Three Essays on the Measurement of Productivity

by

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Abstract

This doctoral thesis consists of three essays. In the first essay I investigate the presence of productivity convergence in eight regional pulp and paper industries of U.S. and Canada over the period of 1971–2005. Expectation of productivity convergence in the pulp and paper industries of Canadian provinces and of the states of its southern neighbour is high since they are trading partners with fairly high level of exchanges in both pulp and paper products. Moreover, they share a common production technology that changed very little over the last century. I supplement the North-American regional data with national data for two Nordic countries, Finland and Sweden, which provides a scope to compare the productivity performances of four leading players in global pulp and paper industry. I find evidence in favour of the catch-up hypothesis among the regional pulp and paper industries of U.S. and Canada in my sample. The growth performance is at the advantage of Canadian provinces relative to their U.S. counterparts. However, it is not good enough to surpass the growth rates of this industry in the two Nordic countries.

It is well-known that econometric productivity estimation using flexible functional forms often encounter violations of curvature conditions. However, the productivity literature does not provide any guidance on the selection of appropriate functional forms once they satisfy the theoretical regularity conditions. The second chapter of my thesis provides an empirical evidence that imposing local curvature conditions on the flexible functional forms affect total factor productiv-

ity (TFP) estimates in addition to the elasticity estimates. Moreover, I use this as a criterion for evaluating the performances of three widely used locally flexible cost functional forms — the translog (TL), the Generalized Leontief (GL), and the Normalized Quadratic (NQ) — in providing TFP estimates. Results suggest that the NQ model performs better than the other two functional forms in providing TFP estimates.

The third essay capitalizes on newly available high frequency energy consumption data from commercial buildings in the District of Columbia (DC) to provide novel insights on the realized energy use impacts of energy efficiency standards in commercial buildings. Combining these data with hourly weather data and information on tenancy contract structure I evaluate the impacts of energy standards, contractual structure of utility bill payments, and energy star labeling on account level electricity consumption. Using this unique panel dataset, the analysis takes advantage of detailed building-level characteristics and the heterogeneity in the building age distribution, resulting in buildings constructed before and after mandatory energy standards came into effect. Estimation results suggest that in commercial buildings constructed under a code, electricity consumption is lower by about 0.48 kWh per cooling degree hour. When tenants pay for their own utilities, consumption is lower by 0.82 kWh per cooling degree hour. The Energy Star effect is a 0.31 kWh reduction per cooling degree hour. Finally, peak savings for all three variables of interest occur at 2pm in the summer months, whereas peak summer marginal prices at DC's local electric utility occur at 5pm.

To my parents,

Jutsna Talukder and **Johir Uddin Talukder**

— You ignited the torch of knowledge in me,

my son,

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— You are my joy of life. May you carry forward the torch of knowledge,

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— God knew whom I needed the most — A true friend.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Productivity is a permanent concern to economic policy decision makers, especially because of its role in determining the competitive position of a national industry in the world market.[1] Chambers and Gordon (1966) argue that under constant returns to scale, productivity of the trade exposed sector determines the wage rate not only of this sector but also of the whole economy. This important indicator has attracted the attention of researchers and academicians who have developed a large literature dealing with various measurement issues,[2] and of national statistical agencies that implement specific programs designed to assess productivity of parts or the whole economy.[3]

My doctoral thesis consists of three essays on the measurement of productivity. In my research I aim to understand: (i) whether productivity convergence exists in the regional pulp and paper industries of Canada and its southern neighbour, the U.S., (ii) the impacts of imposing curvature conditions on different flexible functional forms in parametric productivity estimation, and (iii) the realized energy use impacts of energy efficiency standards in commercial buildings.

In the first essay of my thesis I examine the presence of productivity conver-

[1] Other local factors such as taxation and government regulations also play a role in this respect.

[2] For a brief survey, see Hulten (2001).

[3] OECD provides guidance to member countries in this endeavour. See OECD (2011).

gence in eight regional pulp and paper industries of U.S. and Canada over the period of 1971–2005. In doing so, I take advantage of regional disaggregated data on four Canadian provinces — Alberta, British Columbia, Ontario, and Québec — and on four U.S. states — Georgia, Illinois, Maine, and Washington. In addition to industry size, an important criterion in selecting the U.S. states is the proximity to the Canadian border in order to compare fairly homogeneous entities in terms of available wood fiber, and final goods market access. Expectation of productivity convergence in the pulp and paper industries of Canada and U.S. is high since they are trading partners with fairly high level of exchanges in both pulp and paper products. Moreover, they share a common production technology that changed very little over the last century. I supplement the North-American regional data with national data for two Nordic countries, Finland and Sweden, which provides a scope to compare the productivity performances of four leading players in global pulp and paper industry.

The second essay deals with a particular aspect of parametric productivity estimation — imposing curvature conditions on flexible functional forms. Theoretical curvature properties are crucial, especially, in estimating the flexible functional forms. It is well-known that econometric productivity estimation using flexible functional forms often encounter violations of curvature conditions. However, the productivity literature does not provide any guidance on the selection of appropriate functional forms once they satisfy the theoretical regularity conditions. In this essay, I provide an empirical evidence that imposing local curvature conditions on the flexible functional forms affect total factor productivity estimates in addition to the elasticity estimates. Moreover, I use the difference in TFP estimates, with and without curvature constraint, as a criterion for comparing the performances of three widely used locally flexible cost functional forms — the translog (TL), the Generalized Leontief (GL), and the Normalized Quadratic (NQ) — in providing TFP estimates. In particular, I cover all possible cases one might encounter in terms of curvature violations while estimating these three locally flexible functional forms: (i) curvature conditions are satisfied without curvature restrictions being imposed, (ii) curvature conditions are satisfied when curvature restrictions are imposed, and (iii) curvature conditions are not satisfied even with curvature restrictions being imposed.

While the first two essays of my thesis deal specifically with the measurement of total factor productivity, the last essay measures the impact of building energy efficiency code on realize energy use in commercial buildings. Building energy efficiency codes play a vital role in implementing national and regional environmental policies. As building codes are expected to reduce GHG emissions, they have become a key instrument in implementing climate change policies. Simulation studies, which constitute the vast majority of works done so far on assessing the effectiveness of building codes, typically fail to account for the behavioural characteristics of tenants at the building level. This essay helps to fill these gaps in our understanding of the impact of energy efficiency policy on energy use in multi-tenanted space. While neither building-level energy use data or statistics on the prevalence of tenanted space are available for Canada, a unique policy adopted by the District of Columbia (DC) in the U.S. has resulted in the availability of detailed data on both these fronts. Beginning in August 2013, the DC municipal government has made detailed hourly energy use and building characteristic data available as part of its Sustainable DC policy. At present, energy use data for almost 400 institutional buildings are available. Combining these data with hourly weather data and information on tenancy contract structure I evaluate the impacts of energy standards, contractual structure of utility bill payments, and energy star labeling on account level electricity consumption.

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Chapter 2

Regional Productivity Convergence: An Analysis of the Pulp and Paper Industries in U.S., Canada, Finland, and Sweden

2.1 Introduction

Productivity is one of the major determinants of the competitive position of a national industry in the world market.[1] Chambers and Gordon (1966) argue that under constant returns to scale, productivity of the trade exposed sector determines the wage rate not only of this sector but also of the whole economy. This important indicator has attracted the attention of researchers and academicians who have developed a large literature dealing with various measurement issues,[2] and of national statistical agencies that implement specific programs designed to assess productivity of parts or the whole economy.[3] In this paper I investigate the presence of productivity convergence in eight regional pulp and paper industries of U.S. and Canada over the period of 1971–2005.

The Canadian pulp and paper manufacturing industry is fairly large according

[1] Other local factors such as taxation and government regulations also play a role in this respect.

[2] For a brief survey, see Hulten (2001).

[3] OECD provides guidance to the member countries in this endeavour. See OECD (2011).

to the usual economic indicators and it is one of the major industrial sectors in national and regional economies of Canada. The economic significance of Canadian pulp and paper industry lies on the fact that this industry has always been a net contributor to the balance of payments. In the world market, Canada and U.S. are the two leading players for the pulp and paper industry.[4] Moreover, they are direct competitors, particularly in the U.S. market. The level of integration between the two countries is also very high and both countries are trading partners in cases of both pulp and paper products.

According to Denny et al. (1992), productivity growth over longer periods is primarily determined by the technological advancement in an industry and that advance is highly correlated across nations. In the case of pulp and paper, the global industry share a common production technology and the basics of paper making have changed very little over the last century (Kuhlberg, 2015). At the first stage, wood fiber that is the main raw material is freed from raw wood through chemical and/or mechanical processes to yield pulp, and at the second stage, the mixture is spread over a rolling screen to be dried and to obtain various paper and cardboard products. Moreover, mill owners purchase their equipment form a very small group of manufacturers that serve the world market and they are the main innovators in this industry. According to Ghosal (2009), the U.S. pulp and paper industry perform little R&D and its R&D intensity (0.5 percent) is one of the lowest among U.S. manufacturing industries.[5] Here are three major challenges that the pulp and paper industry in industrialized countries faced since the early seventies: First, the oil crisis of the seventies opened the way to other energy sources including biomass use. Second, fiber supply changed from round

[4]According to the most recent statistics published by F.A.O. (2013), U.S. is the leading producer of wood pulp, accounting for almost 30 percent of total world production, followed by Canada which accounts for almost 11 percent of the global production. In case of paper and paperboard production both U.S. and Canada are among the top five producers in the world and they jointly account for 22 percent of total world production. In both type of products, they are among the top five exporting countries.

[5]The R&D intensity of the Canadian pulp and paper industry was 0.6 percent in 2008.

wood to wood chips, and recycled paper brought a growing contribution. Third, governments enforced more stringent environmental regulations on water and air emissions.

The above discussion makes it clear that we have two leading players of the global pulp and paper industry which share a common production technology that changed little during the last century and are trading partners with high level of exchanges in both pulp and paper products. Furthermore, they compete on the world market for fairly homogeneous products. Such a setting should lead to total factor productivity (TFP) convergence. While multiple reasons to expect TFP convergence between the pulp and paper industries in Canada and U.S. are present, productivity performance of the industry may or may not be uniform even across regions within a country.

In this paper I analyze the productivity performance of the pulp and paper industries in Canada and the U.S. over the period extending from 1971 to 2005 by taking advantage of regional disaggregated data on four Canadian provinces — Alberta, British Columbia (BC), Ontario, and Québec — and on four U.S. states — Georgia, Illinois, Maine, and Washington. Canada and U.S. have huge forestlands that support diverse forestry due to soil and climate conditions, and hence the wood fiber supply differ significantly from one region to the next. Furthermore, most of the forestlands in Canada are owned by the provinces[6] that have their own forestry regime to provide access to industrial uses, and that apply their own environmental regulations. In order to take the diversity of conditions at the regional level into consideration, I build my sample to include the four largest Canadian forestry provinces, and the U.S. states are selected to represent regional industry conditions as well as to represent the industry of similar size. The use of regional disaggregated data allows me to investigate whether the regional industries within a country follow a uniform path over the course of time. Moreover, this also allows

[6]Public forestland ownership in the four provinces in my sample ranges from 90 percent in Québec to approximately 100 percent in Alberta and BC.

me to investigate the presence of convergence in terms of TFP in the pulp and paper industry.

I supplement the North American regional level data with national data for two Nordic countries — Finland and Sweden. The inclusion of Finland and Sweden is justified in the sense that this gives me the opportunity to compare performances of the North American regions with those of others who are competing with them in the global market.[7] Furthermore, the input mix is disaggregated into five components — labour, capital, materials, electricity, and other energies, which are mostly fossil fuels. To the best of my knowledge there are only three studies available that investigate the productivity performance of the pulp and paper industry at regional levels in Canada (see Denny et al., 1981; Hailu, 2003; Shahi et al., 2011) and there is no empirical study that examines the performance of this industry at regional levels in U.S.

