Technological Chang, Technical Efficiency and Canada's Post-2000 Productivity Performance

Jianmin Tang (ISED)

Weimin Wang (Statistics Canada)

Abstract

Productivity growth has decelerated in Canada since 2000. The deceleration has attracted a great attention from researchers and policy makers, which has an important implication for economic growth and living standard improvements. Despite an extensive research on this important topic, however, the cause is still unclear. In this paper, we shed more light on the productivity slowdown. Unlike most studies that focus directly on the actual productivity, in this paper we decompose the actual productivity into two components: technological change and technical efficiency. Technological change measures the maximum productivity potential (or productivity frontier) while technical efficiency reflects the ability/technique in achieving the potential. Using a linked firm level data, we intend to show if the productivity slowdown is mainly due to the decline in technological progress or in efficiency improvement. We also extend the analysis to provide further evidence on the driving forces (for example, investments in R&D, ICTs and intangibles) that underlie the developments.

1. Introduction

Productivity growth has decelerated over the past decades in most developed countries. For Canada, the slowdown was substantial since 2002, despite some recovery after the financial crisis (Figure 1). This observation was coupled with an increased dispersion in productivity among firms even within a narrowly defined industry. The productivity growth deceleration and the increased dispersion have attracted a great attention from researchers and policy makers as they undermine the efficient reallocation of production resources, which has an important implication for economic growth and living standard improvements. Despite an extensive research on this topic, however, the causes of these phenomena are still subject to debate. Various conjectures have been put forward. For example, Gordon (2012) argues that the productivity growth deceleration is because the slowdown in important innovation and diminishing returns of the innovation process. Others suggest that the waning of ICT-related productivity boom in the decade around 2000 and the weak demand and great uncertainty associated with the financial crisis in 2008 were mainly responsible (for example, McKinsey Global Institute 2018).



In this paper, we also shed light on the cause of the productivity problems. Unlike most studies that focus directly on the actual productivity, in this paper we decompose the actual productivity into two components: technological change and technical efficiency. Technological change measures the productivity potential (or productivity frontier) while technical efficiency reflects the ability in achieving the potential. Factors in affecting technological change may be different from those in influencing technical efficiency. The separation is important as it not only allows us to distinguish technological progress from efficiency improvement but also directly link factors to each of the components they affect. This necessarily improves estimation efficiency and the significance of those factors.

2. Methodology

To empirically determine the factors that affect technological change and technical efficiency, we conduct a stochastic frontier analysis. The stochastic frontier model was pioneered by Aigner

et al. (1977).¹ We tailor the model here to estimate the potential effect of factors in affecting technological change and how the actual effect depends on a number of other factors.

For simplicity, we ignore the time dimension and assume that the production function for firm i is:

$$Y_i = A_i f\left(L_i, K_i, M_i\right),\tag{1}$$

where Y_i is gross output; A_i is the productivity parameter; L_i , K_i , and M_i are the inputs representing labour, capital and intermediate inputs, respectively.

The productivity parameter indicates how efficiently the firm can produce output by using the inputs. It is a multiplier, reflecting the firm's efficiency in transforming inputs into outputs. As discussed earlier, it depends on technological change and the ability of firms to achieve technical efficiency. Denote A_i^* as the technological change, which is the maximum technical efficiency level, for firm *i*.

Technological change reflects technological development. It depends on the firm's innovation, that is, the firm's deliberate application of new ideas and information to produce products or services from the inputs. In this paper, we assume that technological change is mainly driven by research and development (R&D) and foreign ownership. Aghion and Howitt (1992) suggests that the innovative capacity depends on R&D spending and the technological or innovative capacity feeds on past and current investment in R&D. In addition, we consider foreign ownership to be a factor that is more important for productivity frontier. It has been generally believed that foreign-controlled firms in Canada are significantly more productive than Canadian-controlled firms mainly because they benefit from advanced technology from their parents (Rao et al. 2009; Tang and Rao 2003). Technological change is, however, not entirely under the control of the firm, and is subject to a random error, v_i . In formulation, the maximum output for firm *i*, Y_i^* , under full technical efficiency is

$$Y_i^* = A^* \left(\mathbf{R}_i, \mathbf{Z}_i \right) f\left(L_i, K_i, M_i \right) \exp(v_i), \tag{2}$$

where $Y_i^* \ge Y_i$, that is, the maximum output is larger or equal to the actual output. A_i^* is the frontier (maximum) of productivity level, which is a function of R&D and other control variables. \mathbf{R}_i is a vector of R&D variables related to past and current R&D investments of firm i.² \mathbf{Z}_i is a vector of controlling variables that may also influence technical change such as foreign ownership and industry specific effect. v_i is a random error term independently and identically distributed as $N(0, \sigma_v^2)$, which reflect the stochastic nature of the frontier as the frontier is not entirely under the control of the firm.

