LINKING R&D, INNOVATION, AND PRODUCTVITY IN CANADA, SECTOR LEVEL ANALYSIS

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Contents

Abstract

This paper uses a structural three-step estimation process to examine the connectivity between, research and development, innovation, and productivity in Canada, using sector level data from CANSIM. The paper aims to reproduce some of the results found in previous studies on the subject, particularly that of Dany Brouillette (2013), which investigated the relationship above for Canada at the firm-level using a Crépon-Duguet-Mairesse (CDM) model (Crépon et al., 1998). Building a similar model at the sector-level, will allow to investigate whether the positive link between R&D, innovation, and productivity is maintained at aggregated levels. The paper will show that determining this link between R&D, innovation, and productivity at this level of aggregation is a difficult task, and that the relationship between the three is weak at best.

I. Introduction

For several years, the question of business innovation and productivity has been at the centre of political discussions in Canada. This is mainly due to Canada's weak productivity, and consequently its widening productivity gap with the United States (starting in the 1980s). Productivity growth in Canada has dropped substantially and continually over the past five decades, from an average of 3 percent in 1961-1980 to less than 1 percent after 2000 (Institute for Competitiveness & Prosperity, 2011). By 2012, the productivity level in Canada (private sector only) was 30 percent lower than in the United States (Leonard, 2014). In their 2011 report on Canada's Innovation Imperative, the Institute for Competitiveness & Prosperity attributes this gap to Canada's inability to realize the full potential of its industries. The report attributes this to a smaller population with at least one university degree, weaker urbanization levels, less efficient clustered industries, and weaker managerial competencies compared with the United States. Moreover, Canada also has smaller domestic expenditures on research and development, and most of the government grants on R&D come from tax credits, these two factors have also been associated with lower levels of innovation and productivity within Canada (Globerman, 2012).

The combination of productivity stagnation, and an aging population is jeopardising Canada's long-run prosperity and well-being. Productivity stagnation is not only an economic problem, but also a social one, as productivity translates in the long-run to growth of real wages, and higher standards of living. Thus, it is important to understand the drivers of innovations, in particular the relationship between R&D, innovation, and productivity. Previous research on the subject found positive links between the three, while focusing on firm-level links. Thus, this paper examines if this relationship is maintained at a sector-level analysis[1].

The next sections are organized as follows: section II will provide a literature review on the subject, highlighting relevant information pertaining to this paper. Section III will discuss the data issues and the model proposed by this paper. Section IV will analyze and discuss the results of the model, as well as offer a detailed investigation of its non-convergence. Finally, Section V will conclude the paper by highlighting the difficulty of establishing a clear relationship between R&D, innovation, and productivity at the sector-level with the model proposed, as well point to possible multicollinearity between the innovation survey variables and productivity. Moreover, it will stress the importance of missing data, as well as access to detailed innovation expenses in order to establish a better relationship between the variables.

II. Literature Review

The Role of Innovation in Productivity

Innovation is defined by the OECD (Oslo Manual, 3rd Edition, 2005) as the development of new or significantly improved products, processes, organizational, and marketing methods (specifically in the past three years). It is important to distinguish between invention and innovation. Invention refers to the development of new ideas, while innovation requires the implementation of these ideas, often requiring substantial funding, and most importantly market demand (Hall, 2014). Economic researchers, point to the importance of innovation as a key driver of productivity growth (see for example, Hall 2011, and Pilat 2015). Earlier studies measured this relationship using an augmented production function, with various types of R&D as inputs, to estimate the returns to R&D through an increase in Total Factor Productivity (TFP), and wages (Sanchez, 2015). Most recently, many studies have used various variations of Crépon-Duguet-Mairesse (CDM) model, which proposes a structural relationship at the firm-level using three main equations. First by predicting R&D investments for all firms, then using predicted R&D investments to measure innovation output, and lastly using innovation output to measure

[1] The analysis in this paper is limited by the publicly available data on R&D, innovation, and productivity through CANSIM. The availability of this data severely limited the extent of the analysis, and its explanatory power.

productivity (Crépon et al., 1998; Mairesse et al., 2005; Griffith et al., 2006; OECD, 2009)[2]. These studies are based on cross-sectional data, and have generally found a significantly positive relationship between R&D on innovation output, and innovation output on productivity. Though, not all types of innovations exhibit this relationship, in particular, process innovation is generally found to be either negatively correlated with productivity, or not correlated at all (Griffith et al. 2006; Brouillette, 2013). Brouillette (2013) explains that this could be due to the disruptive effects of process innovation, where in the short-run the enterprise is focused on integrating the new and improved process rather than utilizing it for productivity increases. Though, another possible explanation is that the type of measure used for productivity alters the results. For example, if productivity is measured by an increase in sales rather than profits, then process innovation will most likely not have a significant effect on productivity, as process innovation mainly affects costs.

Moreover, due to limitations in data availability, many studies were not able to focus on the dynamic linkages between innovation and productivity, which only compounds the problem. Focusing on the dynamic relationships between R&D, innovation, and productivity allows to take into account the opportunity cost, and uncertainty inherent in R&D investments; taking into account that investment in R&D today does not immediately (if at all) translates into innovation (Majd and Pindyck, 1987; Raymond et al., 2015). Moreover, past success of innovation has been shown to be significantly associated with innovation success in the future (Brouillette, 2013; Peters, 2009). As well as, firms have been shown to have a preference for reliance on internal funding, rather than external (Bhattacharya and Ritter, 1983)

In their paper, Raymond et al. (2015) have addressed the dynamic relationship of innovation and productivity by using three waves of the Community Innovation Survey (CIS) for France and The Netherlands. They use an unbalanced panel to show that both countries exhibit a unidirectional causality going from innovation to labor productivity. Moreover, they corroborate previous research that past innovation affects productivity, but also show that productive enterprises are not necessarily the most innovative ones, in terms of product innovations, and shares of innovative sales.

[2] R&D is predicted for all firms, even the ones that do not invest in R&D. Since, the underlying assumption is that all firms are capable to invest in R&D, if they would chose to do so.

The Role of Green Technologies on Innovation

The recently elected government led by Prime Minister Justin Trudeau has put great emphasis on sustainable low-carbon economic growth. This is detailed in Chapter 4- A Clean Growth Economy, of the recent proposed Budget 2016. The proposed budget is divided into two types of proposed government spending: "Clean Technology", and "Securing a Cleaner, More Sustainable Environment". Investment in "Clean Technology" includes: accelerating clean technology development through investing in R&D of new clean technologies; investing in electric vehicle and alternative transportation fuels infrastructure; expanding tax support for clean energy through the expansion of tax credits (Capital Cost Allowance, CCA); investing in leading researchers in the clean and sustainable technology field; advancing regional electricity cooperation; developing cleaner oil and gas technologies; and, improving data on the Clean Technology sector. Some of proposed budget spending for "Securing a Cleaner, More Sustainable Environment" include: moving to a cleaner transportation sector through the development of regulations and standards for clean transportation technology; supporting energy efficiency and renewable energy development; tax treatment of emission allowance regimes pertaining to provinces who have introduced or are in the course of introducing emissions trading regimes (such as, Ontario, Quebec, and British Columbia through the Western Climate Initiative); and, reducing air pollution (for example see: Bill 172 on Climate Change Mitigation and Low Carbon Economy Act). More specifically, the federal government aims to invest in the 2016-17 fiscal year $51 million on Clean Technology, and additional $333 million on Securing a Cleaner, More Sustainable Environment[3]. By 2017-18 these amounts are planned to significantly increase to $350 million and $1.4 billion, respectively. In total, the federal government budget for a "Clean Growth Economy" for 2016-2018 is $2.4 billion. Moreover, starting in 2017-18, Budget 2016 proposes to provide additional $1 billion over four years to support clean technology, particularly in the forestry, fisheries, mining, energy, and agriculture sectors.

Investing in clean technologies and a sustainable environment, as well as increasing environmental regulations on pollutions will impact businesses in Canada through advancing and growing clean technology enterprises, as well as impose regulations on existing businesses. All

[3] For a detailed list of what of is included under Clean Technology spending, and Securing a Cleaner, More Sustainable Environment, as well as the exact budget allocated please see the Chapter 4 of Budget 2016.

of these measures are bound to have an impact on the industries in Canada, as a significantly large proportion of them is comprised of small-medium businesses, where the effect of small increases in prices, or regulations is more profound. Similarly, many industries and firms across the world are experiencing the impacts of such regulations as global efforts on CO2 emissions and other harmful gases tighten (see for example, 2015 Paris Agreement).