In order to estimate TFP, I employ two widely used methods of productivity measurement — the index number technique and the econometric estimation approach. With the index number technique I exploit an extension of the translog transitive multilateral productivity index (Caves et al., 1982b) by using the relationship between the price indexes of output and inputs and the translog cost function. The econometric approach involves estimating a translog system that allows non-neutral technical change. Following Jin and Jorgenson (2010) I decompose the TFP growth rate into autonomous and induced technical change components. The use of direct parametric estimation enables me to provide estimates of price elasticities and of factor biases to technical change. I also provide confidence intervals of my elasticity estimates.[8]

Keay (2000) provides Canada relative to U.S. TFP ratios for nine manufac-

[7]According to F.A.O. (2013), in 2011, both Finland and Sweden were among the top five leading paper and paperboard exporters in the world. They jointly account for 13 percent of global wood pulp production which places them among the top five producers in the world.

[8]For a discussion on the importance of parameters of the elasticity of substitution and the direction of technical change, see León-Ledesma et al. (2010).

turing industries covering the first ninety years of the twentieth century. He finds little evidence of productivity gap on behalf of the Canadian manufacturers and concludes that the Canadian manufacturers were equally productive as their U.S. counterparts during the sample period. The pulp and paper industry, which is by far the largest industry in his sample, displayed an above average performance.

My findings do not support the productivity assessment of Keay (2000) for the pulp and paper industry when I compare the weighted average TFP levels of the four U.S. and four Canadian regions for the overlapping 1970–1990 period. TFP grew at a higher rate in the Canadian provinces after the 1988 Free Trade Agreement (FTA), and they almost closed the gap by 2005.[9] Overall, Finland and Sweden had the best TFP growth performance while Illinois experienced the worst in this respect. Moreover, based on my results I find statistical evidence of productivity convergence taking place across the pulp and paper industries in the four U.S. states and the four Canadian provinces.

The rest of the paper is organized as follows. Section 2.2 provides a review of the existing literature. Section 2.3 presents the theoretical background of the productivity estimation approaches used in this study. Section 2.4 describes the dataset while Section 2.5 discusses the results. Finally, Section 2.6 adds some concluding remarks.

2.2 Literature Review

Although the pulp and paper industry is of significant importance to the regional economies of several industrialized countries, there have only been a limited number of studies that look into the productivity performance of this industry using

[9] Bernard and Hussain (2017) compare the TFP performance of the pulp and paper industry in three contiguous Canadian provinces and U.S. states (BC/Washington, Ontario/Illinois, and Québec/Maine) for the period of 1971–2005. They find that a positive impact in favour of the three Canadian provinces is associated with the 1988 FTA and that the price of material played a role in this respect.

regional level data. Moreover, existing studies differ in terms of productivity measurement approaches, number and the measure of output(s) and inputs, and the coverage of sample periods. Denny et al. (1981) examine the growth rates of TFP for twenty Canadian manufacturing industries, including the paper industry, covering the period of 1961–75 in four regions of Canada — BC, Ontario, Québec, and the 'Rest of Canada'. Their estimated annual TFP growth rates vary between 0.80–1.04 percent across regions. Hailu (2003) compares the TFP growth rates in four regions of Canada — Ontario, Québec, BC, and the Atlantic and Prairie region — for the period of 1970–93. His results indicate that the productivity of the pulp and paper industry in those regions were decreasing by 0.85 percent per year. Shahi et al. (2011) is the other regional study, and it estimates negative TFP growth rates, -0.5 to zero percent, for the pulp and paper industry in Ontario during 1967–2003. To the best of my knowledge, there is no empirical study that examines the productivity performance of regional pulp and paper industries in U.S.

Few other studies examine the productivity performance at the national level. Studies on the Canadian pulp and paper industry include Sherif (1983), Martinello (1985), Nautiyal and Singh (1986), and Frank et al. (1990). Estimated annual growth rates of TFP varies from 1.2 to 2 percent across these studies. For the U.S. industry, Borger and Buongiorno (1985) estimate TFP growth rates of paper and paperboard industries for the period of 1958–81. Their estimated TFP growth rate for paper is 2.89 percent or 4.54 percent, depending on the index, while it is slightly over 1 percent for paperboard.

A set of other studies compares the productivity performances of pulp and paper industries in U.S. and Canada. For example, Denny et al. (1992) provide a comparison of TFP growth rates in the paper industries of Canada, U.S., and Japan for the period of 1953–86. According to their results, during the period of 1973–86 the average annual growth rate of TFP for U.S. paper industry is

0.78 percent while the Canadian paper industry has a negative growth rate, -0.01 percent.[10] Hseu and Buongiorno (1994) estimate 0.5 percent annual TFP growth rate for this Canadian industry during 1959–1987 while it is 0.7 percent for its U.S. counterpart. Moreover, Hseu and Shang (2005) examine the productivity of pulp and paper industry in OECD countries over 1991–2000. According to their results the industry in Canada was enjoying an average annual growth rate of 2 percent while that in U.S. had almost no growth rate, 0.2 percent per year. Among the Nordic countries, the pulp and paper industry in Sweden had 1.5 percent growth per year while that in Finland was growing at 1.2 percent.

Results on relative TFP levels are more uniform than the results on TFP growth rates across studies. For example, Denny et al. (1992) also provide a relative Canada-U.S. TFP comparison for three sub-periods: 1964–66, 1974–76, and 1983–85. Paper and lumber are the only two industries in which Canadian manufacturers were more productive than their American counterpart in all the three sub-periods. Superior relative TFP level performance of Canadian pulp and paper industry is also confirmed by Keay (2000). He finds that the Canadian paper industry is more productive than its American counterpart.

All of the above mentioned studies use conventional TFP measures in the sense that they only use marketable outputs while calculating TFP. However, Hailu and Veeman (2000, 2001) introduce a productivity measure which accounts for the undesirable pollutant outputs and yields higher TFP estimates relative to the conventional measures. The TFP growth rates of Canadian pulp and paper industry in their studies for the period of 1959–94 varies from -0.15 percent to 2.1 percent depending on the estimation technique.

Based on the findings of existing literature it is clear that the estimates of TFP growth rates varies across studies. Findings on the direction of factor biases

[10] This sub-period is chosen to facilitate a comparison of their estimates of TFP growth rates with the ones calculated in the present study. This is the most suitable sub-period in their sample periods for which I can compare my results with.

to technical change as well as the substitution possibilities among factors of production also vary across studies that rely on explicit functional forms. See, for example, Sherif (1983), Martinello (1985), Nautiyal and Singh (1986), Borger and Buongiorno (1985), and Shahi et al. (2011), among others. One obvious explanation of this variation in results could be the difference in the coverage of sample periods. However, the difference also holds when comparable study periods are used. Methodological difference may be another source of variation in TFP estimates across studies. In this study, I make use of two widely used approaches to productivity measurement – index number and econometric estimation of the translog cost function. In what follows, I briefly discuss the theoretical background of the measurement approaches before presenting my data and estimation results.

2.3 Theoretical Background

Two most frequently used approaches to productivity measurement are the index number technique and econometric estimation.[11] With the index number approach, rate of change in TFP indexes are calculated as a measure of productivity growth, and the most commonly used index is the Tornqvist-Theil index. Econometric estimation, on the other hand, can be done by using either a production function or a cost function. First, the production or the cost function is estimated econometrically and then it is differentiated with respect to time. Under constant returns to scale this gives us the productivity growth rate. Moreover, if we assume that the function takes the translog functional form, then together under the assumptions of profit maximization for production function (or cost minimization for cost function) and of perfect competition in factor markets, both the Tornqvist index number and econometric estimation approaches would provide similar TFP

[11] See Feng and Serletis (2008) for a discussion on various approaches to productivity measurement, and Van Biesebroeck (2007) for a comparison of productivity estimates obtained from different measurement approaches.

growth rates. The correspondence between the Tornqvist and the translog is well established by Diewert (1976) and Caves et al. (1982a).[12] Although a set of studies uses other flexible functional forms, translog is the most frequently used flexible functional form in studies assessing production technology and technical change (Dissou and Ghazal, 2010).

In this study I calculate TFP growth rates by using both the index number and econometric estimation approaches. With the index number approach I extend the correspondence established by Caves et al. (1982b) between Tornqvist quantity index of productivity and translog production function to Tornqvist price index of productivity and translog cost function that allows for transitive and multilateral TFP comparisons. With the econometric estimation method I estimate a translog cost system of equations. Constant returns to scale is assumed in both approaches.

2.3.1 Index Number Approach

I assume that the industry is operating under perfect competition in both product and factor markets, and that the production technology is characterized by constant returns to scale. Under these conditions, we have the equality between output price and unit cost,

$$p_{yt}^k = c^k(\mathbf{p}_t^k) \tag{2.1}$$

where p_{yt}^k is the price of output in region k ($k = 1, ..., K$) at time t, $c^k(\mathbf{p}_t^k)$ is the well behaved unit cost function in region k at time t, and $\mathbf{p}_t^k$ is the vector of input prices, p_{it}^k, for inputs i ($i = 1, ..., n$) in region k at time t.

[12] Diewert (1976) describes the relationship between the estimation of production technology and the measurement of productivity index in terms of exact and superlative index numbers. An index number is exact for a particular functional form if the index of outputs between any two periods is identically equal to the ratios of output obtained from the functional form. He classifies an index number as superlative if it is exact for a second order aggregator function. As shown by Caves et al. (1982a), if technology can be represented by the translog transformation function then under the assumption of constant returns to scale and profit maximization the index number technique of calculating productivity must be exact for the translog. Tornqvist indexes are superlative for the linear homogenous translog aggregator function.

I assume that the unit cost function in (2.1) has the translog functional form as follows,

$$\ln c^k(\mathbf{p}_t^k) = \alpha_0^k + \sum_i \alpha_i^k \ln p_{it}^k + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ln p_{it}^k \ln p_{jt}^k \tag{2.2}$$

where $\alpha_{ij} = \alpha_{ji}$, for $i \neq j$. The translog cost function in (2.2) is assumed to satisfy the properties of a well behaved cost function, in particular, it is nonnegative and non-decreasing, linear homogeneous, and concave in p_{it}^k. Linear homogeneity in prices implies that,

$$\sum_i \alpha_i^k = 1, \text{ and } \sum_j \alpha_{ij} = 0, \qquad \text{for } i = 1, ..., n. \tag{2.3}$$

The translog functional form in equation (2.2) allows for some specific regional characteristics in the linear terms, and hence allows for non-neutral technological change.

Following the same development as in Caves et al. (1982b), under constant returns to scale and profit maximization with perfectly competitive markets, the relationship that they established between Tornqvist output and input quantity index and the translog transformation function can be extended to the relationship between Tornqvist output and input price index and the translog cost function. This leads to the following TFP formula:

$$\ln \lambda_t^k = \frac{1}{2}\sum_i \left(S_{it}^k + \overline{S_i}\right)\left(\ln p_{it}^k - \overline{\ln p_i}\right) - \left(\ln p_{yt}^k - \overline{\ln p_y}\right) \tag{2.4}$$

where λ_t^k represents the productivity level of region k at time t, S_{it}^k is the cost share of factor i in region k at time t, $\overline{\ln p_y}$ is the average of $\ln p_{yt}^k$ over regions and time, $\overline{S_i}$ is the average of S_{it}^k over regions and time, and $\overline{\ln p_i}$ is the average of $\ln p_{it}^k$ over regions and time.