¹ Kumbhakar and Lovell (2000) provide an excellent introduction to stochastic frontier analysis.

² R&D variables include R&D intensity and lagged R&D intensity.

Equation (2) represents the maximum potential output under full technical efficiency or operation along the production possible frontier. However, not all firms are able to exploit production technology efficiently and operate along the frontier. In this paper, we assume that the technical efficiency in production depends on the firm's capacity in exploitation of the technological change, $\theta(X_i)$, which is influenced by a number of internal factors (X_i) associated with firms' operations. Re-formulating equations (1) and (2), we derive the following

$$Y_i = A^* (\mathbf{R}_i, \mathbf{Z}_i) \theta(\mathbf{X}_i) f(L_i, K_i, M_i) \exp(v_i)$$
(3)

where θ_i is the technical efficiency of firm *i*, with $0 < \theta_i \le 1$ and being independent with the error term v_i . It is determined by a set of x variables. How closely the firm operates near the production possible frontier depends on the technical efficiency level (θ_i) of the firm in transforming inputs into output.

The advantage of this model, equation (3), decomposes productivity into two components: technological change (A_i^*) and technical efficiency (θ_i). The formulation allows us to trace the productivity problem to technological change or technical efficiency or both. More interestingly, it enables us to explore the factors underlying the change associated each component.

To illustrate how equation (3) is estimated, we assume that $\ln \{A^*(\mathbf{R}_i, \mathbf{Z})\}$ is linear in R&D and control variables and $f(L_i, K_i, M_i)$ is a Cobb-Douglas function. In addition, we follow the tradition under the stochastic production frontier framework and define $u_i = -\ln \theta_i$. This yields the following stochastic frontier regression model:

$$\ln(Y_i) = \alpha_0 + \alpha_L \ln L_i + \alpha_K \ln K_i + \alpha_M \ln M_i + \sum_{j=1}^k \beta_j \ln R_{i,j} + \sum_{j=k+1}^s \beta_j Z_{i,j} + v_i - u_i, \qquad (4)$$

where $u_i \ge 0$ is an additional error term, which a measure of technical inefficiency or the distance to the production possible frontier.³

Following Stevenson (1980), we specify u_i as a one-sided error term, independently and normally distributed with nonzero mean and truncation point at 0, $N^+(\mu_i, \sigma_u^2)$.⁴ We hypothesize that the mean of the distribution of inefficiency is heterogeneous across firms, depending on a set of the factors that may influence technical efficiency.

$$\mu_i = \gamma_0 + \sum_{h=1}^m \gamma_h X_{i,h} \tag{5}$$

³ Note that $u_i = -\ln(\theta_i) \approx 1 - \theta_i$.

⁴ The superscript "+" refers to truncation on the left at zero.

where \mathbf{X}_{i} is a vector of the covariates that may affect technical efficiency.

There are many factors that affect productivity. In additional to R&D, we also consider firm specific factors such as ownership, firm age, and investments in ICTs and intangibles. These factors may affect both technological change and technical efficiency although to a different extent. If a factor most likely affects technological change, we assign the factor to be an underlying variable for technological change. The same is true for technical efficiency. In this paper, besides R&D, we have also considered foreign ownership to be an important factor in influencing productivity frontier.

We consider the rest of the factors to be underlying factors that affect efficiency. The first x variable is investment in information and commutation technologies (ICTs). The adoption of ICTs allows firms to be more efficiently organize their inputs, manage their inventories, and conduct international business activities. In other words, ICTs play a substantive role in the generation, storage and transmission of information and in the reduction of market failures (Biagi, 2013).

The next x variable for efficiency improvement is investment in intangibles other than R&D such as firm-specific human, knowledge or business organization capital. The intangible capital enables efficient business execution (e.g., Battisti et al., 2012). Corrado et al. (2009) shows that intangible capital played a significant role in economic growth in the United States, and Ilmakunnas (2013) also linked investments in intangibles to higher productivity performance in Finland. For measuring investment in non-R&D intangibles at the firm level, we generally follow Corrado et al. (2005, 2009), with non-scientific innovative properties (architect fees) and economic competencies that include organizational capital (20% of director and management salaries plus consulting fees), brand equity (60% of advertising) and firm-specific human capital (training).