However, these impacts are not necessarily negative as increased environmental protections acts and regulations imposed on firms, could “nudge” firms to become more competitive and innovative. This essentially is the Porter Hypothesis, hypothesized by Michael Porter in 1990s (Porter, 1991; Porter and Van der Linde, 1995). Ambec and Lanoie (2008) corroborated the Porter Hypothesis, by showing that even though reduction of pollution is not always accompanied by increased economic performances, the expenses incurred by these reductions are often offset by gains in other places. Thus, imposing environmental regulations can create a win-win situation for the firms, as well as the citizens of the country. Moreover, investing and developing the Clean Technology sector could increase employment opportunities and productivity, or at the very least, not reduce them as the economy moves towards more sustainable energy uses.

Moreover, Chen et al. (2006) investigate the relationship of environmental regulations on businesses in Taiwan, which are also compromised of mostly small business like Canada. They find that, firms who used green product and process innovations were able to achieve positive corporate competitive advantage, generally defined as the ability of a company to occupy a certain space within a market, where its competitors cannot copy its successful strategy, and the company is able to gain sustainable benefits from said strategy[4]. Similarly, Sezen and Cankaya (2013), show that green process innovations have significant positive impact on corporate sustainability, and other social factors in the automotive, chemistry and electronic sectors in Turkey. However, they found that green product innovations did not have a significant effect.

[4] Corporate competitive advantage is comprised of eight indicators: (1) competitive advantage of low cost compared to other competitors; (2) better the quality of products or services than that of the competitor’s products or services; (3) greater R&D and innovation capabilities than its competitors; (4) the company has better managerial capability than the competitors; (5) the company is more profitable; (6) the growth of the company exceeds that of the competitors; (7) the company is a primer “player” in the market; (8) better corporate image than that of the competitors. These eight indicators are not examined separately, but rather their aggregate measure.

On the other hand, Giovanni (2014) uses a modified CDM model to show that the use of environmental technologies and innovations by big polluting firms may crowd out other more profitable innovations in the short-run.

III. Data Issues and Model

The Model

The model constructed below mainly follows that of Brouillette (2013), who's model is similar to that of Polder et al. (2010) and Hall et al. (2011). Though, this model differs from the above models in that it examines the structural relationship at the sector level, investigating whether greater R&D expenses lead to a higher proportion of innovative enterprises, which in turn lead to greater economic welfare in these sectors (value added, labour productivity, total compensation, and total compensation per hour). Moreover, it differs from Brouillette's (2013) paper in that it aims to focus on the influence of the use of advance green technologies on all three structural equations. The few examples discussed in the literature review, highlight the importance of investigating the effects of green technology on innovation, and productivity. Thus, this paper incorporates the use of advance green technologies into the standard CDM model.

Model Equations

The model equations below are estimated using Stata's Structural Equation Modelling (SEM) builder. SEM models are comprised of linear structural equations, which describe a path of dependence between endogenous, exogenous, observed, and unobserved variables. The models often use Maximum Likelihood estimation (ML), and assume a multivariate normal distribution. More specifically the proposed model describes the relationship between the equations below:

R&D Equation (1): the dependent variable in the first-stage structural model is the log of average R&D expenditure between 2007 and 2009.

$$lnRD_i^{2007-2009} = \alpha + \beta \begin{pmatrix} Past\ RD_i^{2004-2006} \\ Green\ Tech_i^{2009} \\ X_i \end{pmatrix} + \epsilon_{i1}$$

Where i denotes sector i and $\in_{1i}$ is the error term. The right-hand side variables include average R&D expenditures between 2004 and 2006, in thousands of dollars, and the proportion of enterprises in each sector that used advance green technologies in 2009. The control variables are dummy variables for province or regions[5], and the proportion of enterprises that indicated Canada as the location of their head-office in 2009 (CAN Office). These control variables are used in all three equations.

Innovation Equations (2): the Innovative Activity in Canada is modelled simultaneously in two stages. First by estimating an innovation output equation (2010-2012), using past innovation input variables (mainly for the year 2007-2009). Second, using estimated innovation outputs, an unobservable latent variable is measured estimating the "Innovative Activity" in Canada between 2010 and 2012.

i. **Innovation Output:** the dependent variable ($Current\ Innovation_i^k$), which measured innovation output, takes on five possible variables: overall innovation (INNO), process (PRCS), marketing (MRKT), organizational (ORG), and product (PRDT). This differs from Brouillette's (2013) research, which uses all four innovation measures (process, marketing, organizational, and product) and their combinations to construct 16 different innovation output equations. The reason for this difference is explained below in the data discussion.

$$Current\ Innovation_i^k \ = \ \delta_1^k\left(Past\ Innovation_1^k\right) + \delta_2^k \begin{pmatrix} Predicted\ RD_i^{2007-2009} \\ Green\ Tech_i^{2009} \\ Educated_i^{2009} \\ X_i \end{pmatrix} + \in_{i2}^k$$

Where k denotes the five different types of innovations: overall innovation (INNO), process (PRCS), marketing (MRKT), organizational (ORG), and product (PRDT). Each equation is estimated separately. As above, i denotes sector i and $\in_{i2}$ is the error term. Past Innovation refers to innovation variables from 2007-2009 SIBS survey, while Current Innovation refers to variables from 2010-2012 SIBS survey. Each type of past innovation is estimated with its own type of current innovation. For example, past process innovation and current process innovation are regressed together. The predicted variable of $lnR\&D_i^{2007-2009}$ from the first

[5] There controlled provinces and regions are: Quebec, Ontario, Alberta, Atlantic Region, and the Rest of Canada. The Rest of Canada region is used as the reference point.

equation is included ($Predicted\ R\&D_i^{2007-2009}$), along with the proportion of enterprises using advance green-technologies ($Green\ Tech_i^{2009}$), and the percent of employees with a bachelor's degree in each sector ($Educated_i^{2009}$).

ii. **Innovative Activity:** the dependent variable is measured using an unobserved Innovative Activity latent variable. This relies on the assumption that innovation as a whole is an unobserved variable, which cannot be fully explained by the Innovation Output variables.

$$Innovative\ Activity *_i^k = \varphi *\ Current\ Innovation_i^k\ + \in_{i3}^k$$

Where k denotes the five different types of innovations: overall innovation (INNO), process (PRCS), marketing (MRKT), organizational (ORG), and product (PRDT). Each equation is estimated separately, through the productivity equation below. As before, i denotes sector i and $\in_{i3}$ is the error term.

Growth Equations (3):

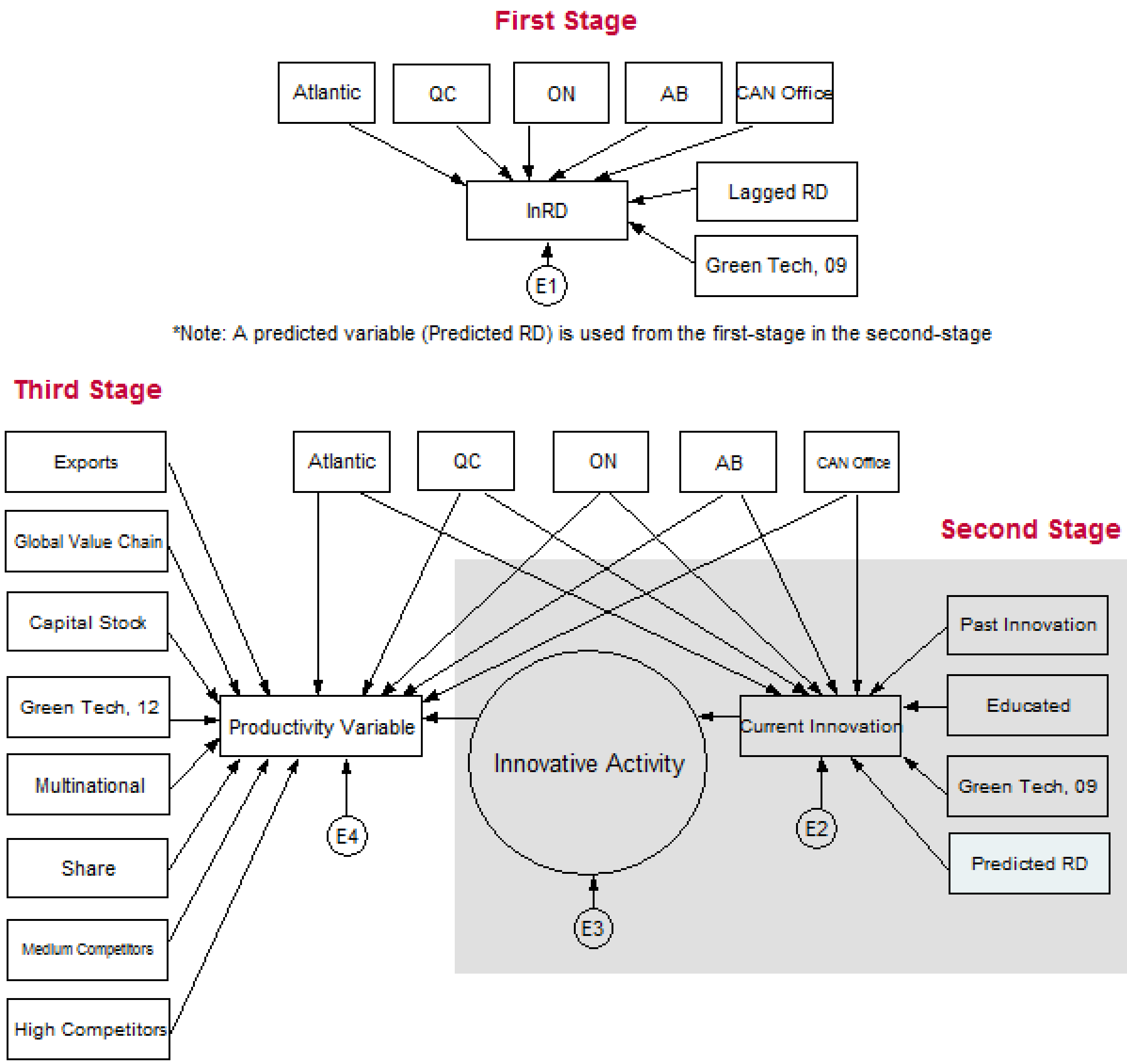
$$\Delta PROD_i^j = \gamma_1^j Innovation\ Activity *_i^k + \gamma_2^j \begin{pmatrix} Exports_i^{2010-2012} \\ GVC_i^{2010-2012} \\ \Delta Capital\ Stock_i^{2010-2012} \\ Green\ Tech_i^{2012} \\ Multinational_i^{2012} \\ Share_i^{2012} \\ Medium\ Competitors_i^{2012} \\ High\ Competitors_i^{2012} \\ X_i \end{pmatrix} + \in_{i4}^j$$