Equation (2.4) provides a transitive multilateral TFP index which enables me to compare the TFP of region k at time t relative to the overall average over all regions and time periods in the sample. It is independent of the choice of a particular region or time period as a basis for comparison. However, it is dependent on the available sample.

2.3.2 Econometric Technique

For econometric estimation, I assume that the unit cost function in (2.2) takes the translog functional form (Christensen et al., 1971, 1973) as follows,

$$\ln c(\mathbf{p}) = \alpha_0 + \sum_i \alpha_i \ln p_i + \frac{1}{2} \sum_i \sum_j \alpha_{ij} \ln p_i \ln p_j + \sum_i \alpha_{it} t \ln p_i + \alpha_t t + \frac{1}{2} \alpha_{tt} t^2 \quad (2.5)$$

where $i, j = 1, ..., n$.[13] Technical change is assumed to be non-neutral and is modelled through time trend, t.[14] Corresponding input cost share equations can be obtained by using Shephard's Lemma after logarithmic differentiation of the unit cost function (2.5) with respect to input prices,

$$S_i = \alpha_i + \alpha_{ii} \ln p_i + \sum_{j \neq i} \alpha_{ij} \ln p_j + \alpha_{it} t. \quad (2.6)$$

Homogeneity and symmetry restrictions imply the following constraints

$$\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \alpha_{ij} = \sum_{j=1}^{n} \alpha_{ij} = \sum_{i=1}^{n} \alpha_{it} = 0. \quad (2.7)$$

Necessary and sufficient condition for concavity is that the Hessian matrix of the cost function (2.5) be negative semidefinite, which according to Diewert and Wales (1987) implies that

$$\mathbf{H} = \mathbf{A} - \mathbf{S}^n + \mathbf{S}\mathbf{S}' \quad (2.8)$$

[13] For notational simplicity I suppress the region superscript and time subscript.

[14] Assumptions of neutral and no technical change can be tested directly. If $\alpha_{it} = 0$ for all i, then technical change is neutral, and if $\alpha_t = \alpha_{tt} = \alpha_{it} = 0$ for all i, then there is no technological progress.

be negative semidefinite, where $\mathbf{A} = [\alpha_{ij}]$ is the $n \times n$ symmetric matrix of α_{ij}, $\mathbf{S} = [S_1, ..., S_n]'$ is the vector of input shares, and $\mathbf{S}^n$ is the $n \times n$ diagonal matrix of the shares.

TFP is estimated as,

$$TFP = -\frac{\partial \ln c(\mathbf{p}_t)}{\partial t} = -\left(\alpha_t + \alpha_{tt} t + \sum_{i=1}^{n} \alpha_{it} \ln p_i\right). \tag{2.9}$$

A reduction in unit cost due to technological progress will translate into a positive TFP growth. As technical change is modelled through time trend, α_t captures the rate of pure technical change while the second part on the right hand side measures its acceleration rate. Together the first two parts on the right hand side, gives us the rate of unit cost reduction due to autonomous or unbiased technical change. The last part measures the contribution to TFP growth due to the biased effect of technical change on factor cost shares. The coefficients α_{it} represent the rates of input bias due to technical change. With regards to the direction of bias, a positive (negative) α_{it} would indicate a technical change that is factor i using (saving).

Furthermore, I use the estimated parameters and fitted values of factor shares to calculate the price elasticities of factor demand. Own- and cross-price elasticities are calculated as follows,

$$\eta_{ij} = \frac{\widehat{\alpha}_{ij} + \widehat{S}_i \widehat{S}_j}{\widehat{S}_i}, \qquad \text{for } i \neq j, \tag{2.10}$$

$$\eta_{ii} = \frac{\widehat{\alpha}_{ii} + \widehat{S}_i^2 - \widehat{S}_i}{\widehat{S}_i}, \qquad i, j = 1, ..., n, \tag{2.11}$$

where all other factor prices are fixed.

It is to be noted that the elasticity estimates are not the estimated parameters of the system. Rather, they are nonlinear functions of the estimated parameters and fitted shares, and as a result, the statistical properties of those elasticity estimates are often not known. The traditional method of dealing with this problem involves the use of classical statistical procedure after linear approximation.[15] However, Krinsky and Robb (1986) criticize the use of traditional approach to derive the empirical distribution of the elasticity estimates, and instead, they suggest the use of simulation technique for deriving statistical properties. They show that the traditional approach is a poor substitute for their proposed simulation technique. One alternative technique, suggested by Efron (1979, 1982), is the use of bootstrap procedure to estimate the empirical distribution of the parameters. Krinsky and Robb (1991) compare the three approaches using two different data sets and show that the results obtained using bootstrap and their specific simulation are similar. They suggest the use of simulation technique on the ground of ease of application.

In this study I compute 95% confidence interval for the elasticity estimates using the method suggested by Krinsky and Robb (1986). This procedure involves generating the samples of estimated parameters of the model by taking random drawings from a multivariate normal distribution with the means and variance-covariance matrix of the estimated parameters. The central assumption here is that the estimates of the parameters of the model follow their multivariate normal distribution as a limiting case. Then using the generated sample of parameter estimates, elasticity is calculated for each drawing and these simulated elasticity estimates are used to derive the statistical properties. To build the confidence interval, I take 10000 random draws.

2.4 Data

The dataset used in this study includes data for the pulp and paper industry in four countries — Canada, the United States, Finland, and Sweden — and covers

[15] For a list of earlier studies using this procedure, see Krinsky and Robb (1986).

the period from 1971 to 2005.[16] Canadian data are collected at the provincial level, for four provinces, namely, Alberta, BC, Ontario, and Québec, whereas U.S. data are collected for four states, Georgia, Illinois, Maine and Washington. The U.S. states are representative of the four major producing areas – south, north-central, east, and west. National level data are used for Finland and Sweden. The data set contains annual information on prices and values of total output and also on the prices and quantities of five inputs used in the analysis of this study — capital (K), labour (L), materials (M), electricity (E), and other energy (F). Other energies are mainly fossil fuels (coal, natural gas, and refined petroleum products). Data come from official government publications of respective countries and the annual survey of manufacturers is the primary source of data for each country. Detailed description of sources of data and the construction of the sample used in this study are presented in Appendix A and B.

Table 2.1 presents data on output and input quantities of the ten regions in my sample. Sweden and Finland had the largest output in 1971 and 2005, respectively, while Alberta had the smallest in both years. Average annual growth rates of output over the sample period vary to a large extent, ranging from high such as 4.84 percent in Alberta and 3.77 percent in Finland to low such as -0.46 percent in Illinois. Overall, Finland and Sweden were parts of the fast growing regions followed by Canadian provinces while U.S. states were trailing.

Given my focus on TFP, here are the observations that can be formulated with respect to factor use over the sample period: First, capital stock grew in all regions except in BC. Second, the use of labour input declined in all regions except in Alberta. Third, materials use increased in all regions except in Illinois and Maine.[17] Moreover, the use of electricity went up everywhere except in Washing-

[16] The sample ends in 2005 due to data availability and also due to the major structural change that accelerated at that time. According to the information provided by the Forest Products Association of Canada (FPAC), 159 pulp and paper mills operated in Canada in 2005. The number fell to 85 in 2013. The downward spiral over such a short period hit particularly newsprint which has been staple in Canada.

[17] Total output in Illinois declined during the sample period while it stayed more or less constant

ton. Finally, the use of other energy, mostly fossil fuels, decreased in five regions while it increased in the other five regions.

Table 2.2 shows information on input prices, their real changes over the sample period, and average input cost shares. Real return to capital decreased in six regions while it increased in the other four regions.[18] Real wage, in general, increased in all regions. The evolution of electricity prices is quite diverse across regions, even within the same country. Prices of other energies increased in all regions. This is expected, particularly after the oil crisis of the seventies. Average input cost shares fall within the same range across the regions. Material inputs, on average, have the largest share (almost 54 percent) in total cost of production. Capital and labour bring similar contributions while electricity and other energy shares are quite small.

2.5 Results

2.5.1 Index Number Technique

Multilateral productivity index generated by the application of formula (2.4) is reported in Table 2.3. Annual TFP levels and the average annual growth rates of TFP during the sample period are reported in the table. As mentioned earlier, the distinctive feature of the index is multilateral transitivity, that is the productivity figures are comparable across both time and regions, and as a result they are free of the choice of a particular year or a region as a basis of comparison.

The TFP index in Table 2.3 reveals some interesting insights of productivity patterns among the sample regions. The U.S. states, Georgia and Maine, appear to be consistently more productive than any other regions throughout the whole time period. They are the leaders in terms of TFP levels. However, the growth

in Maine.

[18] Returns to capital is the residual obtained by netting out the labour cost from value added. It includes return to equity, bond, capital depreciation, and business taxes.

performance is at the advantage of the Canadian provinces over the U.S. states. The weighted average TFP growth rates of the four Canadian provinces is 0.43 percent while the weighted average TFP growth rate in the four U.S. states is 0.31 percent. However, this superior growth performance is not large enough to make one of the provinces to become a leader. There is not a single year when the best performance is associated with any Canadian province. The pulp and paper industry in Canada has been catching up over the sample period; in 2005 the weighted average TFP level of the four Canadian provinces was 1.075 while it was 1.083 for the four U.S. states. My findings on the four Canadian provinces and the four U.S. states included in my sample do not support the results provided by Keay (2000). He finds that the Canadian pulp and paper industry was more productive than its U.S. counterpart during the period of 1971–90.

For regional pulp and paper industries, the only available Canadian studies which I can compare my results with are Denny et al. (1981), Hailu (2003), and Shahi et al. (2011). My TFP growth rate figures are considerably different than those reported in Denny et al. (1981) when I consider overlapping time periods, 1971–75. My results also do not support the findings of Hailu (2003) and Shahi et al. (2011). To my knowledge, there is no state level TFP estimate available for the U.S. pulp and paper industry to compare my results with. In comparing my results with those of other studies done for the national pulp and paper industry, the following studies deserve some attention. Hailu and Veeman (2000) report 0.41 percent annual average growth rate of productivity in the Canadian pulp and paper industry. I find similar result, 0.43 percent, for this Canadian industry if I take the weighted average TFP growth rate of the four Canadian provinces in my sample. However, my results are different from those reported in Denny et al. (1992) even if I consider the common time period, 1973–86.

Overall the TFP growth scenario in the pulp and paper industry during the period of 1971–2005 is marked by the dramatic improvement in Nordic nations as well as the dismal performance of the U.S. state, Illinois. Finland has the highest average annual growth rate, 1.18 percent, while productivity was growing by 0.76 percent per year in Sweden. However, both countries still had smaller TFP levels in 2005 than the average weighted TFP level of the four Canadian provinces (1.075) and of the four U.S. states (1.083).

Although not reported for brevity, I also calculate TFP using the translog multilateral index, proposed by Caves et al. (1982b), that uses the relationship between Tornqvist quantity indexes of output and inputs and the translog transformation function.[19] One important distinction between the two techniques is the use of physical output and input data in the transformation function technique whereas the cost function technique that I employ in this study uses the prices of output and inputs. As the price indexes of output are not available at the level of disaggregation used in this study, I use the national price indexes of output for all provinces and states of Canada and U.S., respectively. One might expect a bias in the productivity estimates generated using the cost function technique as there is no variation in the price indexes of output among the Canadian provinces as well as among the U.S. states. However, similar results obtained from the transformation and cost function techniques assure the existence of single product markets in the pulp and paper industry in Canada and in the U.S. Simple correlation coefficient between the two series is almost one for all regions.