We also believe that young firms have efficiency issues. Liu and Tang (2014) show that entrants take about 5 years to become as productive as incumbents as it takes time for young firms to overcome some unfavourable conditions associated with start-ups (e.g., demand deficit, scale, learning by doing, and start-up costs). Thus, matured firms have an efficiency advantage over young firms.

3. Data

The stochastic frontier regression model, equation (4), is estimated using a firm-level dataset that consists of three micro-data files compiled by Statistics Canada.⁵ These three databases are administrative microdata, covering all industries and for 2000-2014. The link of these three databases provides us necessary data for our analysis, including output, inputs (labour, capital and intermediate inputs), and factors that may influence technological change (e.g. R&D and

⁵ These micro files can be accessed for empirical analysis at Statistics Canada. Researchers wishing to access these and other micro files must submit a research proposal to the Canadian Centre for Data Development and Economic Research (CDER) at Statistics Canada.

foreign ownership) and technical efficiency (e.g., firm age, and investment in ICTs and non-R&D intangibles). Here we provide a brief description of each of those three micro-data files.

The first micro data is General Index of Financial Information (GIFI). The administrative micro data collects financial statement and balance sheet information from each firm when it files a T2 Corporation Income Tax Return. We extract information from this dataset and derive a firm's gross output, physical capital stock, and intermediate inputs. In addition, we obtain data on R&D stock, ICT stock, and intangible capital, which are also derived from information from the tax file.⁶ The definition of some variables will be discussed in the next section.

The GIFI data is then supplemented by payroll and employment information for each employer business in Canada from National Accounts Longitudinal Microdata File (NALMF). NALMF is an administrative data bank created by the Economic Analysis Division at Statistics Canada. The NALMF makes use of administrative tax records (T2 and PD7), T4 data, information from the Business Register and the Survey of Employment, Payrolls and Hours (SEPH). The T2 data includes corporations that file a T2 tax return with the Canada Revenue Agency (CRA). The T4 data, PD7 and SEPH include corporations and unincorporated firm that hire employees.

In addition, the GIFI data is further supplemented data on foreign ownership and firm age from Business Register (BR). BR is the central repository of information on businesses in Canada. Used as the principal frame for the economic statistics program at Statistics Canada, it maintains a complete, up-to-date and unduplicated list on all active businesses in Canada that have a corporate income tax (T2) account, are an employer or have a goods and services tax account.

To ensure comparison overtime, it is necessary to deflate the nominal variables. Deflators at the firm level are not available so detailed industry deflators based on the KLEMS database are used.⁷ In particular, total sales, physical capital assets, labour compensation, and the derived intermediate inputs at the firm level are deflated by gross output, capital stock, value added and intermediate input deflators at a detailed industry level, respectively.

Data on small firms are not noisy. Many small firms did not even bother to report R&D activities due to the lack of resources and the burden to do so. To eliminate the potential problem and also to reduce the computing time in conducting the stochastic frontier estimation, in this paper, we restrict our sample to include only firms with 10 or more employees. The final sample represents 87.5 percent and 84.1 percent of gross output and employment by all firms, respectively.

⁶ To capture the effort a firm in R&D investment in the current and the past, R&D intensity in this paper is measured as the ratio of R&D stock to physical capital stock. R&D stock for each firm is estimated from real R&D investment using the perpetual inventory method, assuming a capital depreciation rate of 15 percent. Similarly, intangible capital is estimated based on consulting fees, architect fees, advertising, training expense, director fees, and management salaries. These six items are obtained directly from GIFI. The nominal intangible spending is deflated using industry level implicitly price deflator for intermediate inputs (from KLEMS). Then the perpetual inventory method is used for estimating intangible capital stock from real intangible spending, assuming 15 percent of depreciation.

⁷ For a description of the KLEMS database for Canada, please see Baldwin et al. (2007).

With this restriction, we end up with more than 2 million observations for the whole sample period. The number of observations gradually increased for most of the industries from 2000 to 2009, but gave up the gain afterwards, reflecting the general change in the macro condition of the Canadian economy.