Where j denotes the investigated four types of growth variables ($\Delta PROD_i^j$): labour productivity, value added, total compensation, and compensation per hour, between 2010 and 2012. As before, i denotes sector i and $\in_{i4}^j$ is the error term for each type of growth equation. For each dependent growth variable, five different latent $Innovative\ Activity *_i^k$ (2010-2012) equations are used (overall innovation, product, process, market, or organizational) separately. Unlike Brouillette's (2013) paper, the latent Innovative Activity equations are not used together in the growth productivity equations above, as the proportion of respondents to each survey question are not available. This is a limitation of the analysis, and as a consequence are not able to disaggregate between the complementarity and supplementarity effects of the various types of innovation. Each growth variable is defined by its growth rate between 2010 and 2012. Capital Stock, is the ratio between capital stock and total hours worked for all jobs[6], and it is measured similarly to the productivity variables. Green Tech is defined similarity to the previous equations, only now the proportions for the year 2012 are used. The rest of the variables aim to measure the competitive environment in each sector, these include: Exports, presence of business activities abroad (GVC), presence of a multinational enterprise in the main market (Multinational), market share of the main product (Share), and the proportions of enterprises with medium and high number of competitors in the market (Medium Competitors, and High Competitors). Low number of competitors are defined as the reference group (detailed definitions are in Appendix A).

The Structural Equation Model (SEM) Visualized

[6] Total hours worked for all jobs is used as a measure of total labour. Total employment was not used as employment measures from the Survey of Employment, Payrolls and Hours (SEPH), and Labour Force Survey (LFS) did not have complete data for all the sectors estimated, or sectors were aggregated together, and disaggregation was not possible.

Figure 1: Structural Equation Model for R&D, Innovative Activity, and Productivity—Path Diagram



The above figure visualizes the structural relationship between R&D, Innovative Activity, and Productivity. Each arrow in the diagram describes an implied relationship between the various variables. For example, an arrow from Past Innovation points towards Current Innovation indicating that Past Innovation is treated as an exogenous variable, while Current Innovation, which has arrows pointing towards it, is an endogenous variable. Variables in square boxes are observed variables, while the variable Innovative Activity, represented as a circle, is an unobserved latent variable. Thus, the presumed relationship is that Current Innovation and its predictors, predict a latent innovation equation measuring the innovative activity in the market, which in turn influences the four types of Productivity Variables (labour productivity, value added, total compensation, and compensation per hour). The above model was estimated separately for five different types of innovations (overall innovation, market, process, organizational, and product), and four types of Productivity Variables (labour productivity, value added, wages, and wage per hour). Thus, in total 20 different equations were estimated. Though, we may be able to estimate the 20 different equations simultaneously, each equation was estimated separately in an effort to disentangle convergence issues, which will be discussed in detail below. The sources and definitions of all of the variables are provided in Appendix A, and discussed below in the Data section.

Data

All sectorial variables come from Statistics Canada administrative databases or surveys, available on CANSIM (see Appendix A for a complete list of variables used and their data sources). Variables expressed in Canadian dollars (capital, R&D, and total compensation) are deflated and chained to 2007. More specifically, capital variables were downloaded from Statistics Canada, Stock and Consumption of Fixed Non-residential Capital chained, while R&D and total compensation were deflated using Statistics Canada GDP Implicit Price Index (chained=2007)[7].

The paper examines 9 sectors, across 5 provinces and regions (see Appendix A), which produced a sample size of 45 observations[8]. Having only 45 observations limits the results and analysis of this paper. The availability of the data and its level of disaggregation were limited by three main sources:

1. Canadian Productivity Accounts (CPA), which provided the measures for the different types of productivity: value added, labor productivity, total compensation, and compensation per hour, which is only available at the sector-level.

[7] Using the GDP Implicit Price Index to deflate R&D is commonly used (for example see, Brouillette 2013), though it has its drawbacks, as rate of inflation in R&D is difficult to measure. Mansfield et al. (1983) estimated using a Cobb-Douglas production function, and the Laspeyres price index, that the GNP deflator (used in the United States to deflate R&D) underestimated the rate of price increase for R&D inputs during 1969-79 in practically all of the examined industries. This is something to keep in mind when interpreting the results, as a better price index for R&D is not publicly available.

[8] Innovation data from SIBS is available for 14 sectors, while productivity data from CPA is available for 28 sectors. The match between the two produces 13 sector that are available for analysis. Unfortunately, RDCI sector-level data limits the sample to only 9 available sectors.

2. Survey of Innovation and Business Strategy (SIBS)[9], which provided all of the survey data inputs. The limiting factor of this survey is that data on innovators, and type of innovators (marketing, organizational, product, or process), is only available at the sector-level. Data is available by each type of innovation at a greater disaggregated level, though without access to the raw data it is impossible to aggregate these measures into the four innovation categories, as responses are not mutually exclusive[10]. For example, product innovation firms have a choice of two types of product innovations:
    a. New or significantly improved goods, and/or
    b. New or significantly improved services

    Aggregating these responses properly, will require access to the confidential raw data files from CANSIM[11].
3. Research and Development in Canadian Industry (RDCI), provincial data from this database is available from 1997-2013 across 52 industries. Though, only sectors that were available at the aggregation level of the above two data sources were used. For example, SIBS has separate data on the Finance and Insurance sector, and the Real Estate and Rental and Leasing sectors, while RDCI aggregates these two sectors into one. Due to the lack of access to the raw data files, these sectors were not used in the analysis, as they could not be grouped by the data available through SIBS, or disaggregated by the data available through RDCI.

Moreover, data from SIBS is only available for three provinces (Ontario, Quebec, and Alberta), and two regions (Atlantic Canada, and Rest of Canada), thus limiting the sample size from 90 possible observations to 45 observations. Thus, disaggregated provincial data for the two regions from the statistical databases of RDCI, CPA and Input-and-Output Accounts (IO) were aggregated for each region. R&D and Capital Stock data were simply added from each province for their respective regions, labour productivity and value added measures were aggregated using

[9] The 2009 Survey of Innovation and Business Strategy was not stratified to provide provincial or regional estimates.
[10] Even if the fact that the four variables are not mutually exclusive is ignored, the four aggregated variables are highly correlated with each other. All variable except marketing innovation have a correlation of 0.6 and above. Thus, including all four innovation types could lead to the model being unidentified.
[11] The process to gain access to this type of data is lengthy, and unfortunately was beyond the time-frame available for this research. This paper would have greatly benefitted from access to this data, as greater detail and more variance would have been introduced to the variables and their estimates.

the GDP as a weighted average for each province, and compensation measures (total compensation and compensation/hour) were aggregated using total number of jobs as a weighted average for each province[12].

Missing Data Treatment

As aggregated data was used for the analysis, and having maximum 45 observations per variable, the availability and reliability of each data point is of great importance. The data was generally missing due to three main reasons: it is unreliable, unavailable, or confidential. For example, approximately 20 percent of the data available from SIBS (for time period and sectors investigated) is missing due to confidentiality, while another 20 percent is missing due to reliability or availability.

