194	0.396		0.185	0.389
trn	Training (binary)	0.352	0.478		0.306	0.461
hrm	Human resource practices (count)	0.465	1.125		0.376	1.035
incentive	Incentive systems (count)	0.239	0.682		0.222	0.658
competitor	Competitors (Likert)	1.120	1.496		1.177	1.514
cpu	Proportion workers using computer	0.540	0.403		0.526	0.416
non_perm	Proportion non-permanent workers	1.62	20.27		1.44	26.60
now_part	Proportion part-time workers	3.28	19.51		2.62	17.88
prof_tech	Proportion professional-technical employees	0.239	0.320		0.227	0.324
size	Total employment	(not released)			(not released)	
sorg_chg	Organizational change index (standardized)	0.000	1.000		0.000	1.000
tech	Adopted new technology (binary)	0.201	0.401		0.192	0.394
ttl_sep	Number of quits, separations	3.262	15.271		2.94	18.66
union	Union (binary)	0.080	0.237		0.064	0.214
wage	Wage per employee	31,239	22,711		29,498	23,593

*Population weighted.
**

Table A2. Variable definitions	
Variable	Description
trn_exp	Training expenditure in the past year divided by total employment. Training expenditure includes: trainers' salaries, contracts to vendors, direct tuition to schools or training institutions, training materials, travel or living costs for trainers and trainees, overhead or office costs for training, other training expenses.
competitor	How many firms offer product/services directly competing with yours in your most important market (interval: did not answer=0, none=1, 1 to 5=2, 6 to 20=3, over 20=4)
cpu	Proportion relative to total employment of employees who use computers as part of their normal working duties.
hrm	Sum of HR practices offered by the firm (employee's suggestion program, flexible job design, information sharing, problem-solving teams, joint labor-management committees, self-directed work groups). Range is from 0 (no practices) to 6.
incentive	Sum of wage and non-wage benefits and compensation practices (individual incentive systems, group incentives systems, profit-sharing plan, merit pay or skill based pay, employee stock plans). Range is from 0 (no practices) to 5.
non_perm	Proportion relative to total employment of non-permanent employees (includes full-time and part-time)
now_part	Proportion relative to total employment of part-time employees
pc_imp	Introduction of an improved process (binary). Improved processes are those whose performance has been significantly enhanced or upgraded. (within the past year)
pc_new	Introduction of a new process (binary). New processes include the adoption of new methods of goods production or service delivery. (within the past year)
pd_imp	Introduction of an improved product/service (binary). Improved products or services are those whose performance has been significantly enhanced or upgraded. (within the past year)
pd_new	Introduction of a new product/service (binary). New products or services differ significantly in character or intended use from previously produced goods or services. (within the past year)
prc	Did the firm have either a new or improved process (y/n). (within the past year)
prd	Did the firm have either a new or improved product (y/n). (within the past year)
prof_tech	Proportion relative to total employment of full-time plus part-time professionals and technical/trades in the firm.
size	Total employment.
sorg_chg	Did your firm have any of the following organizational changes (y/n), where organizational change is defined as: greater integration among different functional areas, increase/decrease the degree of centralization, downsize, greater reliance on temporary workers/part-time workers, re-engineering, increase in overtime hours, adoption of flexible working hours, delayering of management, greater reliance on job rotation/multi-skilling, implementation of TQM, greater reliance on outsourcing, greater inter-firm collaboration in R&D, production or marketing.
tech	New technology implemented within the past year: major new software application and/or hardware installation, computer controlled/computer-assisted technology, other technologies or machinery (yes/no)
trn	Does the firm offer training: on-the-job or classroom training (yes/no)
ttl_sep	Separations in the past year (resignations, lay-offs with no recall expected, special workforce reductions, dismissal for cause, retirement, other permanent separations).
union	Proportion of employees unionized.
wage	Gross payroll divided by total employment.

Table A3. Industry definitions		
WES industry code	Description	North American Industry Classification System codes (NAICS 2002)
1	Forestry, mining, oil and gas extraction	113, 1153, 211, 212, 213
2	Labour intensive tertiary manufacturing	311, 312, 313, 314, 315, 316, 337, 339
3	Primary product manufacturing	321, 322, 324, 327, 331
4	Secondary product manufacturing	325, 326, 332
5	Capital intensive tertiary manufacturing	323, 333, 334, 335, 336
6	Construction	231, 232, 236, 237, 238
7	Transportation, warehousing and wholesale trade	411, 412, 413, 414, 415, 416, 417, 418, 419, 481, 482, 483, 484, 485, 486, 487, 488, 493
8	Communication and other utilities	221, 491, 492, 562
9	Retail trade & consumer services	441, 442, 443, 444, 445, 446, 447, 448, 451, 452, 453, 454, 713, 721, 722, 811, 812
10	Finance and insurance	521, 522, 523, 524, 526
11	Real estate, rental, leasing operations	531, 532, 533
12	Business services	541, 551, 561
13	Education and health services	611, 621, 622, 623, 624, 8132, 8134, 8139
14	Information and cultural industries	511, 512, 513, 514, 711, 712