Industry	2000	2005	2009	2014	Total 2000-2014
Crop and animal production	6553	8307	8690	6309	121597
Forestry and logging	8339	10204	6622	7148	126044
Fishing, hunting and trapping	776	1047	859	880	14341
Support activities for agriculture and forestry	3749	5274	5049	5063	73661
Oil and gas extraction	1318	1877	2118	1884	29457
Mining and quarrying	3528	3841	3658	3380	54958
Support activities for mining and oil and gas extraction	5678	8676	9083	8183	124149
Utilities	1373	2505	2393	2301	33977
Construction	116032	166124	182938	189906	2532361
Food	22482	25799	25150	23546	370779
Beverage and tobacco	1447	1657	1843	2374	27315
Textile and product mills	6384	6128	4798	3908	82453
Clothing, leather and allied product	11960	10541	7124	4777	133942
Wood product	17575	19620	17017	15216	267310
Paper	4645	5012	4181	3417	66113
Printing	13749	14737	13220	10538	201985
Petroleum and coal	876	934	685	536	11446
Chemical	8232	9386	9189	8553	136147
Plastics and rubber	13019	14683	13879	13031	208659
Non-metallic mineral	7925	9516	9189	8147	133722
Primary metal	3722	3936	3709	3336	55661
Fabricated metal	37127	41731	37408	37028	587725
Machinery	22398	25657	24052	22986	363464
Computer and electronics	8718	10072	9629	8063	140253
Electrical equipment	4700	5711	5328	4924	80092
Transportation equipment	9982	10986	10018	8838	153225
Furniture	14368	17900	16740	14674	248882
Miscellaneous manufacturing	11111	14166	13141	12551	198221
Wholesale trade	129038	151838	153424	148183	2243147
Retail trade	197072	249677	259312	241148	3663469
Transportation and warehousing	56985	71758	71045	73069	1048225
Information and cultural industries	18208	22438	22903	23394	333025
Finance, insurance, real estate, and company management	67610	85805	91656	84915	1274917
Professional, scientific and technical services	64000	92585	102842	99767	1403178
Administrative, waste management	53318	76098	85614	83621	1161539
Arts, entertainment and recreation	24462	34367	35394	31877	492928
Accommodation and food services	172346	225027	240328	220272	3350277
Other services except public administration	57209	83919	95593	97002	1296647
All industries	1208014	1549539	1605821	1534745	22845291

 Table 1: Sample Observation Distribution

Figure 2 plots MFP for the business sector based on our sample, with a comparison to the official estimate. The sample-based MFP is aggregated over firm level using Domar weight that equals the ratio of firm gross output (in nominal dollar) to the aggregate business sector value added (in nominal dollar). The MFP at the firm level is calculated as a residual of gross output minus

contributions from labour, real capital and real intermediate inputs. The elasticities of output with respect to inputs by estimating the stochastic frontier production function in the next section. The movement of the two series are generally consistent. The series based on our sample is more volatile than the official one, and the recovery after the financial crises was more dramatic. This may be due to a number of factors. First, the elasticity of output with respect inputs for our sample is based on regression while the official one is based on input income share. Second, our sample only covers firms with 10 or more employees. Third, our estimate is aggregated over firms using Domar weights while the official one is calculated directly at the business sector.



4. Estimation

Using the sample, we shed light on the decline in productivity and to see if any considered factors were responsible for the weak performance.

4.1. Regressions

To provide a general sense on the impact of the factors on productivity, we first run several regressions without distinguishing technological change from efficiency improvement. For the regressions here, ICT capital stock is entered as the ratio of ICT capital stock in total capital (both tangible and intangible capital stock) as ICT capital has been included in tangible capital. Using this variable, we are trying to see if firms that invest proportionally more in ICTs in total capital investments are more productive.

The estimation results are reported in Table 1. Our first estimation is based on ordinary least squares (OLS) with robust standard errors to ensure our results are autocorrelation and heteroskedastic consistent. We then use clustered standard errors at the firm level so as to address the likely within-firm error correlations. The third regression is based on the Levinsohn-Petrin method to address the endogeneity or simultaneity issue in estimation of production function. The issue arises from any contemporaneous correlations between explanatory variables and the error terms. In the context of this paper, we refer to the problem as the potential

correlation between explanatory variables and the unobserved firm-specific productivity shocks. A firm responds to a positive productivity shock by using more inputs such as investments in capital. Levinsohn and Petrin (2003) show that if the correlation is not addressed, OLS estimation will lead to biased parameter estimates and thus incorrect statistical inference.