Treating missing data and classifying the reasons for it being missing (missing completely at random, missing at random, or not missing at random) is tricky. If the data is assumed to be Missing at Random (MAR)[13], then Stata's default feature of dealing with missing data (listwise deletion) will not be biased. However, listwise deletion may produce larger standard errors, and thus wider confidence intervals, which produce lower power estimates (Little et al., 2014). Thus, since this paper uses a Structural Equation Modelling, Stata's Maximum Likelihood (ML) estimation for missing values, which assumes MAR, is used to treat the missing values, addressing the larger standard errors concern[14].

Stata's MLMV function is a ML estimation of missing values function, which groups the data according to missing-value patterns. The overall log likelihood is computed by summing the log-likelihood values from each of the missing-value patterns (Stata SEM Manual 2013, p.480).

Innovation Related Variables

[12] Another way of aggregating productivity data would have been to use Domar weights, which sum up to more than one, in an effort to reflect that each industry makes two contributions to aggregate Total Factor Productivity (TFP). Once directly and another indirectly through reducing costs for industries that buy from it. The weights hold as long as one assumes that all wages by any given input are the same across industries (UK's Office of National Statistics, The ONS Productivity Handbook, Chapter 3, p. 23)

[13] If the data is assumed to be MAR, then the probability of missing data on any variable in a regression model is assumed to not depend on the dependent variable, while controlling for other variables.

[14] If the data is MAR, ML estimates will produce consistent, and asymptotically efficient and normal estimates (Little et al., 2014). However, using ML estimation in small samples may produce biased estimates, though a sample of 45 is generally considered large enough to circumvent this problem.

All innovation inputs and outputs come from the two waves of SIBS (2009, 2012). All variables from the survey are continuous variables that measure the proportion of enterprises from a particular industry and province that have responded to each question. More specifically, five types of innovation variables are gathered: market, organization, product, and process innovators, as well as overall innovation, which measures the percent of enterprises that use at least one of the four types of innovations[15].

In line with similar CDM models, total business enterprise R&D intramural expenditures are used as one of the main inputs to innovation. The variable is collected from RDCI's data along with measures on the proportion of enterprises that use advance technologies, by type of technology from SIBS. Particularly, the link between of the use of advance green technologies on innovation and productivity is examined. This is of particular interest due to the Porter Hypothesis discussed previously. Moreover, adoption of new technologies improves business activities, and increases the enterprises ability to absorb new information, as specialized and educated employees are either hired or trained to handle the new technological capabilities (Cohen and Levinthal, 1990). This indirectly could increase innovation, as more educated and specialized workforce is able to conceptualize and actualize new ideas for business innovations. Thus, a measure of the percent of workers with a university degree within each sector is also used in the innovation equation.

As in Brouillette's (2013) research, Current Innovation (2010-2012) is modelled using Past Innovation (2007-2009) since innovative activities, such as R&D, are assumed to be persistent. For example, firms who decide to engage in R&D in a given year, will most likely engage in R&D in the next year due to the fixed costs associated with R&D, as well as the length of time it takes to conduct the research and eventually develop the innovation. Moreover, as Brouillette (2013) research shows, past innovation-related activities are important for present innovation, especially when certain types of innovations complement each other (such as: organizational-product innovation combinations). In his analysis, Brouillette (2013) is able to capture the complementarity of the different types of innovations by using 16 different equations that capture the interaction between each innovation. Although this paper does not examine the complementarity or substitution of different types of innovation (due to data limitations), it is

[15] Non-innovators are treated as a reference group for the overall innovation equation.

nevertheless interesting to see how each type of innovation is linked to its respective latent equation, and productivity as a whole.[16]

Moreover, Brouillette (2013) examines the impact of four types of continuous variables that capture the expenditure amounts of each type of innovation. As the paper shows, this offers a much better measure of innovation, as the amount of expenditure on innovation matters more than the incidence of it. This could be explained by the fact that $1 of innovation is not of the same value to productivity as, for example, $50 of innovation. Thus, the amount invested in innovation, per firm, matters to its productivity more than a simple count of innovation incidence. Although the expenditure variables used in Brouillette (2013) study were available, approximately 60 percent of the data is missing. Moreover, as the variables are aggregates, data is available by categories of expenditure, which is difficult to use a dependent variable, but could have been used as a control variable if the data were not missing. Thus, unfortunately these variables were not be used in the analysis[17].

In most CDM models, patent data is also used as an input to innovation. This paper could not consider patents, as this data at an aggregate level is only available through the Survey of Intellectual Property Management, which is only available at the national level for an aggregated select group of industries. However, although patent data is often used as an input to innovation, it is an imperfect measure of it, as patents do not always actualize into innovations and could be used for unproductive activities, such as patent trolls. Moreover, matching patent data from any patent database is difficult, as the patent holders are not always the organizations themselves, or the organizations' name could change between the years in the database and time-frame examined (Nikzad, 2016).

Additional caveats are that Brouillette (2013) paper also uses data on innovation from the Survey of Advanced Technology (SAT). Using data from this survey would have allowed this paper to enter a time-dimension into the analysis, providing greater detail and variance of data. However,

[16] Combining the results from the four types of innovation into the productivity equation would create a bias as respondents would be counted more than once. This is another limitation of the analysis, and the explanatory power of its results, as it is unlikely, for example, that marketing innovations alone would have a strong impact on productivity measures.

[17] For example, process and product innovation expenditures were broken-down into percent of enterprises that had: no expenditures, $1 to $49,999, $50,000 to $149,999, $150,000 to $499,999, and $500,000 and more expenditures.

earlier survey data from the SAT (2005-2007) is not publicly available. Moreover, using the data from the 2012-2014 SAT survey would have limited even further the sectors used for the analysis to six sectors as the Agriculture, Construction, and Information and Cultural Industries are not surveyed by it[18]. Second caveat is the lack of Information and Communication Technology (ICT) variables in the innovation equation, which have been shown by Hall (2011) to play an important role in innovation. However, data from the Survey of Electronic Commerce and Technology (SECT) was not available at a provincial level, and thus could not be used.

Productivity Related Variables

There are four productivity related measures that are used in the analysis, these are: labour productivity, value added, total compensation, and compensation per hour[19]. These four measures all come from the CPA. An exporting indicator from SIBS is used as a proxy for export data, the indicator measures the percent of enterprises that exported or attempted to export goods or provide services outside of Canada. Export data available through Trade Data Online could not be used as it is only available for three out of the nine sectors in this analysis (Agriculture, forestry, fishing and hunting, Utilities, and Manufacturing).

Moreover, SIBS general competition indicators are also used in this analysis, these include: a global value chain (GVC) indicator, measuring the percent of enterprises that conducted business activities outside of Canada between 2010 and 2012. This indicator is considered complimentary to exports, as companies could have off-shore business or research facilities exposing them to outside knowledge, and knowledge-transfer links by networking across borders. Exposure to foreign markets has been shown to be a key factor in the innovativeness of enterprises. Enterprises that export were shown to be more innovative, and perform better (Alvarez and Robertson, 2004; Nikzad, 2016). Thus, both GVC and exports are used as indicators to measure the overall exposure to foreign markets. Other competition indicators are:

[18] The assumption made here is that there will be greater variability in the data between sectors, as opposed to between surveyed years that will allow to capture more changes in the productivity measures. Moreover, it is worth mentioning that the survey population of the SAT has changed between 2005-2007, and 2012-2014. In the earlier version enterprises with 20 or more employees were surveyed, matching the survey method of the SIBS. While in later years enterprises with 10 or more employees were surveyed. This would have been a limitation of the analysis, if the data would have been used.

[19] Wages measures total compensation for all jobs, which consists of all payments in cash or in kind made by domestic producers to workers for services rendered. These include salaries, social contributions made by employers, and income for self-employed workers.

1. The proportion enterprises that indicated that multinational enterprises are present in the main market for the enterprise's main product (Multinational), 2012
2. The proportion of enterprises that indicated the number of competitors they have in the main market for the enterprise's main product, by number of competitors, 2012. These proportions were aggregated into three indicators: Low Competition (0-3 competitors), Low Competition (0-3 competitors), and High Competition (11-20+ competitors). Low Competition is used as a reference group (4-10 competitors).
3. Market share of highest selling good or service in the enterprise's main market (Share), 2012

Control Variables

Five provincial dummy variables, and the proportion of enterprises of which their head office was located in Canada in 2009 (CAN Office) are used as control variables.

IV. Results

The results of this analysis show the complexity of innovation, as well as the difficulty of measuring it using response survey data at an aggregated level. The general results are those of non-convergence for the model specified above, and for all of its various combinations. The presentation below discusses in detail the possible reasons for non-convergence.