2.5.2 Translog Cost Function

After imposing the restrictions in (2.7) on the cost function (2.5), I estimate the translog systems of equations – the unit cost function (2.5) jointly with the input cost share equations (2.6). Error disturbances are added to the equations in the

[19]TFP is measured as: $\ln \mu_t^k = \left(\ln y_t^k - \overline{\ln y}\right) - \frac{1}{2}\sum_i \left(S_{it}^k + \overline{S_i}\right)\left(\ln x_{it}^k - \overline{\ln x_i}\right)$, where μ_t^k represents the productivity level of region k at time t, y_t^k is the output of region k at time t, S_{it}^k is the cost share of factor i in region k at time t, x_{it}^k is the input i in region k at time t, $\overline{\ln y}$ is the average of $\ln y_t^k$ over regions and time, $\overline{S_i}$ is the average of S_{it}^k over regions and time, and $\overline{\ln x_i}$ is the average of $\ln x_{it}^k$ over regions and time.

system and are assumed to have a multivariate normal distribution with zero mean and constant covariance, Ω, over time. I delete the material share equation from the system of equations to be estimated in order to avoid the problem of singularity.

I use the iterative Zellner's technique for Seemingly Unrelated Regression (SUR) to estimate the translog system of equations for each region separately. To check for whether the estimated cost function satisfies the concavity property, I compute the eigenvalues of the estimated Hessian matrix (2.8) at each data point in the sample as well as at the mean of the data. Coverage of concavity by the estimated cost function for each region is reported in Table 2.4. It can be seen that without restriction concavity coverage is very low. To overcome this problem of little or no concavity coverage by the estimated cost function I impose local concavity on the cost function by using the procedure suggested by Ryan and Wales (2000). The procedure is described in detail in Appendix C. I use the nonlinear iterative SUR technique to estimate the system of equations since imposition of local concavity makes the system nonlinear in parameters. Although not perfect, this yields a large improvement in the coverage of concavity. I report the estimation results that yield the best coverage in terms of concavity.

Tables 2.6 and 2.7 report the estimated coefficients of nonlinear system of equations (restricted for local concavity) for all regions. Almost all parameter estimates are statistically significant at 1% level of significance. Estimates of α_i represent the mean factor shares at time zero when input prices are normalized to one. Estimated mean factor shares are positive for all inputs in all regions. Moreover, the fitted cost shares are positive at all data points implying that the input demand functions are all strictly positive. Actual and fitted shares correspond very closely. The α_{ij} parameters that are often termed as share elasticities capture how the demand for inputs respond to the changes in input prices. They are used in calculating the elasticity estimates.

I perform two tests related to technical change – first, I test for the presence of technical change, and second, I test whether the technical change is neutral. Results from the likelihood ratio tests are presented in Table 2.5. Possibilities of the absence of technical change and the presence of neutral technical change are rejected at 1% level for all regions in the sample. I also test whether the Canadian provinces (U.S. states) share the same cost function. Possibility of pooling data for Canadian provinces and for U.S. states is rejected at 1% level.

Own and cross price elasticities of factor demand along with their confidence intervals are reported in Tables 2.8 through 2.10. Elasticities are calculated at the mean of the data.[20] All estimated own price elasticities of demand have the correct sign which is also confirmed by the reported confidence intervals. I find the factor demands inelastic in all regions as the estimated own price elasticities are below one in absolute terms. This indicates a vulnerability of the industry to any policy change that would impact the factor prices. I find the demand for electricity as much more responsive to price changes than the demand for any other factors in all Canadian provinces with the exception of Québec where labour appears to be the most elastic factor. This is not surprising as historically Québec enjoys one of lowest electricity prices in North America and as a result the pulp and paper industry in Québec has not developed its ability to cope with the rise in electricity price. However, capital is the most elastic factor in U.S. states.

Estimated cross price elasticities of demand suggest that capital and labour are complements in most regions. However, the absolute values are very low and the confidence intervals span positive and negative values. Moreover, I do not find any clear substitution possibility between electricity and other energy. Elasticity estimates of substitution possibility between materials and other inputs are of critical importance for this industry as materials account for more than fifty percent

[20] Although not reported, I also compute the price elasticites of factor demand when concavity is not imposed. All elasticity estimates, when concavity is not imposed, are very close to the ones reported in Table 2.8.

of the total production cost. My elasticity estimates indicate substantial substitution possibilities between materials and other inputs. In particular, capital and materials are very strong substitutes in the U.S. They are also quite substitutable in Canada, Finland, and Sweden.

Table 2.11 presents the input biases of technical change which represent the impacts of changes in technology on factor shares over time. They provide us with the information about how the input demand is reacting due to technical change holding the prices of all inputs constant. I find technical change is universally labour saving and in most regions it is other energy saving. However, it is capital, electricity, and materials using in most regions.

Table 2.12 reports the average annual productivity growth rates obtained by using the estimated translog parameters in (2.9). The average TFP growth rates are not identical to the rates presented in Table 2.3, however, they generally provide more or less the same ranking. Table 2.12 also shows the contribution of autonomous and factor biased technological change to the overall TFP growth. Factor using technological change combined with decreasing input prices and factor saving technological change coupled with an increase in input prices contribute to higher productivity. The converse happens when the direction of factor biases to technological change is reversed. Except for BC, Maine, and Sweden, the contribution of factor biases to technological change is quite significant. Almost all regions in my sample had positive autonomous technical change during the 1971–2005 period, with the exception of Illinois and Washington. In fact, Illinois and Washington are the regions that experienced negative total factor productivity growth rates. Finland and Sweden are the leaders in terms of average annual TFP growth rates, with 1.20 and 1.08 percent, respectively. Among the Canadian provinces BC, with 0.46 percent, has the highest growth rate while Maine had the highest growth rate, 0.37 percent per year, among all U.S. states.

2.5.3 Productivity Convergence

As discussed in Section 2.1, there exists several reasons to expect TFP convergence between the pulp and paper industries in U.S. and Canada. Results from the TFP index in Table 2.3 reveal that the standard deviation of TFP across all regions in my sample, including Finland and Sweden, is declining over time.[21] The ratio of $\left(\frac{\text{Standard Deviation}_{2005}}{\text{Standard Deviation}_{1971}}\right)$ is 0.61 for these ten regions. However, the standard deviation of TFP depicted the opposite trend when I consider only the U.S. and Canadian regions in my sample: the ratio of $\left(\frac{\text{Standard Deviation}_{2005}}{\text{Standard Deviation}_{1971}}\right)$ for these eight regions is 1.19. Given the obvious contribution of Finland and Sweden to convergence, I restrict my analysis to U.S. and Canadian regions only.

There is a large literature dealing with industry TFP convergence across regions and countries. For a brief review of studies on industry TFP convergence, see Ball et al. (2004). In order to test the existence of TFP convergence, in this paper I adapt the methodology proposed by Ball et al. (2004) who analyzed TFP convergence in the agricultural sector across U.S. states over the period of 1960 to 1999. In particular, I estimate the following specification:

$$\widehat{TFP}_v^i = \beta_0 + \beta_1 \ln TFP_{1,v}^i + \beta_2 \left(\frac{\widehat{K}}{L}\right)_v^i + \beta_3 \left(\frac{\widehat{M}}{L}\right)_v^i + \beta_4 \left(\frac{\widehat{F}}{L}\right)_v^i + \beta_5 \left(\frac{\widehat{E}}{L}\right)_v^i + \epsilon_{iv} \tag{2.12}$$

where, $\widehat{TFP}_v^i$ is the average growth rate of total factor productivity for province or state i over the time window v, $\left(\frac{\widehat{j}}{L}\right)_v^i$ is the average growth rate of intensity of factor $j = K, M, E, F$, relative to labour (L), in region i over the time window v, $TFP_{1,v}^i$ is the TFP level of region i in the first year of time window v, and ϵ_{iv} is the error term.

Specification (2.12) allows to test two hypotheses — the catch-up hypothesis and the embodiment hypothesis. While the catch-up hypothesis suggests that the regions with lower TFP at the beginning of a period would display higher rates of

[21] This is often referred to as σ–convergence.

productivity growth,[22] the embodiment hypothesis implies that the TFP growth rates will be positively correlated with the growth rates of factors of production.

In estimating (2.12) I use a three-year time window for calculating the average growth rates. Taking the advantage of a larger sample size and longer time periods, Ball et al. (2004) used a five-year window. A smaller sample leads me to use the three-year windows.[23] In addition, I perform the panel unit root test suggested by Im et al. (1997) to detect the presence of non-stationarity in time series variables that could cause spurious regression. Results from estimating (2.12) and the panel unit root test are reported in Table 2.13. The null hypothesis of a unit root is rejected for each series in the panel, and hence I proceed to the estimation of equation (2.12) without further transformation.

As expected, the coefficient of $\ln TFP^i_{1,v}$ is negative and highly significant, confirming the presence of productivity catch-up. All the embodiment coefficients are statistically significant. Positive and significant coefficients for $\left(\frac{\widehat{M}}{L}\right)^i_v$ and $\left(\frac{\widehat{E}}{L}\right)^i_v$ imply that the embodiment of technology in materials and electricity are important sources of productivity growth for this industry during the sample period. Overall, capital and materials brought much larger contribution relative to other energies and electricity, although the negative sign attached to the growth rate of capital is not expected. However, we must keep in mind that the pulp and paper industry was subjected to strict regulations with respect to water and air emissions during the sample period. A large share of capital expenditures had to be devoted to satisfy the growing environmental constraints, thus reducing the contribution to the standard measure of TFP growth.[24]

[22] This is often referred to as conditional β–convergence. Based on the results of σ– and β–convergence for a group of 14 OECD countries, Van Biesebroeck (2009) finds the presence of productivity convergence during 1970–1999 in almost all industries. He estimates β–convergence for each industry by regressing the productivity growth on the logarithm of initial productivity level pooling all countries.

[23] My conclusion regarding the productivity catch-up remains valid when I also estimate specification (2.12) using four and five-year time windows.

[24] Hailu and Veeman (2000, 2001); Hailu (2003) found that the decrease of water pollutants made a positive contribution to the TFP performance of the Canadian pulp and paper industry.

2.6 Conclusion

In this paper I use regional disaggregated data for the pulp and paper industries in Canada and U.S. to investigate the presence of TFP convergence over the period of 1971–2005. National data for Finland and Sweden are added as complements which provide a scope to compare the productivity performances of four leading players in global pulp and paper industry. The TFP growth performance is at the advantage of Canadian provinces relative to their U.S. counterparts in my sample, and at the end of the sample period they had almost closed the productivity gap when weighted average TFP levels are compared. Finland and Sweden enjoyed higher TFP growth rates than their North-American counterparts and got close to their weighted average TFP levels in 2005. TFP convergence in this industry is expected given the existence of world market for pulp and paper products, the high level of exchanges between U.S. and Canada, and the common technology that has evolved little over the last century. The empirical evidence that I gather is in favour of TFP convergence – the Canadian regions that had lower TFP levels at the start of the sample period caught up to the high performance regions in the U.S. Convergence of TFP translated into benefits to workers in the regions of high TFP growth since the simple correlation coefficient between the average annual growth rates of TFP and of real wage rates is 0.83.

My decomposition of average annual growth rates of TFP into autonomous and factor biased technological change by the estimation of translog cost function shed some light on the relative contribution of the factor biased technical change that turns out to be significant in some regions. Let us recall some characteristics of the pulp and paper industry in industrialized countries: it provides a set of fairly homogeneous products, shares a common technology, performs little R&D, and gets its equipment from a small group of manufacturers. This leaves little room for governments to influence technological change targeting production processes.