	OLS		Levinsohn-Petrin
	Robust standard	Firm clustered	
	error	standard error	
Labour (in log)	0.3321***	0.3321***	0.2881***
	(0.0009)	(0.0021)	(0.0016)
Tangible Capital (in log)	0.0398***	0.0398***	0.0406***
	(0.0003)	(0.0007)	(0.0014)
Intermediate inputs (in log)	0.6467***	0.6467***	0.5688***
	(0.0008)	(0.0018)	(0.0033)
R&D stock (in log)	0.0019***	0.0019***	0.0025***
	(0.0002)	(0.0002)	(0.0002)
R&D stock (in log, lag 1 year)	-0.0001	-0.0001	-0.0000
	(0.0003)	(0.0001)	(0.0001)
R&D stock (in log, lag 2 years)	0.0011***	0.0011***	0.0006***
	(0.0002)	(0.0002)	(0.0002)
Ratio of ICT stock to total capital stock	0.2114***	0.2114***	0.2340***
	(0.0031)	(0.0071)	(0.0081)
Intangible capital stock (in log)	0.0009***	0.0009***	0.0028***
	(0.0001)	(0.0001)	(0.0001)
Foreign owned	0.1607***	0.1607***	0.0580***
	(0.0019)	(0.0044)	(0.0042)
Mature firms	0.0135***	0.0134***	0.0103***
	(0.0008)	(0.0013)	(0.0012)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Number of observations	1525001	1525001	1525001
R-square	0.95	0.95	NA

Table 1: Ordinary Least Square and Levinsohn-Petrin Estimation

Note: Standard errors are in parenthesis. "***", "**", and "*" stand for significance at 1%, 5%, and 10% levels, respectively.

The estimation results based on different regressions in Table 1 are general consistent. It shows that all factors considered in the papers are statistically important for productivity. Investments in R&D, ICTs and intangibles are positively associated with productivity performance. In addition, the estimation shows that foreign-owned firms are more productive. Finally, as expected young firms are found to be less productive than established firms.

Was the productivity growth slowdown in the post-2000 driven by the decline in technological change or by the deterioration in technical efficiency improvement? What factors are underlying the developments? To shed light to this question, we estimate the stochastic frontier production

function, which separated technological change from efficiency improvement. Note that, unlike in previous regressions, intangible capital enters into the stochastic frontier estimation as the ratio of intangible stock to total capital stock as it is used to explain technical efficiency.

	All Firms	All Firms	All Firms	Manufacturing	Non-manufacturing
	2000-2014	2009-2014	2000-2008	Firms	Firms
	2000-2014	2007-2014	2000-2008	2000-2014	2000-2014
	(1)	(2)	(3)	(4)	(5)
	(1)	Production		(4)	(3)
Labour (in lag)	0.3282***	0.3367***	0.3201***	0.2759***	0.3336***
Labour (in log)					
	(0.0004)	(0.0006)	(0.0005)	(0.0009)	(0.0004)
Tangible Capital (in log)	0.0490***	0.0458***	0.0528***	0.0558***	0.0488***
	(0.0002)	(0.0003)	(0.0003)	(0.0005)	(0.0002)
Intermediate inputs (in	0.6432***	0.6389***	0.6467***	0.6791***	0.6391***
log)	(0.0003)	(0.0004)	(0.0003)	(0.0006)	(0.0003)
R&D stock (in log)	0.0022***	0.0044***	0.0013***	-0.0000	0.0028***
	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0004)
R&D stock (in log, lag 1	0.0001	-0.0016**	0.0005	-0.0002	0.0003
year)	(0.0003)	(0.007)	(0.0004)	(0.0004)	(0.0005)
R&D stock (in log, lag 2	0.0013***	0.0005	0.0022***	0.0007***	0.0023***
years)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0003)
Foreign	0.1679***	0.1783***	0.1551***	0.0944***	0.1893***
C	(0.0015)	(0.0020)	(0.0024)	(0.0022)	(0.0019)
Constant	4.4075	4.5573	4.2901	3.6139	4.4450
	(16.8358)	(15.7708)	(21.5494)	(4.6678)	(10.8751)
Industry dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
		Ineffici	ency		
ICT stock to total capital	-0.2554***	-0.2533***	-0.2589***	-0.0983***	-0.2635***
stock ratio	(0.0021)	(0.0032)	(0.0029)	(0.0075)	(0.0023)
Intangible stock to total	-0.1178***	-0.1173***	-0.1194***	-00938***	-0.1212***
capital stock ratio	(0.0010)	(0.0015)	(0.0014)	(0.0022)	(0.0011)
Mature Firms	-0.0050***	0.0032***	-0.0116***	0.0217***	-0.0079***
	(0.0008)	(0.0011)	(0.0010)	(0.0017)	(0.0008)
Constant	0.3890	0.3909	0.4038	0.1561	0.3948
	(16.8358)	(15.7708)	(21.5494)	(4.6678)	(10.8751)
Number of observations	1525001	733313	791688	221966	1303035

Table 2: Stochastic Frontier Production Function Estimation

Note: Standard errors are in parenthesis. "***", "**", and "*" stand for significance at 1%, 5%, and 10% levels, respectively.