Disentangling non-convergence results

Reaching convergence results with SEM models is tricky, this is even warned against in great detail by Stata's Manual. Luckily the Manual offers various methods of treating non-convergence, or at the very least diagnosing the reasons for it (Structural Equations Modelling Manual, 2013, p. 112-121). One of the main reasons noted is poor choice of starting points. The models variance-covariance matrix is calculated from its parameter estimates, thus before iteration begins those parameters may be such that the matrix is not positive definite. Thus, as a first measure to overcome this, various starting-point treatment methods were used.

As a first starting-point treatment method, all variables used in the model were standardized. This assists in finding a solution to the model, by ensuring that the starting points and variables are of the same scale. This is particularly important if some of the variables have high kurtosis.

However, this also means that interpreting any output result from the model would be difficult. Unfortunately, standardizing did not assist in convergence.

As a second method, the number of iterations were limited to 100 (near the number of iterations where the model stopped or substantially decreased in improvement steps), and the results of the non-convergence were examined. The results themselves are meaningless, but they could be used as potential starting points to assist in convergence, and to possibly detect the cause of the non-convergence (through examining missing variance-covariance results). This process was repeated 20 times for each possible combination of the equations above, the results were saved, and each model was re-run from a specific starting-point. Unfortunately, this did not assist in converging any of the 20 different versions of the model.

As a third method, various optimization techniques available through Stata's SEM software were used, these include: Newton-Raphson, BHHH, BFGS, and DFP. For further details on each technique, see Stata's SEM Manual 2013. The purpose of each optimization method is to "nudge" the model towards a convergence path. This step was once again repeated 20 times for each of the optimization methods, unfortunately convergence was not reached.

Poor Model Choice?

All of the methods above assumed that the model was specified correctly, and that multicollinearity is not a concern. At this point, the choice of the variables and the modelled dependencies of the variables were called into question. Even though, this model is very similar to that developed by Brouillette (2013), interactions and paths at the sector level may behave differently. Moreover, the possibility of multicollinearity between the variables of the model is examined.

Multicollinearity and Misspecification of Green Tech

Multicollinearity is difficult to detect in SEM models, particularly if the model does not converge. Moreover, if one of the variables is a perfect linear combination of the other variables, a singular matrix (which cannot be inverted) will cause the analysis to fail and not converge. As a first step, to avoid the possibility of linear dependency in the matrices, exogenous variables with a correlation of 0.58 and higher were temporarily removed from the model. These included: Green Technology 2012, Medium Competition, Exports, and Multinational variables. See the correlation table of the various exogenous variables below. Highlighted in red are correlations that could be considered high, while highlighted in grey are the variables that were removed to control for the high correlations.

Table 1: Correlation Matrix of Exogenous Variables, Second and Third Stage Estimation

Exogenous variables (2 & 3 stage)	Predicted RD	Green Tech 2009	Green Tech 2012	Total Past Innovation (2007-2009)	Multinational	Share	GVC	Exports	Educated	Medium Competition	High Competition	CAN Office 2009	Capital Stock
Predicted RD	1.00												
Green Tech 2009	-0.33	1.00											
Green Tech 2012	-0.42	0.92	1.00										
Total Past Innovation (2007-2009)	0.34	-0.27	-0.40	1.00									
Multinational	0.41	-0.60	-0.64	0.25	1.00								
Share	-0.32	0.21	0.31	-0.48	-0.41	1.00							
GVC	0.57	-0.28	-0.40	0.38	0.58	-0.55	1.00						
Exports	0.62	-0.28	-0.44	0.58	0.32	-0.54	0.77	1.00					
Educated	-0.05	-0.13	-0.02	0.07	0.18	-0.38	0.26	-0.03	1.00				
Medium Competition	0.52	-0.52	-0.63	0.40	0.31	-0.32	0.42	0.63	0.11	1.00			
High Competition	-0.22	0.19	0.16	-0.23	0.03	0.10	-0.22	-0.37	-0.43	-0.69	1.00		
CAN Office 2009	-0.37	-0.08	-0.05	0.22	-0.14	0.26	-0.37	-0.29	-0.17	-0.49	0.45	1.00	
Capital Stock	-0.42	0.13	0.36	-0.45	0.00	0.19	-0.25	-0.26	-0.11	-0.46	0.20	0.00	1.00

Next, the remaining Green Technology variables were replaced one-by-one by other advance technology variables available through SIBS. For a complete list see the robustness testing variables for Green Tech in Appendix A. These tests were conducted for each of the possible combinations of the model, as well as each additional variable was added to the original model for possible missing links (except ADVTECH, which is the composite variable of all of the advance technology variables). Unfortunately, convergence was not reached.

Weak Relationship among the Components of the Model

Another possible explanation for non-convergence is that the relationship between Current Innovation, Innovative Activity, and Productivity is weak. Estimating weak relationships using SEM is possible when the sample size is greater than 200. Though, for strong relationships, 10 observations per estimated parameter may be sufficient (Wolf et al., 2015; Corrado and Giuseppe, 2016). With that said, lower sample sizes could be used for models with no latent variables (path analysis), models where all the latent variables are fixed (usually to one), models with strong correlations, and simpler models (Kenny, 2015). Thus to account for the above, different paths connecting between Current Innovation, Innovative Activity, and Productivity are modified. These modifications include:

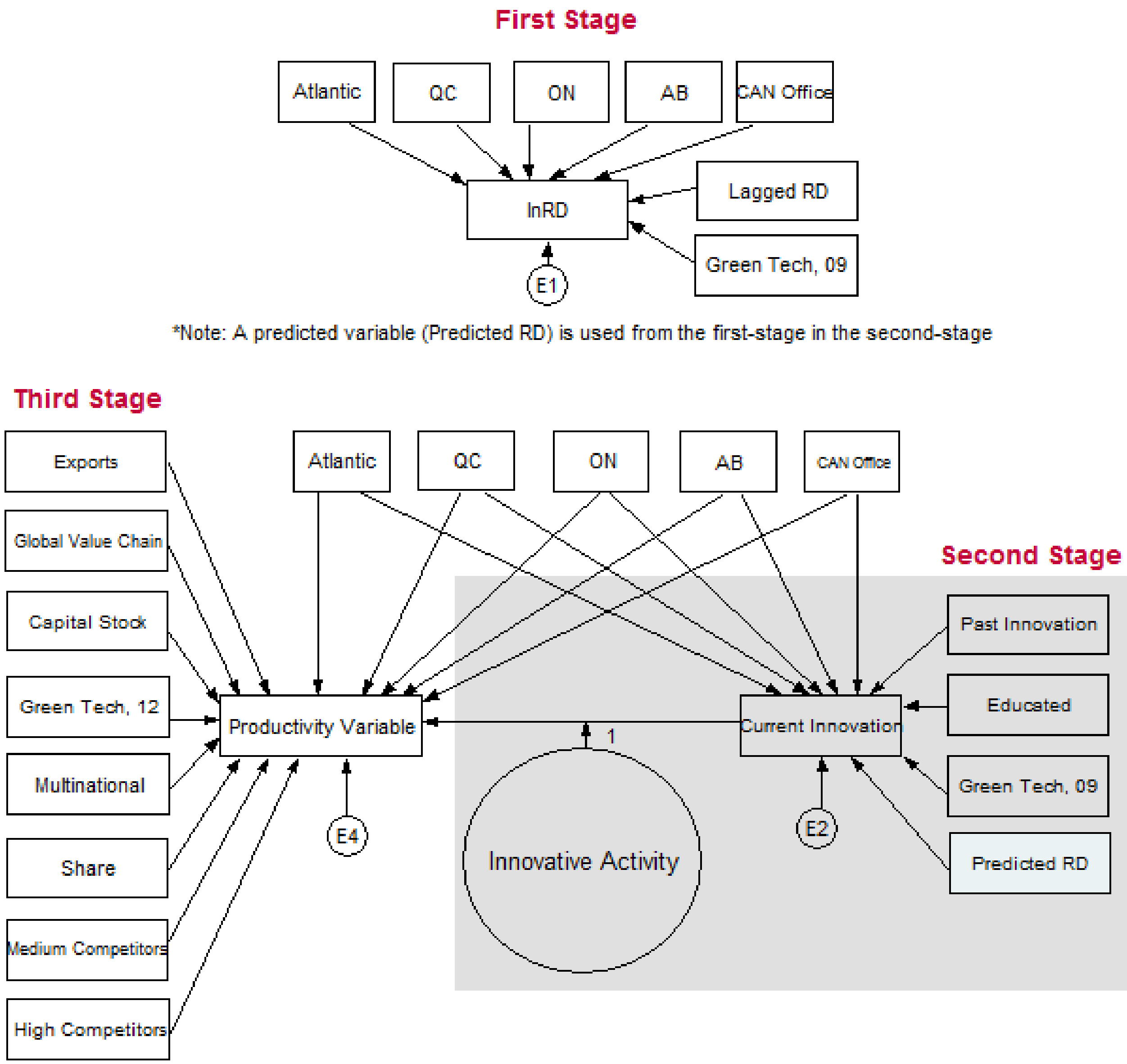
1. Removing the latent variable completely (path analysis model)
2. Simplifying the model by removing some control variables from the model (except dummy provincial variables), these include: GVC, Multinational, Share, Medium Competition, High Competition, and Educated. This leaves the Productivity equation with four identifying variables: Exports, Capital Stock, Green Tech (2012), and the latent Innovative Activity variable; and the Current Innovation equation with three identifying variables: Past Innovation, Green Tech (2009), and Predicted RD
3. Including a direct link between the Current Innovation equation, and the Productivity equation
4. Linking the latent variables' path to the path between Current Innovation, and the Productivity equation (random slope model)—or in other words, fixing the latent variable to one

The first three methods did not assist in converging the model, while the fourth option did. Below is a discussion of the model, and the possible causes of convergence.