However, this is not necessarily the case for factor biased technical change. My estimation results show that technical change has been generally capital and material using, and labour saving. The contribution of factor using technical change and decreasing relative price of the relevant factor add a positive contribution to TFP growth. Taxation of capital is a policy tool under government control and it influences the user price of capital goods. My results draw the attention on one aspect of capital taxation that is often left out in policy analysis. However, it must be kept in mind that it is the rate of change of relative input price that influences TFP change. Thus relative input prices must keep changing to support TFP growth.

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Table 2.1: Output and Input Quantities: 1971–2005

	AB	BC	ON	QC	GA	IL	ME	WA	FIN	SWE
Output (1992 CAN$ in millions)										
1971	256	3113	5476	5609	5125	5879	3315	4010	4718	8042
2005	1332	4251	8527	8520	8494	5025	3326	4470	17011	16835
(71–05)[a]	4.8	0.9	1.3	1.23	1.4	-0.4	0.01	0.3	3.7	2.1
Labour (man years)										
1971	1562	18327	43867	42125	24788	37988	16856	18048	57448	55387
2005	2957	12123	29681	26995	23716	25477	9177	12175	32700	36096
(71–05)[a]	1.8	-1.2	-1.1	-1.3	-0.1	-1.2	-1.8	-1.2	-1.7	-1.3
Capital (1992 CAN$ in millions)										
1971	175	5045	3079	3537	3639	2117	1521	2864	12134	8134
2005	1158	2465	3252	4571	6171	3590	2580	4856	15917	12995
(71–05)[a]	5.5	-2.1	0.2	0.8	1.5	1.6	1.6	1.6	0.8	1.3
Materials (1992 CAN$ in millions)										
1971	152	1730	3116	3031	3404	3497	2334	2572	1829	5622
2005	781	3023	5836	5869	4714	2669	1834	2717	11021	11568
(71–05)[a]	4.8	1.6	1.8	1.9	0.9	-0.8	-0.7	0.2	5.2	2.1
Electricity (TJ)										
1971	337	13329	15275	33485	3482	6052	1624	9556	31356	25024
2005	9850	33038	26096	76434	10195	10324	1839	8496	83830	70747
(71–05)[a]	9.2	2.7	1.6	2.4	3.2	1.5	0.4	-0.3	2.9	3.1
Other Energy (TJ)										
1971	2587	33953	50434	49494	61534	106012	18238	73025	40802	81945
2005	10574	14975	39722	19938	113828	84799	19272	61605	56799	95659
(71–05)[a]	4.1	-2.4	-0.7	-2.7	1.8	-0.7	0.2	-0.5	0.9	0.5

Notes: *a.* Average annual growth rate (%). Units of electricity and other energies are in terajoule.

Table 2.2: Input Prices and Cost Shares: 1971–2005

	AB	BC	ON	QC	GA	IL	ME	WA	FIN	SWE
Wage (1992 CAN$ per man year)										
1971	30418	40042	31368	32464	41301	40847	43396	47477	18631	25444
2005	53865	56586	45761	44582	46804	40885	49049	52659	55274	55843
(71–05)[a]	1.6	0.9	1.1	0.9	0.4	0.0	0.4	0.3	3.2	2.3
Rate of Return (%)										
1971	0.40	0.12	0.33	0.28	0.29	0.29	0.26	0.18	0.14	0.10
2005	0.26	0.34	0.52	0.46	0.25	0.14	0.22	0.14	0.22	0.29
(71–05)[a]	-1.2	3.1	1.4	1.4	-0.4	-2.1	-0.6	-0.7	1.3	3.1
Materials (1992=1.00)										
1971	0.86	0.91	0.91	0.97	0.90	0.91	0.90	0.91	0.94	0.75
2005	0.94	0.72	0.81	0.73	0.98	0.96	1.19	0.95	1.01	0.93
(71–05)[a]	0.2	-0.7	-0.3	-0.8	0.2	0.2	0.8	0.1	0.6	3.1
Electricity ($/TJ)										
1971	7443	5916	7847	5053	15177	18260	17481	4805	12266	11095
2005	4937	8302	18186	7269	14107	12322	19445	11400	9878	8987
(71–05)[a]	-1.2	1.0	2.5	1.1	-0.2	-1.1	0.3	2.5	-0.6	-0.6
Other Energy ($/TJ)										
1971	1841	3360	2494	3349	3491	4031	3107	3691	2573	2328
2005	7862	16299	5739	19390	6958	9120	4989	7753	5706	5192
(71–05)[a]	4.3	4.6	2.5	5.2	2.0	2.4	1.4	2.2	2.3	2.4
Input Cost Share (%)										
Capital	0.30	0.24	0.23	0.24	0.17	0.11	0.13	0.12	0.22	0.24
Labour	0.15	0.19	0.19	0.19	0.15	0.20	0.16	0.16	0.15	0.13
Materials	0.50	0.49	0.50	0.47	0.60	0.55	0.66	0.60	0.52	0.55
Electricity	0.02	0.04	0.03	0.04	0.01	0.02	0.01	0.01	0.07	0.04
Other Energy	0.02	0.05	0.02	0.03	0.05	0.09	0.02	0.08	0.02	0.02

Notes: *a*. Average annual growth rate (%). TJ refers to terajoules.

Table 2.3: Total Factor Productivity Index, 1971–2005

Year	AB	BC	ON	QC	GA	IL	ME	WA	FIN	SWE	σ_{10}	σ_8
1971	0.97	0.82	0.95	0.95	0.95	1.01	1.00	0.93	0.69	0.79	0.10	0.06
1972	0.85	0.84	0.96	0.95	0.99	1.06	1.00	0.98	0.67	0.82	0.12	0.07
1973	0.82	0.85	0.98	0.95	1.02	1.12	1.05	0.99	0.65	0.89	0.13	0.10
1974	0.91	0.86	1.01	0.97	1.03	1.13	1.07	0.99	0.72	0.82	0.12	0.09
1975	0.86	0.83	0.98	0.96	1.01	1.06	1.05	0.98	0.60	0.60	0.17	0.08
1976	0.91	0.87	0.96	0.94	1.06	1.05	1.09	1.01	0.69	0.63	0.15	0.08
1977	0.91	0.87	0.96	0.95	1.03	1.09	1.12	1.01	0.70	0.66	0.15	0.09
1978	0.92	0.88	0.97	0.97	1.05	1.12	1.17	1.00	0.71	0.77	0.14	0.10
1979	0.87	0.89	1.00	0.98	1.07	1.14	1.18	1.03	0.72	0.73	0.16	0.11
1980	0.90	0.89	1.01	0.98	1.07	1.11	1.15	1.01	0.74	0.72	0.15	0.09
1981	0.93	0.87	1.00	0.97	1.06	1.10	1.13	0.98	0.75	0.69	0.14	0.09
1982	1.01	0.88	1.00	0.95	1.07	1.11	1.12	0.97	0.72	0.72	0.14	0.08
1983	1.00	0.88	1.00	0.96	1.06	1.09	1.11	1.02	0.76	0.80	0.12	0.07
1984	1.07	0.87	1.01	0.96	1.13	1.09	1.17	1.03	0.74	0.82	0.14	0.10
1985	1.04	0.90	1.01	0.95	1.07	1.11	1.16	1.00	0.75	0.80	0.13	0.08
1986	0.96	0.91	1.02	0.94	1.13	1.12	1.15	1.05	0.75	0.83	0.13	0.09
1987	0.97	0.94	1.03	0.92	1.12	1.06	1.12	1.07	0.77	0.86	0.12	0.08
1988	0.81	0.93	1.03	0.93	1.17	1.06	1.21	1.12	0.80	0.85	0.15	0.14
1989	0.70	0.88	1.03	0.92	1.16	1.05	1.15	1.07	0.83	0.85	0.15	0.15
1990	0.73	0.85	1.03	0.93	1.10	1.05	1.11	1.01	0.84	0.81	0.13	0.13
1991	0.80	0.87	1.02	0.92	1.09	1.06	1.04	0.98	0.87	0.89	0.10	0.10
1992	0.84	0.88	1.02	0.92	1.13	1.06	1.01	0.94	0.87	0.93	0.09	0.10
1993	0.82	0.90	1.03	0.93	1.13	1.13	1.05	0.99	0.88	1.06	0.11	0.11
1994	0.90	0.88	1.04	0.94	1.13	1.14	1.06	1.00	0.92	1.03	0.09	0.10
1995	0.85	0.87	1.05	0.94	1.09	0.99	1.27	0.96	0.90	0.88	0.13	0.14
1996	0.80	0.91	1.05	0.94	1.08	1.04	1.18	0.93	0.90	0.88	0.11	0.12
1997	0.86	0.91	1.06	0.96	1.12	1.08	1.14	0.99	0.94	0.93	0.10	0.10
1998	0.78	0.91	1.08	0.96	1.10	1.04	1.16	0.94	0.94	0.94	0.11	0.12
1999	0.88	0.93	1.08	0.97	1.12	1.00	1.21	0.92	0.95	1.00	0.10	0.11
2000	1.01	0.96	1.10	0.99	1.09	0.92	1.15	0.92	0.96	1.01	0.08	0.09
2001	0.88	0.95	1.11	1.00	1.07	0.93	1.12	0.89	0.94	0.98	0.09	0.10
2002	0.95	0.96	1.13	1.03	1.10	0.96	1.13	0.90	0.98	1.01	0.08	0.09
2003	1.04	0.99	1.12	1.01	1.10	0.96	1.13	0.97	1.02	1.07	0.06	0.07
2004	1.04	1.02	1.12	1.02	1.13	0.99	1.14	0.97	1.06	1.05	0.06	0.07
2005	1.04	1.03	1.13	1.06	1.12	1.00	1.18	0.98	1.03	1.02	0.06	0.07
(71–05)[a]	0.19	0.67	0.49	0.31	0.48	-0.04	0.49	0.17	1.18	0.76	–	–

Notes: *a*. Average annual growth rate (%). σ_{10} refers to the standard deviation of TFP levels across the ten regions. σ_8 refers to the standard deviation of TFP levels across the eight U.S. and Canadian regions.

Table 2.4: Coverage of Concavity by the Estimated Translog Cost Function

Region	Concavity Coverage when Not Imposed		Concavity Coverage when Imposed		
	Number of Data Points	At the Mean of Data	Number of Data Points	At the Mean of Data	Point of Imposition*
Alberta	5 (14%)	No	27 (77%)	Yes	17
British Columbia	8 (23%)	No	29 (83%)	Yes	5
Ontario	11 (31%)	Yes	27 (77%)	Yes	4
Québec	9 (26%)	No	28 (80%)	Yes	13
Georgia	7 (20%)	No	33 (94%)	Yes	19
Illinois	0 (0%)	No	29 (83%)	Yes	3
Maine	1 (3%)	No	25 (71%)	Yes	1
Washington	9 (26%)	Yes	17 (49%)	Yes	1
Finland	2 (6%)	No	25 (71%)	Yes	31
Sweden	14 (40%)	Yes	30 (86%)	Yes	25

Note: * Highest number of data points satisfies concavity when concavity is imposed at this data point.

Table 2.5: Test Statistics for Likelihood Ratio Tests

Region	No Technical Change	Neutral Technical Change	Pooling
Alberta	121.84	111.56	
BC	96.20	44.02	1089.40*
Ontario	154.45	107.55	
Québec	131.72	80.69	
Georgia	138.82	132.45	
Illinois	108.59	70.88	1415.17**
Maine	67.90	58.50	
Washington	54.20	44.28	
Finland	145.14	84.59	—
Sweden	93.46	56.49	—

Notes: Test for no technical change in the TL model requires 6 parameter restrictions. Test for neutral technical change in the TL model involves 4 restrictions. * Test statistic for poolability of data for Canadian Provinces. ** Test statistic for poolability of data for US states. In all cases, $prob > \chi^2 = 0.0000$.