The stochastic frontier estimation results are reported in Table 2. The first regression is based on observations for all firms in the whole sample period. Several interesting results emerge. For the

productivity frontier, it is found that the current R&D variable was positive and highly significant. The one-year-lagged R&D variable is not significant while the two-year-lagged R&D variable is positively significant. In addition, it shows that foreign-ownership is positive and significant. Thus, the estimation shows that R&D investments and foreign ownership are important for raising productivity through technological change. For inefficiency, investments in ICTs and intangibles are found to be positive and significant while young firms are found to be negative. Inefficiency measures the distance of actual productivity from the productivity frontier. Variables that are negative for inefficiency means positive for efficiency, and vice versa. Thus, firms that invested in ICTs and intangibles tend to be closer to the frontier while young firms tend to have a distance from the frontier. Except the coefficient on intangibles, the magnitudes of the coefficients on other variables are generally consistent with those based on OLS or the Levinsohn-Petrin method. For the intangible variable, the difference is expected as it is the ratio of intangible stock to total capital stock in the stochastic frontier production function estimation while it is in intangible stock before.

Regressions (2) and (3) are done for sub-periods 2009-2014 and 2000-2008, respectively. The estimation is to see if the effect of any those factors changed significantly over these two sub-periods. Overall, we don't see significant changes for R&D, foreign ownership, ICTs and Intangibles. However, matured firms in the second sub-period showed some decline in efficiency compared to young firms. This is an interesting result, and may be due to the tremendous pressure on matured firms from the financial crisis.

Does any of those factors behave differently across different industries? We re-run the same estimation for manufacturing and non-manufacturing industries separately. In general, we see a smaller effect of R&D and foreign ownership on manufacturing than on non-manufacturing (regressions (4) and (5)). The same is true for the effect of either ICTs or intangibles on efficiency. Furthermore, the estimation shows that unlike those in non-manufacturing industries, matured firms in manufacturing tend to be less efficient than young firms.

4.2. Elasticities of Productivity With Respect to Control Factors

How is technological change or technical efficiency sensitive to each of their control factors? In this sub-section, we estimate the elasticity with respect to each of those factors. According to equation (4), gross output is a function of both deterministic components and random components. This means that the actual gross output is also random. To be meaningful, we avoid the randomness and calculate the elasticity of productivity with respect to a factor based on the mean of actual gross output.

Denoting the average of actual gross output as \tilde{Y}_i for firm *i*. Mathematically, the mean (average) of the logs of variables is approximately equal to the log of the original mean of the variables. Applying this approximation to equation (4), we have $ln(\tilde{Y}_i)$ approximately equals the mean of the logs of actual productivities. This yields the following:

$$ln(\widetilde{Y}_{i}) \approx \alpha_{0} + \alpha_{L}lnL_{i} + \alpha_{K}lnK_{i} + \alpha_{M}lnM_{i} + \sum_{j=1}^{k} \beta_{j}lnR_{i,j} + \sum_{j=k+1}^{s} \beta_{j}Z_{i,j} - \gamma_{0} - \sum_{h=1}^{m} \gamma_{h}X_{i,h}, \qquad (6)$$

With equation (6), we can now estimate elasticity of productivity with respect to each of those variables in the equation. The factors associated with β are related to technological change and those associated with γ are related to technical efficiency. We separate factors that are continuous from those that are binary. For a binary variable, say mature firm X_3 , in the efficiency function, the impact on technical efficiency when the binary variable switches from 0 to 1 equals the estimated coefficient, that is, $ln(T\widehat{E}_i^1) - ln(T\widehat{E}_i^0) = -\widehat{\gamma}_3$. As $ln(T\widehat{E}_i^1) - ln(T\widehat{E}_i^0) \approx T\widehat{E}_i^1/T\widehat{E}_i^0 - 1$, the percent change in TE_i with respect to X_3 switching from 0 to 1 thus approximately equals $-\widehat{\gamma}_3 \times 100$. For a continuous variable in log, which is R&D, the elasticity of productivity with respect to a variable is the estimated coefficient corresponding to the variable. For other continuous variables in level, say ICTs $(X_{i,1})$, the corresponding elasticity is $-\widehat{\gamma}_1 \overline{X}_1$, with \overline{X}_1 being the average of the variable across firms in the group.