Generalized Structured Equation Modelling (GSEM): Random Slope Model

The GSEM model is designed to better handle multilevel models, thus binding paths, and specifying random slopes/intercepts are options that are available through GSEM. Unfortunately, Stata's GSEM model does not treat missing variables in the same way the SEM model does, and thus the sample size was reduced to 18 observations. Below is a path diagram of the model that converged.

Figure 2: Generalized Structural Equation Model, Random Slope Model for R&D, Innovative Activity, and Productivity—Path Diagram



Before examining the results, it is important to understand the relationship that is implied by this diagram. Notice there now appears the number one right next to "Innovative Activity". This is because, in SEM models, the scale of each independent variable must be fixed to a constant, typically to one or to that of one of the measured variables. Thus, the regression coefficient for the path from the latent variable, “Innovative Activity”, is fixed to one as it is not connected to any measured variable, but rather to the path between Current Innovation and Productivity. Linking a latent variable to a path, allows for the slope between the Productivity Variable and Current Innovation to vary. Therefore, the model assumes that there exists some form of clustering in the model, which occurs between Current Innovation and Productivity (Stata SEM Manual 2013, p.32-33). However, it is worth mentioning that when trying to regress each model with clustered variances, the model does not converge. Moreover, performing a simple sensitivity test of adding or removing any of the variables once again leads to non-convergence. This is another indication of a possible poor model fit or multicollinearity, which were not accounted for. Another possible explanation, is that the model is not identified, as the latent variable has only one indicator (Current Innovation) that loads on it. Models with only one latent variable, have a greater likelihood of being identified if they have at least three indicators that load on it, and the errors of the indicators are not correlated with one another (Tabachnick and Fidell, 2007). Thus, this could provide an explanation as to why fixing the latent variable to one, solves the identification problem of the model[20].

Nevertheless, it is interesting to examine the results from this analysis. Table 2 below summarizes the parameters by presenting only significant parameters. Green boxes indicate a positive relationship, while red boxes indicate a negative relationship. It is worth noting, that SEM/GSEM models are best used for investigating links and relationships, and not for determining exact effects. Moreover, since all variables were standardized interpreting the results is difficult. The table below also reports AIC & BIC measures of good-fitness (low numbers are considered better).

[20] Although from looking at the log-likelihood of each iteration, the model did not show signs of misidentification, which include the output of the log-likelihood from each iteration remaining “stuck” on the same value (Stata’s SEM Manual 2013, p.112-121).

Table 2: Significant Estimated Parameters, at least a 0.1 level[21][22]

	Current Innovation		Current Marketing	Current Org	Current Process		Current Product	
Predicted RD								
Green Tech, 2009								
CAN Office, 2009								
Past Innovation								
Education								
AB								
Atlantic								
QC								
ON								
	Labour Productivity	Value Added	Value Added	Labour Productivity	Value Added	Labour Productivity	Value Added	Labour Productivity
Current Innovation								
Green Tech, 2012								
CAN Office, 2009								
Multinational								
Share								
Medium Competition								
High Competition								
Capital Stock								
GVC								
Exports								
AB								
Atlantic								
QC								
ON								
N	18	18	19	18	**18**	**18**	19	19
AIC	65	66	90	72	**41**	**58**	60	88
BIC	89	90	116	96	**65**	**82**	86	114

[21] Models that did not converge were not included, specifically models using wage and wage per hour as dependent variables, market innovation and labour productivity, and organizational innovation and value added.

[22] Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) presented in the table are both comparative measures of model fit, which are meaningful only when comparing between models. One advantage of both measures is that they both can be computed for models with zero degrees of freedom (Kenny, 2015).

Firstly, from the table we can see that the Process model for both labour productivity and value added, provides a better fitted model, as evident from the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values, where smaller values indicate a better fitted model. Secondly, we can see that the relationship between Green Technology, and Total Innovation, and Process Innovation is positive. This could indicate that the adoption of advance green technologies forces companies to implement process innovations in the short-run, increasing the likelihood of the incidence of innovation. However, in the short-run adopting advance green technologies does not generally translate towards labour productivity or value added improvements. This is in in line with current research on the Porter Hypothesis (see Ambec et al., 2011, for a summary of 20 years of research on the Porter Hypothesis). Moreover, the results are generally in line with Brouillette's (2013) findings, in that the incidence of innovation is persistent to future periods. Meaning, enterprises that innovate today are also likely to innovate in the following years (evident by positive sign of Past Innovation). A possible explanation for this, which is also evident in the results above (predicted R&D is positive when it's significant) is that investing in R&D create sunk costs, as well as a long term plan for innovation. However, the results above differ from Brouillette's (2013) research in that the relationship between process innovation and the two productivity measures, and product innovation and the two productivity measures is reversed. Brouillette's (2013) research shows that product innovation is positive and significant with respect to productivity, while process innovation is either insignificant or negatively correlated. On the other hand, Mairesse et al. (2005) find that process innovations yield higher returns than product innovations, as product innovations can take more time to materialize into measurable productivity increases.

With that said, the results above should be taken with a grain of salt for two main reasons: the model is not stable, and the sample size is fairly small. Although recent research on SEM/GSEM models has shown that even samples as small as 20-30 could have explanatory powers (Wolf et al., 2015; Corrado and Giuseppe, 2016).

Investigating the Individual Effects of each Equation

Since the relationship and the combined effects of the structural model above could not be investigated, and the random slope model was not stable, the next section aims to investigate each endogenous variable and its components separately, using SEM's path analysis in the following way:

1. Similar to the SEM model, the R&D equation is estimated, and its predicted values are saved. The results are then discussed, with an emphasis on the effect of the use of advance green technology by each sector
2. Next, similar to the SEM model above, the predicted values from the first equation are used in the Current Innovation equation, and its predicted values are saved. The results are then discussed, with an emphasis on the effect of the use of advance green technology by each sector
3. Lastly, the predicted values from the second equation, predicting Current Innovation output, are used in the productivity equation. The results are then discussed.

For simplicity sake, only the relationship between R&D, Total Innovation, and Labour Productivity are investigated. Each equation is estimated using SEM's ML estimation (Labour Productivity is also estimated using OLS). Using SEM's ML estimation without a latent variable allows to investigate the path dependencies between the variables, while accounting for the missing variables in each equation. However, it should be noted that each equation only measures the relationship between the endogenous and exogenous variables, and thus causality could not be inferred.

R&D and Advance Green Technology

From estimating equation (1) from The Model section (Predicted R&D equation), both exogenous variables Past R&D (2004-2006) and Green Tech (2009) are significant at 1% level of significant. Past R&D is found to have a positive relationship with the endogenous variable, average log of R&D (2007-2009). While, Green Tech is found to have a negative relationship with the average log of R&D (2007-2009). The relationship with Past R&D could be explained by the fact that R&D much like innovation is persistent. Meaning, enterprises that perform R&D today are most likely to perform R&D in the near future due to sunk costs, and long-run investment plans. The relationship with Green Tech could possibly be explained by taking into account the decision-process of firms to perform each type of advance technology. Using advance green technologies could be an unplanned decision, mandated by government regulations for example, and thus in the short-run it draws away from R&D expenditures as funds are relocated.

These results hold, even after adding an additional advance technology variable. See table Robustness Testing: Green Tech in Appendix A for a complete list of all of the variables that were added each in their turn. In total 11 equations were estimated for the robustness test (nine types of advance technology use, total advance technology used, and no advance technology used)[23]. While performing the tests, two additional variables were found to be positively significant:[24] ADVNANO and ADVOTHER[25]. ADVNANO is defined as the proportion of enterprises that used advanced nanotechnologies in 2009, while ADVOTHER is the proportion of enterprises that used other types of advance technology (not defined by the other eight types of advance technologies in the survey). Estimating all three variables together in the same model maintains the relationships already established. This further corroborates the theory proposed above, that the use of advance green technologies reduces R&D expenditures by drawing away funds from it. While other types of advance technologies either do not influence R&D, or increase the expenditures on R&D as they were planned ahead of time by the enterprises.