Table 2.6: Translog Parameter Estimates for Canadian Provinces

Parameter	Alberta	BC	Ontario	Québec
α_K	.3872 (.0274)	.1810 (.0093)	.2628 (.0086)	.1836 (.0049)
α_L	.1336 (.0042)	.2424 (.0044)	.2047 (.0022)	.2229 (.0027)
α_F	.0179 (.0017)	.0409 (.0022)	.0214 (.0013)	.0646 (.0022)
α_E	.0141 (.0013)	.0232 (.0018)	.0161 (.0008)	.0518 (.0029)
α_{KK}	.1451 (.0147)	.1230 (.0066)	.1066 (.0104)	.1318 (.0055)
α_{LL}	.0867 (.0113)	.0643 (.0156)	.0770 (.0065)	.0903 (.0116)
α_{FF}	.0135 (.0015)	.0213 (.0029)	.0197 (.0012)	.0330 (.0034)
α_{EE}	.0135 (.0015)	.0213 (.0029)	.0197 (.0012)	.0330 (.0034)
α_{KL}	.0135 (.0015)	.0213 (.0029)	.0197 (.0012)	.0330 (.0034)
α_{KF}	-.0109 (.0016)	-.0094 (.0020)	-.0084 (.0012)	-.0141 (.0028)
α_{KE}	-.0139 (.0016)	-.0116 (.0016)	-.0097 (.0028)	-.0121 (.0028)
α_{LF}	-.0112 (.0024)	-.0056 (.0008)	-.0028 (.0018)	.0067 (.0036)
α_{LE}	-.0097 (.0045)	.0077 (.0020)	.0099 (.0030)	-.0270 (.0074)
α_{FE}	-.0043 (.0013)	.0080 (.0020)	-.0019 (.0004)	-.0004 (.0004)
α_{Kt}	.0023 (.0010)	-.0011 (.0005)	.0020 (.0004)	.0026 (.0004)
α_{Lt}	-.0034 (.0003)	-.0023 (.0003)	-.0030 (.0001)	-.0031 (.0002)
α_{Ft}	.0003 (.0001)	-.0003 (.0001)	-.0002 (.0001)	-.0010 (.0001)
α_{Et}	.0017 (.0001)	.0007 (.0001)	.0006 (.0000)	.0008 (.0002)
α_t	-.0015 (.0025)	-.0090 (.0016)	-.0018 (.0007)	-.0031 (.0005)
α_{tt}	.0009 (.0002)	.0004 (.0001)	-.0001 (.0000)	-.0001 (.0001)
Constant	.0779 (.0274)	-1.3494 (.0118)	-.9168 (.0086)	-.2166 (.0051)
R^2 values				
Cost Eq.	0.78	0.90	0.97	0.93
Capital Eq.	0.20	0.74	0.61	0.73
Labour Eq.	0.54	0.87	0.98	0.96
Other Energy Eq.	0.58	0.69	0.90	0.58
Electricity Eq.	0.90	0.87	0.98	0.82

Note: Standard errors of the parameter estimates are reported in parenthesis.

Table 2.7: Translog Parameter Estimates for U.S. States, Finland, and Sweden

	US					
Parameter	Georgia	Illinois	Maine	Washington	Finland	Sweden
α_K	.1913 (.0060)	.1349 (.0039)	.0936 (.0084)	.1154 (.0057)	.2669 (.0067)	.3194 (.0026)
α_L	.1315 (.0041)	.2387 (.0068)	.2154 (.0035)	.2034 (.0037)	.1077 (.0066)	.1039 (.0026)
α_F	.0420 (.0008)	.0752 (.0024)	.0182 (.0016)	.0872 (.0033)	.0156 (.0014)	.0162 (.0009)
α_E	.0145 (.0003)	.0211 (.0006)	.0088 (.0004)	.0179 (.0011)	.0503 (.0026)	.0380 (.0018)
α_{KK}	.0248 (.0042)	.0459 (.0050)	.0264 (.0094)	.0555 (.0062)	.1235 (.0060)	.1516 (.0030)
α_{LL}	.0903 (.0180)	.1132 (.0290)	.1475 (.0150)	.1284 (.0210)	.0774 (.0130)	.0541 (.0100)
α_{FF}	.0383 (.0040)	.0664 (.0030)	.0164 (.0016)	.0651 (.0046)	.0152 (.0016)	.0152 (.0010)
α_{EE}	.0140 (.0010)	.0207 (.0012)	.0086 (.0012)	.0142 (.0011)	.0477 (.0024)	.0175 (.0040)
α_{KL}	-.0352 (.0078)	-.0600 (.0080)	-.0494 (.0070)	-.0403 (.0044)	-.0240 (.0050)	-.0389 (.0030)
α_{KF}	-.0240 (.0040)	-.0244 (.0034)	-.0051 (.0015)	-.0312 (.0039)	-.0044 (.0017)	-.0038 (.0010)
α_{KE}	-.0037 (.0010)	-.0021 (.0009)	-.0017 (.0008)	-.0040 (.0012)	-.0115 (.0028)	-.0144 (.0020)
α_{LF}	-.0075 (.0060)	-.0273 (.0065)	-.0027 (.0020)	-.0217 (.0040)	-.0002 (.0000)	-.0033 (.0006)
α_{LE}	.0009 (.0018)	-.0033 (.0027)	-.0017 (.0020)	-.0089 (.0030)	-.0065 (.0008)	-.0244 (.0050)
α_{FE}	-.0006 (.0008)	-.0013 (.0009)	-.0005 (.0002)	-.0051 (.0012)	-.0007 (.0002)	.0009 (.0002)
α_{Kt}	.0029 (.0003)	.0010 (.0003)	.0020 (.0004)	.0015 (.0003)	-.0028 (.0004)	.0002 (.0001)
α_{Lt}	-.0007 (.0002)	-.0029 (.0005)	-.0023 (.0002)	-.0019 (.0002)	-.0054 (.0006)	-.0030 (.0002)
α_{Ft}	.0005 (.0001)	-.0012 (.0003)	.0001 (.0001)	-.0012 (.0002)	-.0004 (.0001)	-.0002 (.0000)
α_{Et}	.0003 (.0000)	.0003 (.0000)	.0001 (.0000)	-.0002 (.0001)	.0003 (.0002)	.0006 (.0001)
α_t	-.0013 (.0004)	-.0088 (.0012)	-.0138 (.0017)	-.0103 (.0016)	-.0238 (.0012)	-.0135 (.0025)
α_{tt}	.0007 (.0001)	.0008 (.0001)	-.0006 (.0001)	.0007 (.0001)	-.0006 (.0001)	-.0004 (.0001)
Constant	-.0325 (.0047)	-1.2044 (.0108)	-1.3256 (.0167)	-1.3683 (.0157)	.2683 (.0131)	.4101 (.0194)
R^2 *values*						
Cost Eq.	0.76	0.60	0.70	0.35	0.84	0.73
Capital Eq.	0.80	0.64	0.49	0.72	0.76	0.98
Labour Eq.	0.55	0.63	0.84	0.72	0.77	0.90
Other Energy Eq.	0.90	0.76	0.77	0.80	0.80	0.87
Electricity Eq.	0.86	0.76	0.75	0.73	0.77	0.74

Note: Standard errors of the parameter estimates are reported in parenthesis.

Table 2.8: Point Estimates and Confidence Intervals for Input Price Elasticities in Canadian Provinces

Factor i	Region	Price Elasticities η_{Ki}	η_{Li}	η_{Mi}	η_{Ei}	η_{Fi}
(K)	Alberta	-0.21 (-0.37, -0.16)	0.04 (0.02, 0.08)	0.21 (0.17, 0.34)	-0.02 (-0.04, -0.02)	-0.01 (-0.02, 0.00)
	BC	-0.23 (-0.29, -0.19)	-0.01 (-0.04, 0.03)	0.24 (0.19, 0.30)	-0.01 (-0.02, 0.01)	0.01 (-0.01, 0.02)
	Ontario	-0.3 (-0.29, -0.19)	-0.02 (-0.04, 0.03)	0.34 (0.19, 0.30)	-0.01 (-0.02, 0.01)	-0.01 (-0.01, 0.02)
	Québec	-0.2 (-0.24, -0.17)	-0.04 (-0.07, -0.01)	0.26 (0.21, 0.32)	0.00 (-0.02, 0.02)	-0.02 (-0.04, 0.00)
(L)	Alberta	0.07 (0.03, 0.14)	-0.28 (-0.42, -0.10)	0.29 (0.07, 0.44)	-0.04 (-0.10, 0.02)	-0.05 (-0.08, -0.01)
	BC	-0.01 (-0.05, 0.03)	-0.47 (-0.65, -0.32)	0.38 (0.26, 0.53)	0.08 (0.03, 0.14)	0.02 (-0.03, 0.07)
	Ontario	-0.02 (-0.05, 0.01)	-0.41 (-0.48, -0.34)	0.34 (0.29, 0.38)	0.08 (0.05, 0.12)	0.01 (-0.00, 0.03)
	Québec	-0.05 (-0.08, -0.01)	-0.34 (-0.48, -0.23)	0.40 (0.31, 0.52)	-0.03 (-0.16, -0.00)	0.07 (0.03, 0.11)
(M)	Alberta	0.12 (0.10, 0.20)	0.09 (0.02, 0.13)	-0.32 (-0.42, -0.26)	0.06 (0.05, 0.10)	0.05 (0.04, 0.06)
	BC	0.11 (0.09, 0.13)	0.14 (0.10, 0.20)	-0.28 (-0.34, -0.23)	0.01 (-0.01, 0.02)	0.02 (0.01, 0.04)
	Ontario	0.14 (0.11, 0.18)	0.13 (0.11, 0.15)	-0.3 (-0.34, -0.26)	0.01 (0.01, 0.02)	0.01 (0.007, 0.02)
	Québec	0.13 (0.10, 0.15)	0.16 (0.13, 0.21)	-0.33 (-0.40, -0.28)	0.05 (0.03, 0.09)	-0.01 (-0.03, 0.01)
(E)	Alberta	-0.25 (-0.43, -0.17)	-0.22 (-0.55, 0.13)	0.47 (0.38, 0.91)	-0.61 (-1.04, -0.58)	-0.14 (-0.19, 0.02)
	BC	-0.06 (-0.12, 0.03)	0.37 (0.13, 0.63)	0.08 (-0.09, 0.27)	-0.64 (-0.77, -0.55)	0.24 (0.17, 0.31)
	Ontario	-0.06 (-0.11, -0.01)	0.49 (0.31, 0.69)	0.21 (0.11, 0.31)	-0.6 (-0.82, -0.52)	-0.03 (-0.07, 0.06)
	Québec	-0.01 (-0.12, 0.10)	-0.34 (-0.62, -0.01)	0.51 (0.29, 0.95)	-0.19 (-0.78, -0.08)	0.04 (-0.07, 0.22)
(F)	Alberta	-0.14 (-0.23, 0.02)	-0.29 (-0.48, -0.08)	0.94 (0.73, 1.21)	-0.14 (-0.20, 0.02)	-0.45 (-0.61, -0.36)
	BC	0.04 (-0.03, 0.11)	0.07 (-0.11, 0.25)	0.21 (0.05, 0.41)	0.20 (0.14, 0.26)	-0.52 (-0.61, -0.45)
	Ontario	-0.09 (-0.19, 0.01)	0.10 (-0.04, 0.24)	0.28 (0.14, 0.43)	-0.04 (-0.08, 0.08)	-0.24 (-0.41, -0.19)
	Québec	-0.13 (-0.24, 0.02)	0.37 (0.17, 0.54)	-0.18 (-0.42, 0.08)	0.05 (-0.10, 0.26)	-0.11 (-0.33, -0.08)

Note: Elasticities are calculated at the mean of the data, and 95% confidence intervals for the estimates are reported in parenthesis.