Factors	Elasticities	
Technological change with respect to its factors		
R&D	0.004	
Being foreign-controlled	16.8	
Technical efficiency with respect to its factors		
Ratio of ICT to total capital	0.016	
Ratio of intangibles to total capital	0.024	
Being a mature firm	0.5	

Table 4:	Average Elasticities of Technological Change or Technical Efficiency With Respect to
Their Fac	ors

We put the elasticities in perspective. Doubling R&D will lead to a 0.4 percent increase in technological change or productivity. Similarly, foreign owned firms are on average 16.8 percent more productive than a domestically-owned firm. For technical efficiency or productivity, if the ratio of ICT capital to total capital and the ratio of intangibles to total capital are doubled from 6.1 percent to 12.2 percent and from 20 percent to 40 percent, then efficiency or productivity will increase by 1.6 percent and 2.4 percent, respectively. Finally, being a mature firm has 0.5 percent efficiency advantage over a young firm.

5. The Movement of Technological Change and Technical Efficiency

With the stochastic frontier production estimation, we can now study technological change (TC) and technical efficiency (TE) individually. Figure 3 plots the technical efficiency distribution for

2002, 2005, 2009 and 2014.⁸ Most of firms had efficiency about 68 percent or more. Interestingly, the distribution did not change much visually over the period.



Figure 3 Firm Technical Efficiency Distribution

Note: TC and TE stand for technological change and technical efficiency respectively.

MFP -

TE -TC

⁸ Technical efficiency for firm *i* at time *t* is estimated as $_{TE} = \exp(-\hat{u}_{i,t})$. Also, the period starts at 2002 instead of 2000 since the regressions have 2-year-lag variables.

The movements of aggregate MFP, TC and TE are in Figure 4. In log terms, MFP equals TC plus TC. Notably, the figure shows that the movement of MFP was almost entirely driven by the movement of technological change, while technical efficiency was fairly stable over this period. The stability of technical efficiency was consistent with the firm technical efficiency distribution in Figure 3, which shows little changes over time.

5.1. Technological Change and Factors

What are underlying the change in technological change? To shed light on this question, we regress firm technological change against a number of factors, including industry specific effects, year effects (business cycles), R&D, and foreign ownership. In other words, we would like to see the changes after controlling for the effects from those factors. We first control each of those factors individually and then all factors together. The exercise aims to see if a factor had a change that affects technological change, with 2002 as a reference. The movement of aggregate technological change after the controls is plotted in Figure 5.



Note: TC_0 stands for technological change without any control. TC_1, TC_2, TC_3, and TC_4 are after controlling for industry effects, year effects, R&D and foreign ownership, respectively. And TC_5 is after controlling for all these factors at the same time.

We first notice that after controlling for industry specific effects, the aggregate TC_1 was slightly above the original TC_0 during 2004-2209 while in other years, the two series were almost identical. The largest gap during 2004-2009 was almost 3.0 percentage points. This suggests that the Canadian industry structure had some negative impact on aggregate technological change over 2004-2009, and had virtually no impact in other years.

After controlling for year specific effects, the TC_2 was below the original TC_0 except for 2003, meaning that given other factors being constant, all firms experienced some increase in technological change after 2003. The increase was more dramatic in the final year 2014, up to 12.7 percentage points.

The change in TC_3 after controlling for R&D was always below the original series TC_0. This indicates that without R&D, the aggregate technological change would be lower, ranged from 1.3 percentage points in 2003 to 7.4 percentage points in 2014.

The most influential factor is foreign ownership. After controlling for this factor, the technological change was substantially lower, ranged from 1.3 percentage points in 2003 to 14.9 percentage points in 2014. Thus, the impact of foreign-controlled firms on Canada's productivity increased over time.

After controlling all these factors together, we will see a drop of technological change TC_5 from 0.2 percentage points in 2003 to 18.7 percentage points.

In sum, the decline in technological change was not due to change in industrial structure, R&D and foreign ownership. In fact, without R&D and foreign ownership, the decline in technological change would be more dramatic.

5.2. Technical Efficiency and Factors

Similar to the analysis to technological change, we also conduct the same exercise to technical efficiency. We would like to see whether or not a factor played an important role in keeping the stability in technical efficiency. Here, the control factors are the ratio of ICT stock to total capital stock, the ratio of intangible stock to total capital stock, and being a mature firm. Again, we first control each of those three factors individually and then all together. The results are illustrated in Figure 6.

In this enlarged chart, we observe a slightly decline in technical efficiency (TE_0), only about 0.5 percent over the 2002-2014 period. After controlling for the ICT factor, we observe a slightly lower technical efficiency, which means that the ICT factor had played a slightly better role in enhancing technical efficiency over the period.

In contrast, after controlling intangibles or being mature, the technical efficiency line was above the original line. Thus, both factors had become slightly weaker in supporting technical efficiency over the sample period.