Appendix B, Table 1 presents the results of both models and compares between them using goodness of fit statistics. Unlike OLS, SEM models require the examination of several goodness of fit measures to arrive at a conclusion that a proposed model fits the data well, and to decide which model is better. Thus, the table offers four different goodness of fit measures: Comparative Fit Index (CFI), R^2, Root Mean Squared Error of Approximation (RMSEA), and chi-square, and two comparative fit measures: Akaike information criterion (AIC), and Bayesian

[23] While estimating the relationship between total advance technology used and Current Innovation, and no advance technology used and Current Innovation, each variable was naturally used on its own without the inclusion of advance green technologies.
[24] Statistical significance is assumed at below 10% level of significance.
[25] The investigation of why each advance technology variable, aside from advance green technology, is either positively or negatively associated with R&D is outside of the scope of this paper. The variables are used only for robustness and model validation.

information criterion (BIC)[26]. Reviewing the measures, we can see that both models fit the data well, though the first model, using advance green technologies only, fits it slightly better (chi-square is smaller). Moreover, reviewing the AIC and BIC measures for both models, we can see that the first model fits better than the second (using all three significant advance technology variables) as the models AIC and BIC values are smaller. Thus, only the first model is used to generate predicted values.

Current Innovation, Predicted R&D, Past Innovation, and Green Tech

From estimating equation (2) from The Model section (Current Innovation equation), Past Innovation and Green Tech are both significant (5% and 1% level, respectively) and have a positive relationship with Current Innovation, while Past R&D is insignificant. The relationship between Past Innovation and Current Innovation could be explained by innovation being persistent. While, the positive relationship between the use of green technology and innovation could partially corroborate the Porter Hypothesis, hinting that using green technology leads to greater innovation in each sector. As discussed previously, the lack of relationship between Predicted R&D and Current Innovation could hint at the fact that R&D takes longer to actualize into innovative activity (if at all). This results are supported by the Random Slope model proposed above.

As was done previously, the robustness of the relationship between the use of green technology and Current Innovation is examined by adding each advance technology variable in its turn to the model proposed. The results highlight the complex relationship the use of the various types of advance technologies have on Current Innovation. As well as, the results are generally consistent with Green Tech remaining statistically significant and positive, except for when ADVINFO (proportion of enterprises that used advanced information integration and control technologies in 2009) is added. In this case, Green Tech becomes insignificant.

[26] CFI measures the discrepancy function and adjusts it for sample size. It ranges from 0 to 1, with values closer to 1 indicating a better model fit (value of 0.9 or higher is considered an acceptable model fit). R^2 measures how well the data fits the model proposed, with measures of 0.5 and higher generally considered acceptable model fits. RMSEA is related to the residual in the model, its values range from 0 to 1, with smaller RMSEA value indicating better model fit. Values of 0.06 or less are considered an indication of a good model fit. Chi-square measures the difference between expected and observed covariance matrices. Values closer to 0 indicate little difference between the expected and observed covariance matrices. In general, a smaller chi-square with a larger probability level is desirable (Hu & Bentler, 1999). Both AIC and BIC are a comparative measure of fit, and can only be used to compare between different models proposed (Kenny, 2015).

Moreover, from this investigation three other advance technology variables are found to be significant (ADVAUTO, ADVCOMM, and ADVCOMP_3). ADVAUTO measures the proportion of enterprises that used advanced automated material handling technologies in 2009. ADVCOMP_3 measures the proportion of enterprises that used advanced computerized inspection technologies in 2009. Both of these variables have a positive relationship with Current Innovation. While ADVCOMM, which measures the proportion of enterprises that used advanced communication technologies in 2009, has a negative relationship with Current Innovation. When estimating all four statistically significant variables in the same model, ADVCOMM and Predicted R&D are no longer significant, and ADVCOMP_3 becomes negatively associated with Current Innovation[27]. Next, ADVCOMM is removed from the model, and only the remaining statistically significant advance technology variables are maintained. The results are similar to the model with all four advance technology variables present.

In addition, ADVTECH and NOADV, were both found to be statistically significant, and with expected associated signs to Current Innovation. ADVTECH is the measure of the total use of advance technologies regardless of the type—it is found to be positive. NOADV is the proportion of enterprises that did not use any advance technologies—it is found to be negative. In the ADVTECH and NOADV models, Predicted R&D becomes statistically significant with a negative associated relationship to Current Innovation. This is in line with the previous assumption that the benefits of R&D take time to actualize. Throughout this investigation, Past Innovation remains significant and positive.

Next, as in the R&D equation, two models are compared for their goodness of fit. The first model is the original one, with the Green Tech only, while the second model includes Green Tech, ADVAUTO, and ADVCOMM. The results of both models along with the various goodness of fit models are presented in Appendix B, Table 2. As with goodness of fit investigation, the first model is found to be a better fit for the exact same reasons (smaller chi-squared, AIC, and BIC values). Thus, only the first model is used to generate predicted values.

Productivity, Predicted Current Innovation, and Green Tech

[27] The investigation of why each advance technology variable, aside from advance green technology, is either positively or negatively associated with Current Innovation is outside of the scope of this paper. The variables are used only for robustness and model validation.

Using SEM to estimate equation (3) from The Model section (Productivity equation), all the variables estimated are insignificant (except Atlantic). This result holds when removing variables one by one, as well as when estimating the model using OLS. Moreover, when estimating equation (3) using OLS the F-statistic for overall significance is insignificant for all various combinations of the variables, except for when regressing labour productivity on Predicted Current Innovation, while controlling for provincial effects. This is an indication that there is a relationship between labour productivity and Current Innovation, though this relationship is distorted by multicollinearity in the model.

Table 3: SEM Goodness of Fit Results, Productivity Model

Statistic	Result
R^2	0.336
CFI	1.00
Chi-square (P >chi-square)	16.9 (0.264)
RMSEA	0.00

Table 3 above summarizes key goodness of fit measures from the SEM estimation for equation (3). It shows that while R^2 is low, the Comparative Fit Index (CFI), Root Mean Squared Error of Approximation (RMSEA), and chi-square fit measure indicate that the model is generally a good fit[28]. This further corroborates the possibility of multicollinearity in the models proposed, which could explain why the original model in Section III did not converge.

[28] CFI is as high at it could range, RMSEA is as low as it could range, and chi-squared is fairly low and insignificant.

V. Conclusion

In this paper the relationship between R&D, innovation, and productivity was examined by using a variation of a structural CDM model, by examining the relationship at the sector-level, as well as incorporating the use of advance green technologies. Due to data limitations and possible multicollinearity within the model, the relationship that was established between the three variables at the sector-level is weak, and thus a concrete conclusion could not be reached with regards to the results found in the Random Slope model. However, the results that were found using the Random Slope, and investigating the individual effects of each endogenous equation, are generally in-line with previous research on the subject, and do show a positive relationship between the use of advance green technologies and the proportion of innovation incidence within each sector. This relationship is most evident for the total current innovation, and was also found to be positive for current process innovation when examining the results of the Random Slope model. Moreover, the general results found in other research for the persistence of inputs to innovation are also corroborated here. Further research with greater access to confidential data, even at the industry level could significantly improve the results of this paper, and shed some light on the aggregate effects of firm's decisions to innovation on productivity and the long-run well-being of Canadians.

Appendix A: Sample, Variables Used, and Data Sources

Sample

SECTORS	PROVINCES AND REGIONS
Agriculture, forestry, fishing and hunting	Ontario
Mining, quarrying, and oil and gas extraction	Quebec
Utilities	Alberta
Construction	Atlantic Canada: New Brunswick, Newfoundland and Labrador, PEI, and Nova Scotia
Manufacturing	Rest of Canada: British Columbia, Territories, Saskatchewan, and Manitoba
Wholesale trade	
Retail trade	
Transportation and warehousing	
Information and cultural industries	

Data Sources

STATISTICS CANADA ADMINISTRATIVE DATABASES	
Name	Years
Research and Development in Canadian Industry (RDCI)	2004-2009
Canadian Productivity Accounts (CPA)	2010-2012
i. Labour Productivity Measures - Provinces and Territories (Annual)	
Input and Output Accounts (IO)	2010-2012
i. Stock and Consumption of Fixed Non-residential Capital ii. Provincial and Territorial Gross Domestic Product by Income and by Expenditure Accounts a. Gross Domestic Product at basic prices b. Implicit Price Indexes	
STATISTICS CANADA SURVEYS	

Survey of Innovation and Business Strategy (SIBS)	2009, 2012

Variables Used, Definitions, and CANSIM Table Numbers

R&D – Equation (1)			
Variable	Description	Source	CANSIM
$lnRD_i^{2007-2009}$	Log average of total business enterprise R&D intramural expenditures, in $1000, chained=2007[29], (2007-2009)	RDCI	358-0161
$Past\ RD_i^{2004-2006}$	Lagged R&D expenditure (same variable as above), in $1000 (average 2004-2006)	RDCI	358-0161
$Green\ Tech_i^{2009}$	Proportion of enterprises using advance green technologies, in 2009	SIBS	358-0237