Table 2.9: Point Estimates and Confidence Intervals for Input Price Elasticities in U.S. States

Factor i	Region	Price Elasticities η_{Ki}	η_{Li}	η_{Mi}	η_{Ei}	η_{Fi}
(K)	Georgia	-0.68	-0.05	0.83	-0.01	-0.08
		(-0.97, -0.37)	(-0.18, -0.01)	(0.69, 1.06)	(-0.08, 0.05)	(-0.18, 0.05)
	Illinois	-0.50	-0.29	0.88	0.01	-0.11
		(-0.59, -0.40)	(-0.43, -0.15)	(0.74, 1.16)	(-0.02, 0.01)	(-0.21, -0.10)
	Maine	-0.67	-0.17	0.80	0.00	0.00
		(-0.52, 0.78)	(-0.34, -0.11)	(0.72, 1.12)	(-0.04, 0.04)	(-0.06, 0.02)
	Washington	-0.43	-0.16	0.36	-0.01	0.00
		(-0.54, -0.34)	(-0.23, -0.08)	(0.24, 0.68)	(-0.04, 0.02)	(-0.18, 0.03)
(L)	Georgia	-0.06	-0.25	0.29	0.02	-0.01
		(-0.19, -0.01)	(-0.49, -0.11)	(0.25, 0.57)	(-0.01, 0.08)	(-0.11, 0.04)
	Illinois	-0.16	-0.25	0.44	0.01	-0.03
		(-0.24, -0.09)	(-0.62, -0.07)	(0.26, 0.63)	(-0.04, 0.03)	(-0.16, -0.02)
	Maine	-0.13	-0.11	0.23	0.00	0.01
		(-0.19, -0.02)	(-0.22, 0.06)	(0.18, 0.32)	(-0.06, 0.04)	(-0.06, 0.08)
	Washington	-0.06	-0.12	0.22	-0.04	0.01
		(-0.17, -0.06)	(-0.41, -0.09)	(0.20, 0.57)	(-0.08, 0.09)	(-0.02, 0.13)
(M)	Georgia	0.24	0.07	-0.35	0.00	0.05
		(0.18, 0.37)	(0.02, 0.16)	(-0.57, -0.18)	(-0.11, 0.10)	(0.03, 0.24)
	Illinois	0.19	0.17	-0.44	0.00	0.07
		(0.16, 0.25)	(0.10, 0.36)	(-0.74, -0.39)	(-0.00, 0.09)	(0.06, 0.21)
	Maine	0.16	0.06	-0.22	0.00	0.01
		(0.02, 0.23)	(0.01, 0.08)	(-0.36, -0.14)	(-0.17, 0.05)	(-0.04, 0.12)
	Washington	0.07	0.06	-0.33	0.04	0.06
		(0.04, 0.9)	(0.01, 0.12)	(-0.41, -0.17)	(0.02, 0.10)	(0.03, 0.14)
(E)	Georgia	-0.07	0.21	0.05	-0.25	0.01
		(-0.13, 0.01)	(0.17, 0.59)	(0.02, 0.12)	(-0.39, -0.15)	(-0.12, 0.09)
	Illinois	0.04	0.09	0.03	-0.21	0.05
		(-0.14, 0.06)	(-0.34, 0.25)	(-0.04, 0.50)	(-0.60, -0.13)	(-0.34, 0.20)
	Maine	-0.03	0.02	0.27	-0.25	-0.02
		(-0.10, 0.12)	(-0.23, 0.17)	(0.18, 0.42)	(-0.30, -0.08)	(-0.16, 0.12)
	Washington	-0.06	-0.31	0.68	-0.31	-0.17
		(-0.08, 0.04)	(-0.47, 0.04)	(0.44, 0.76)	(-0.59, -0.08)	(-0.30, -0.09)
(F)	Georgia	-0.26	-0.02	0.50	0.00	-0.25
		(-0.39, -0.12)	(-0.21, 0.05)	(0.41, 0.67)	(-0.05, 0.18)	(-0.42, -0.09)
	Illinois	-0.13	-0.07	0.41	0.01	-0.22
		(-0.30, -0.13)	(-0.38, -0.04)	(0.38, 0.90)	(-0.36, 0.06)	(-0.62, -0.13)
	Maine	-0.02	0.05	0.30	-0.01	-0.29
		(-0.26, 0.08)	(0.00 0.06)	(0.14, 0.48)	(0.04, 0.06)	(-0.62, -0.20)
	Washington	0.00	0.01	0.52	-0.04	-0.32
		(-0.15, 0.02)	(-0.04, 0.08)	(0.38, 0.71)	(-0.08, 0.02)	(-0.35, -0.11)

Note: Elasticities are calculated at the mean of the data, and 95% confidence intervals for the estimates are reported in parenthesis.

Table 2.10: Point Estimates and Confidence Intervals for Input Price Elasticities in Finland and Sweden

		Price Elasticities				
Factor i	Region	η_{Ki}	η_{Li}	η_{Mi}	η_{Ei}	η_{Fi}
(K)	Finland	-0.22	0.05	0.14	0.02	0.01
		(-0.29, -0.16)	(-0.00, 0.11)	(0.06, 0.47)	(-0.01, 0.08)	(-0.07, 0.06)
	Sweden	-0.13	-0.03	0.16	-0.01	0.01
		(-0.16, -0.10)	(-0.05, -0.00)	(0.11, 0.21)	(-0.03, 0.01)	(0.00, 0.02)
(L)	Finland	0.08	-0.36	0.23	0.03	0.02
		(-0.00, 0.15)	(-0.61, -0.26)	(0.17, 0.35)	(-0.04, 0.13)	(-0.04, 0.09)
	Sweden	-0.05	-0.46	0.64	-0.14	0.00
		(-0.09, -0.00)	(-0.63, -0.33)	(0.47, 0.84)	(-0.21, -0.05)	(-0.04, 0.05)
(M)	Finland	0.06	0.07	-0.16	0.02	0.00
		(0.01, 0.11)	(0.01, 0.19)	(-0.47, -0.11)	(-0.16, 0.10)	(-0.08, 0.15)
	Sweden	0.07	0.16	-0.32	0.08	0.01
		(0.04, 0.09)	(0.11, 0.21)	(-0.39, -0.25)	(0.06, 0.11)	(-0.00, 0.02)
(E)	Finland	0.07	0.07	0.12	-0.28	0.01
		(0.01, 0.14)	(0.01, 0.21)	(0.03, 0.19)	(-0.41, -0.13)	(-0.15, 0.18)
	Sweden	-0.07	-0.39	0.79	-0.58	0.05
		(-0.17, 0.02)	(-0.63, -0.17)	(0.72, 1.41)	(-0.90, -0.44)	(-0.03, 0.16)
(F)	Finland	0.05	0.16	0.26	0.04	-0.43
		(-0.01, 0.10)	(-0.01, 0.21)	(0.20, 0.57)	(-0.01, 0.12)	(-0.69, -0.31)
	Sweden	0.11	0.02	0.23	0.08	-0.43
		(0.00, 0.20)	(-0.20, 0.21)	(-0.05, 0.55)	(-0.06, 0.27)	(-0.57, -0.39)

Note: Elasticities are calculated at the mean of the data, and 95% confidence intervals for the estimates are reported in parenthesis.

Table 2.11: Factor Biases of Technical Change in the Pulp and Paper Industry

Region	Capital	Labour	Materials	Other Energy	Electricity
Alberta	0.0023	-0.0034	-0.0009	0.0003	0.0017
British Columbia	-0.0011	-0.0023	0.0030	-0.0003	0.0007
Ontario	0.0020	-0.0030	0.0006	-0.0002	0.0006
Québec	0.0026	-0.0031	0.0007	-0.0010	0.0008
Georgia	0.0029	-0.0007	-0.0030	0.0005	0.0003
Illinois	0.0010	-0.0029	0.0028	-0.0012	0.0003
Maine	0.0020	-0.0023	0.0001	0.0001	0.0001
Washington	0.0015	-0.0019	0.0018	-0.0012	-0.0002
Finland	-0.0028	-0.0054	0.0083	-0.0004	0.0003
Sweden	0.0002	-0.0030	0.0024	-0.0002	0.0006

Table 2.12: Average Annual Growth Rates of TFP in the Pulp and Paper Industry

Region	Autonomous Technical Change (%)	Biased Technical Change (%)	Growth Rates of Productivity
Alberta	0.06	0.14	0.20
British Columbia	0.44	0.02	0.46
Ontario	0.31	0.12	0.43
Québec	0.33	-0.10	0.23
Georgia	0.20	0.09	0.29
Illinois	-0.34	0.06	-0.28
Maine	0.39	-0.02	0.37
Washington	-0.16	0.06	-0.10
Finland	1.62	-0.42	1.20
Sweden	1.08	0.00	1.08

Table 2.13: Results for Convergence and Panel Data Unit Root Test

Variable	Coefficient	Standard Error	Unit Root Test Statistics*
$\ln TFP$	-0.1657	0.0304	-2.6801
$\left(\frac{\widehat{K}}{L}\right)$	-0.1605	0.0220	-4.0294
$\left(\frac{\widehat{M}}{L}\right)$	0.1324	0.0261	-3.9738
$\left(\frac{\widehat{E}}{L}\right)$	0.0037	0.0010	-4.3852
$\left(\frac{\widehat{F}}{L}\right)$	-0.0109	0.0194	-3.6082
$\widehat{TFP}$	—	—	-4.0030
Province/State Fixed Effects		Yes	
Time Fixed Effects		Yes	

Note: * Variable $\ln TFP$ included a time trend in the unit root test. The asymptotic standard normal 5% critical value is -1.65.

A Appendix: Data Framework

Total revenue can be decomposed into factor payments:

$$P_t Q_t = P_{lt} L_t + P_{kt} K_t + P_{mt} M_t + P_{ft} F_t + P_{et} E_t \tag{A.1}$$

where,

Q_t = total shipments in constant dollars;

L_t = number of workers;

K_t = value of net capital stock in constant dollars;

M_t = value of materials in constant dollars;

F_t = quantity of purchased fossil fuels (coal, petroleum products, and natural gas) in Terajoules (TJ);

E_t = purchased electricity in TJ;

P_t = industry selling price index;

P_{lt} = average annual wage in current dollars;

P_{kt} = gross rate of return to capital in current dollars;

P_{mt} = material price index;

P_{ft} = unit price of fossil fuels, current dollars per TJ;

P_{et} = unit price of purchased electricity, current dollars per TJ.

Note that:

$$P_t Q_t = \text{ total value of shipments } (TVS_t) \text{ in current dollars;}$$

$$P_{lt} L_t + P_{kt} K_t = \text{ value added } (VA_t) \text{ in current dollars.}$$

Data on P_t, P_{lt}, L_t, K_t, P_{ft}, F_t, P_{et}, E_t, and also on TVS_t, and VA_t are either directly obtained or constructed from publicly available information. Transformations yield the following variables:

$$Q_t = TVS_t/P_t \tag{A.2}$$

$$P_{kt} = (VA_t - P_{lt}L_t)/K_t \tag{A.3}$$

$$P_{mt}M_t = TVS_t - VA_t - P_{ft}F_t - P_{et}E_t \tag{A.4}$$

The same development can be performed in constant dollars. Then the equivalent to expression (A.4) yields the value of materials in constant dollars, which is identified as the quantity of materials. The ratio of value of materials in current dollars to its value in constant dollars yields P_{mt}, *i.e.*, the materials price index. Constant dollar values are expressed in 1992 Canadian dollars using the exchange rate of this mid-smaple year.