Note: TE_0 stands for technical efficiency without any control. TE_1, TE_2, and TE_3 are after controlling for ICT, intangibles and being mature, respectively. And TE_4 is after controlling for the three factors at the same time.

Interestingly, after controlling all these factor together, the technical efficiency line almost become constant. This suggests that the slightly change in technical efficiency over the sample period was entirely driven by those factors.

6. Conclusions

What explain the decline in Canada's productivity in the post-2000 period? In this study, we traced it to technological change (or productivity frontier) and technical efficiency. Using micro data, we showed that the decline in Canada's productivity was largely driven by a decline in technological change, and technical efficiency had virtually unchanged over the sample period 2000-2014. In addition, we demonstrated that ICT investments had played a small positive role in supporting technical efficiency while intangibles and being mature firms had a small negative effect on efficiency. Furthermore, we showed that the change in technological change was not due to a change in industrial structure, R&D investments or foreign ownership. If these factors were not responsible, the remaining question is why the controlled technological change, the residual after those factors, declined in the post-2000?

There is some evidence showing that Canada's economy and so productivity was affected negatively by a number of factors over the 2002-2008 period. The Canadian dollar appreciated from 62 cents in the U.S. currency in 2002 to parity in 2008. The sharp appreciation of the Canadian dollar reduced the cost competitiveness of Canadian tradable industries (especially manufacturing) in international markets. The great financial crisis in 2008 led to tremendous business uncertainty. Other factors that might play a role include increased competition from emerging economies (e.g., China), and the shifting of production activities by multinationals to overseas. These developments reduced demand for Canadian products, leading to under utilization of production resources. Research shows almost all of the productivity growth

slowdown in the Canadian manufacturing sector in the post-2000 period was due to a large decline in capacity utilization, driven by large exporters (Baldwin et al., 2013 and Tang, 2016). This is consistent with the finding by Gu and Wang (2013) who shows that the post-2000 decline in MFP growth in both mining and manufacturing was largely the result of the decline in capacity utilization in that period.

The good news is that the controlled technological change has recovered most of the loss during 2005-2009. Although investments in R&D, ICTs or intangibles did not play an important role in the decline in Canada's productivity, those investments are found to be important for productivity improvements either through technological change or technical efficiency. Thus, government policies in encouraging investments in those areas will certainly benefit Canada's productivity improvements.

References

Baldwin, J. R., W. Gu and B. Yan (2013), "Export Growth, Capacity Utilization, and Productivity Growth: Evidence from the Canadian Manufacturing Plants," *Review of Income andWealth*, 59, 665–688.

Battisti, M., Belloc, F., and Gatto, M. D., "Unbundling Technology Adoption and TFP at the Firm Level. Do Intangible Matter?", *Fondazione Eni Enrico Mattei, Working Papers*, 2012, *JEL Classification Numbers: C29, D24, F12, O32*

Biagi, Federico (2013), "ICT and Productivity: A Review of the Literature," European Commission, Joint Research Centre technical Reports, Institute for Prospective Technological Studies, Digital Economy Working Paper 2013/09.

Corrado, C., Hulten, C., and Sichel, D., "Measuring Capital and Technology: an Expanded Framework", in C. Corrado, J. Haltiwanger, and D. Sichel (eds), *Measuring Capital in the New Economy. Studies in Income and Wealth*, 2005, *Vol.65, University of Chicago Press, Chicago*.

Corrado, C., Hulten, C., and Sichel, D., "Intangible Capital and U.S. Economic Growth", *Review* of Income and Wealth, September, 2009, Series 55, Number 3

Gu, W. and W. Wang (2013), "Productivity Growth and Capacity Utilization in Canadian Business Industries," Analytical Paper, Statistics Canada.

Ilmakunnas, P., "Intangible Investment in People and Productivity", *J Prod Anal*, 2014, 41:443–456

Liu, H. and J. Tang (2017), "Age-productivity profiles of entrants and exits: evidence from Canadian manufacturing," <u>Structural Change and Economic Dynamics</u> 40, 2017.

Rao, S. M. Souare, and W. Wang. 2009. "The Economics of FDI: A Canadian Perspective," *Transnational Corporations Review* 1(4), 28-41

Tang, J (2017) "Industrial structure change and the widening Canada–US labor productivity gap in the post-2000 period," *Industrial and Corporate Change* 26(2), 259–278

Tang, J. and S. Rao. 2003. "Are Foreign-controlled Manufacturing Firms Less R&D-intensive than Canadian-controlled Firms?" *Canadian Public Policy* 29(1), 111-117