[29] As mentioned previously, R&D was deflated using the GDP Implicit Price index, chained=2007

Inputs, Past Innovation– Equation (2)			
Variable	Description	Source	CANSIM
$PRCS_i^{2007-2009}$	Proportion of enterprises that implemented a new or significantly improved production process, distribution method, or support activity for goods or services, 2007-2009	SIBS	358-0221
$PRDT_i^{2007-2009}$	Proportion of enterprises that introduced a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems, 2007-2009	SIBS	358-0221
$ORG_i^{2007-2009}$	Proportion of enterprises that introduced a new organizational method in an enterprise's business practices (including knowledge management), workplace organization or external relations that has not been previously used by the enterprise, 2007-2009	SIBS	358-0221
$MRKT_i^{2007-2009}$	Proportion of enterprises that implemented a new marketing concept or strategy, significantly differing from the enterprise's existing marketing methods, 2007-2009	SIBS	358-0221
$INNO_i^{2007-2009}$	The proportion of innovative enterprises who introduced any product, process, organizational or marketing innovation, 2007-2009	SIBS	358-0221
$Green\ Tech_i^{2009}$	Proportion of enterprises using advance green technologies, in 2009	SIBS	358-0237
$Educated_i^{2009}$	Percentage of employees with a university degree for each sector, in 2009	SIBS	358-0322

Outputs, Current Innovation– Equation (2)			
Variable	Description	Source	CANSIM
$PRCS_i^{2010-2012}$	Proportion of enterprises that implemented a new or significantly improved production process, distribution method, or support activity for goods or services, 2010-2012	SIBS	358-0221
$PRDT_i^{2010-2012}$	Proportion of enterprises that introduced a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems, 2010-2012	SIBS	358-0221
$ORG_i^{2010-2012}$	Proportion of enterprises that introduced a new organizational method in an enterprise's business practices (including knowledge management), workplace organization or external relations that has not been previously used by the enterprise, 2010-2012	SIBS	358-0221
$MRKT_i^{2010-2012}$	Proportion of enterprises that implemented a new marketing concept or strategy, significantly differing from the enterprise's existing marketing methods, 2010-2012	SIBS	358-0221
$INNO_i^{2010-2012}$	The proportion of innovative enterprises who introduced any product, process, organizational or marketing innovation, 2010-2012	SIBS	358-0221

Productivity– Equations (3)			
Variable	Description	Source	CANSIM
3.1 $\Delta WAGES_i^{2010-2012}$	Change in total compensation for all jobs for employees and self-employed, chained=2007, 2010-2012	SIBS	383-0031
3.2 $\Delta WAGES\_HR_i^{2010-2012}$	Change in total compensation divided by the number of hours worked in all jobs, chained=2007, 2010-2012	SIBS	383-0031
3.3 $\Delta LP_i^{2010-2012}$	Change in labour productivity, chained=2007, 2010-2012	SIBS	383-0011
3.4 $\Delta VA_i^{2010-2012}$	Change in real value added, chained=2007, 2010-2012	SIBS	383-0011
$Predicted\ RD_i^{2007-2009}$			Eq. (1)
$Innovative\ Activity\ *_i^k$	Five possible latent variables generated from the second stage of equation 2		Eq. (2)

Control Variables			
Variable	Description	Source	CANSIM
$Exports_i^{2010-2012}$	Enterprises that exported or attempted to export goods or services outside of Canada	SIBS	358-0300
$\Delta Capital\ Stock_i^{2010-2012}$	Change in the ratio of capital/labour stock, 2010-2012. Labour was gathered from CPA database and it is measured by the total hours worked for all jobs	SIBS	383-0031
$GVC_i^{2010-2012}$	Proportion of enterprises that had activities outside of Canada, 2010-2012	SIBS	358-0279
$Green\ Tech_i^{2012}$	Proportion of enterprises using advance green technologies	SIBS	358-0238
$Share_i^{2012}$	Market share of main products 2012	SIBS	358-0329
$Low\ Competitors_i^{2012}$	Proportion of enterprises with 0-3 competitors in their main market	SIBS	358-0331
$High\ Competitors_i^{2012}$	The proportion of enterprises with 11-20+ competitors in their main market	SIBS	358-0331
$Educated_i^{2012}$	Percentage of employees with a university degree for each sector, in 2012	SIBS	358-0322
$CAN\ Office_i$	Proportion of enterprises with a head office in Canada, 2009	SIBS	358-0272

ROBUSTNESS TESTING: GREEN TECH			
Variable	Description	Source	CANSIM
$ADVTECH_i$	Proportion of enterprises using advance technologies in 2009 & 2012 (total)	SIBS	358-0237
$ADVCOMP\_1_i$	Proportion of enterprises using advanced computerized design and engineering in 2009 & 2012	SIBS	358-0237
$ADVCOMP\_2_i$	Proportion of enterprises using advanced computerized processing, fabrication, and assembly technologies in 2009 & 2012	SIBS	358-0237
$ADVCOMP\_3_i$	Proportion of enterprises using advanced computerized inspection technologies in 2009 & 2012	SIBS	358-0237
$ADVCOMM_i$	Proportion of enterprises using advanced communication technologies in 2009 & 2012	SIBS	358-0237
$ADVAUTO_i$	Proportion of enterprises using advanced automated material handling technologies in 2009 & 2012	SIBS	358-0237
$ADVINFO_i$	Proportion of enterprises using advanced information integration and control technologies in 2009 & 2012	SIBS	358-0237
$ADVBIO_i$	Proportion of enterprises using advanced biotechnologies/bio-products in 2009 & 2012	SIBS	358-0237
$ADVNANO_i$	Proportion of enterprises using advanced nanotechnologies in 2009 & 2012	SIBS	358-0237
$ADVOTHER_i$	Proportion of enterprises using other type of advanced technology in 2009 & 2012	SIBS	358-0237
$NOADV_i$	Proportion of enterprises using no advanced technology use in 2009 & 2012	SIBS	358-0237

Appendix B: Individual Effects Models Results

Table 1: Modelling the Relationship between R&D, Past R&D, and Green Tech

Variables	SEM MLMV Estimation[30]	
	Model 1	**Model 2**
Past RD	1.027*** (0.206)	0.926*** (0.141)
Green Tech, 09	-0.080*** (0.029)	-0.122*** (0.228)
ADVNANO		0.136*** (0.053)
ADVOTHER		0.888 (0.229)***
CAN Office, 09	-0.037 (0.050)	-0.026 (0.339)
AB	-0.409 (0.746)	-1.421** (0.687)
QC	-0.476 (0.859)	-0.986 (0.638)
ON	-0.416 (0.679)	-1.492*** (0.563)
Atlantic	-1.388* (0.758)	-1.783*** (0.577)
Constant	8.558** (4.309)	8.012*** (2.892)
N	45	45
R^2	0.663	0.858
CFI	1.00	1.00
Chi-square (P >chi-square)	30.31 (0.00)	44.9 (0.00)
RMSEA	0.00	0.00
AIC	773.6	987.7
BIC	853.1	1105.1

[30] Observed Information Matrix (OIM) standard errors are used.

*10% level of significance
**5% level of significance
***1% level of significance

Table 2: Modelling the Relationship between Current Innovation, Past Innovation, Predicted R&D, and Green Tech

Variables	SEM MLMV Estimation[31]	
	Model 1	**Model 2**
Past Innovation	0.536** (0.238)	0.295*** (0.119)
Predicted RD	-0.005 (0.192)	0.032 (0.1048)
Green Tech, 09	0.561*** (0.165)	0.755*** (0.148)
ADVAUTO		0.447*** (0.116)
ADVCOMP_3		-0.375*** (0.121)
Educated, 09	0.332* (0.192)	0.446*** (0.113)
CAN Office, 09	-0.066 (0.216)	-0.122 (0.129)
AB	0.152 (0.149)	0.251*** (0.086)
QC	0.349* (0.186)	0.504*** (0.126)
ON	0.098 (0.133)	0.033 (0.075)
Atlantic	0.028 (0.186)	0.215* (0.121)
Constant	0.147 (3.045)	1.377 (1.960)
N	45	45
R^2	0.799	0.947
CFI	1.00	1.00
Chi-square (P >chi-square)	13.8 (0.126)	30.5 (0.001)
RMSEA	0.00	0.00
AIC	1318.6	1662.6
BIC	1436.0	1825.2

[31] Observed Information Matrix (OIM) standard errors are used, as well as standardized estimates

*10% level of significance
**5% level of significance
***1% level of significance

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