B Appendix: Data Sources

B.1 U.S. Data Sources

Data on U.S. variables come from the following U.S. government sources: Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Census Bureau, and Energy Information Administration (EIA).

Table B.1: U.S. Data Sources

Total value of shipments and materials including energy	Annual Survey of Manufactures, Census Bureau
Industry selling price index	Producer Price Index-Commodities (Series WPU09), BLS
Value added in current and constant dollars	Annual GDP by State, BEA
Number of workers	State Annual Personal Income–Total Full-Time and Part-Time Employment by Industry, State Level, (SA-25), BEA
Average annual wage in current dollars	State Annual Personal Income–Total Full-Time and Part-Time Wage and Salary Employment by Industry, State Level, (SA-27), BEA
Materials including energy	Annual Survey of Manufactures, Census Bureau

Data on energy purchases by the pulp and paper industry at the state level are not available. Industrial Sector Energy Consumption Estimates, State Energy Data System (SEDS), EIA, provide information for census regions which are used to compute the ratio,

$$q_{it}^{s} = q(pp)_{it}^{s}/q(ind)_{it}^{s} \tag{B.1}$$

where $q(.)_{it}^{s}$ is the purchase of energy source s in census region i in year t for the pulp and paper industry (pp), and the industrial sector (ind), respectively. These ratios are then applied to total annual industrial energy consumption. Maine is part of the north-east region, Illinois is part of the mid-west region, and Washington is part of the west region. State average prices of energy sources come from Industrial Sector Energy Price and Expenditures Estimates, and Average Retail

Price of Electricity, SEDS, EIA.

Data on stock of capital for the pulp and paper industry at the state level is not available. The following steps were followed to ensure consistency between the available Canadian published data and my own US estimates: First, the Canadian national data is used to calculate the ratio of value of net stock of capital based on the linear and geometric depreciation methods, separately, for buildings and the rest of capital in 1964, 1965, and 1966. These ratios are then applied to the published values of U.S. national geometric depreciation to obtain estimates based on linear depreciation method. Second, the building and the rest of capital estimates are added together. Third, national industry value added (net of wages and salaries) are divided by the estimated value of net stock of capital in 1964, 1965, and 1966 to yield to national rate of return to capital in these three years. Fourth, assuming that the rate of return in the three U.S. states was the same as the estimated national rate of return, the state industry value added (net of wages and salaries) are used to obtain the estimated value of state net capital in 1964, 1965, and 1966. Finally, the average value over the three years is taken as the starting value in 1965 which is updated by the application of the following identity:

Net Stock of Capital$_t$ = Net Stock of Capital$_{t-1}$ - Depreciation$_{t-1}$ + Investment Expenses$_{t-1}$

Information on national capital stock for the U.S. pulp and paper industry (NAICS 322) come from Detailed Data for Fixed Assets – Current Cost and Chain-Type Quantity Index for Net Capital Stock of Private Non-Residential Fixed Assets, BEA, while the Annual Survey of Manufactures, Census Bureau, provides data on investment expenditures for the pulp and paper industry at the state level.

B.2 Canadian Data Sources

Data on all Canadian variables come from Statistics Canada. The following table lists the variables and their specific sources.

Table B.2: Canadian Data Sources

Total value of shipments and materials including energy in current dollars	CANSIM Table 301-0002, for years 1971–82 CANSIM Table 301-0001, for years 1983–97 CANSIM Table 301-0003, for years 1998–2003 CANSIM Table 301-0006, for years 2004–05
Industry price indexes	CANSIM Table 329-0038
Implicit GDP deflator	CANSIM Table 379-0025
Total number of employees, and total salaries and wages	CANSIM Table 301-0002, for years 1971–82 CANSIM Table 301-0001, for years 1983–97 CANSIM Table 301-0003, for years 1998–2003 CANSIM Table 301-0006, for years 2004–05
Real stock of capital	CANSIM Table 031-0002 CANSIM Table 029-0005 CANSIM Table 029-0034
Energy	CANSIM Table 128-0002 CANSIM Table 128-0009
	Consumption of purchased fuel and electricity by the manufacturing, mining, logging and electric power industries, Statistics Canada, Catalogue 57-208
	Consumption of purchased fuel and electricity, Statistics Canada, Catalogue 57-506
	Electric power generation, transmission and distribution, Statistics Canada, Catalogue 57-202

B.3 Data Sources for Finland and Sweden

Data for Finland come from Statistics Finalnd's PX-Web Databases and the World Energy Balances database of OECD while data for Sweden are obtained by special request to Statistics Sweden and also from Swedish Statistical Yearbook of Forestry 2008, chapters 10-14, published by the Swedish Forest Agency.

C Appendix: Imposing Local Concavity

Ryan and Wales (2000) propose a method to impose concavity on the translog cost function locally, at a chosen reference point, since imposing global concavity destroys its flexibility property. Although their method of imposing concavity on a single data point resulted in global concavity coverage for their dataset, this procedure does not guarantee concavity for all data points in the sample. They expect that a judicious choice of point of imposition may lead to concavity coverage at most or all data points.

To impose local concavity on the cost function I rewrite the unit cost function as:

$$\begin{aligned}\ln\left(\frac{c}{p_M}\right) = \alpha_0 + \sum_i \alpha_i \ln\left(\frac{p_i}{p_M}\right) + \frac{1}{2}\sum_i\sum_j \alpha_{ij}\ln\left(\frac{p_i}{p_M}\right)\ln\left(\frac{p_j}{p_M}\right)+ \\ \sum_i \alpha_{it}\left(t-t^*\right)\ln\left(\frac{p_i}{p_M}\right) + \alpha_t\left(t-t^*\right) + \frac{1}{2}\alpha_{tt}\left(t-t^*\right)^2\end{aligned} \tag{C.1}$$

where, t^* is the chosen reference point — the point of imposition of local concavity, and $i, j = K, L, E, F$. The corresponding input share equations are:

$$S_i = \alpha_i + \alpha_{ii}\ln\left(\frac{p_i}{p_M}\right) + \sum_{j\neq i}\alpha_{ij}\ln\left(\frac{p_j}{p_M}\right) + \alpha_{it}\left(t-t^*\right). \tag{C.2}$$

All input prices are normalized to one at t^*. Normalizing all input prices to one at t^* makes $S_i = \alpha_i$, for all i at this data point. So the Hessian of the cost function (C.1) will be negative semi-definite if and only if the matrix $\mathbf{H}$ in (2.8) is negative definite. The ij^{th} element of $\mathbf{H}$, evaluated at t^*, is defined as:

$$H_{ij} = \alpha_{ij} - \alpha_i\delta_{ij} + \alpha_i\alpha_j \tag{C.3}$$

where, $\delta_{ij} = 1$ if $i = j$ and 0 otherwise. Imposing curvature at the reference point, t^*, is done by setting $\mathbf{H} = -(DD')$, where D is a lower triangular matrix with elements d_{ij} for $i \geq j$ and 0 elsewhere,

$$D = [d_{ij}] \quad \text{with } d_{ij} = 0 \text{ for } i < j. \tag{C.4}$$

Substituting this in (C.3) and solving for **A** gives us:

$$\alpha_{ij} = -\left(DD^{'}\right)_{ij} + \alpha_i \delta_{ij} - \alpha_i \alpha_j \tag{C.5}$$

where $\left(DD^{'}\right)_{ij}$ is the ij^{th} element of $DD^{'}$. This gives us the following relationship between the parameters α_{ij} and d_{ij},

$$\begin{aligned}
\alpha_{KK} &= -\, d_{KK}^2 + \alpha_K - \alpha_{KK}^2 & \alpha_{EE} &= -\, d_{KE}^2 - d_{LE}^2 - d_{FE}^2 - d_{EE}^2 + \alpha_E - \alpha_E^2 \\
\alpha_{LL} &= -\, d_{KL}^2 - d_{LL}^2 + \alpha_L - \alpha_{LL}^2 & \alpha_{FF} &= -\, d_{KF}^2 - d_{LF}^2 - d_{FF}^2 + \alpha_F - \alpha_F^2 \\
\alpha_{KE} &= -\, d_{KK} d_{KE} - \alpha_K \alpha_E & \alpha_{LE} &= -\, d_{KL} d_{KE} - d_{LL} d_{LE} - \alpha_L \alpha_E \\
\alpha_{KF} &= -\, d_{KK} d_{KF} - \alpha_K \alpha_F & \alpha_{FE} &= -\, d_{KE} d_{KF} - d_{LE} d_{LF} - d_{FF} d_{FE} - \alpha_E \alpha_F \\
\alpha_{KL} &= -\, d_{KK} d_{KL} - \alpha_K \alpha_L & \alpha_{LF} &= -\, d_{KL} d_{KF} - d_{LL} d_{LF} - \alpha_L \alpha_F
\end{aligned}$$

Replacing $\mathbf{A} = [\alpha_{ij}]$ in the system of equations (C.1) and (C.2) by the above relationships and estimating d_{ij} will ensure that **H**, and as a result the estimated translog will be concave at the normalization point, t^*. Nonlinear iterative SUR technique is employed to estimate the system of equations since this replacement makes the system of equations nonlinear in parameters, d_{ij}. As the choice of reference point is arbitrary, if imposition of local concavity at all reference points fails to provide global concavity coverage for the sample, then I choose data point that provides the maximum number of concavity coverage as the ideal reference point.

Chapter 3

Flexible Functional Forms and Curvature Conditions: Parametric Productivity Estimation in Canadian and U.S. Manufacturing Industries

3.1 Introduction

The standard econometric approach to modelling technical change, introduced by Binswanger (1974a,b), involves representing the rate and biases through constant time trends in a flexible functional form and estimating the unknown parameters using econometric methods.[1] See Jin and Jorgenson (2010) for a list of studies that rely on this widely used approach for modelling technical change. It is well known that among the regularity conditions — positivity, monotonicity, and curvature — that are implied by economic theory, curvature conditions are often violated in empirical applications of flexible functional forms (see Diewert and Wales, 1987; Ryan and Wales, 2000).

Theoretical curvature properties are crucial, especially, in estimating the flex-

[1] Slade (1989) criticizes the traditional method of modelling the state of technology by including time trend in the production or cost function and, instead, suggests the use of state-space approach through the Kalman filter in estimating technical change. More recently, Jin and Jorgenson (2010) replaces the constant time trend by latent variables and use the Kalman filter to estimate the latent variables in the translog model.

ible functional forms. For example, Diewert and Wales (1987) noted that it is necessary for the estimated production and utility functions used in applied general equilibrium models to globally satisfy the theoretical curvature conditions. Empirical rejection of concavity by the estimated cost function casts a doubt on the underlying true model of production as it could lead to a non-continuous input demand function. Moreover, any inferences based on this result would be unconvincing since the input demand functions derived from the cost function may not be cost minimizing due to the violation of curvature property. This casts a serious doubt on the assumption that firms in the sample are cost minimizers.

No parametric restrictions can ensure global curvature conditions while maintaining flexibility in the translog (TL) and the Generalized Leontief (GL) functional forms as this property is data dependent. Violation of curvature conditions by the translog and the GL has led Diewert and Wales (1987) to develop a more complex locally flexible functional form — the Normalized Quadratic (NQ) (see Diewert and Wales, 1987) — which allows imposing global curvature conditions and maintaining flexibility at the same time. However, instead of imposing global concavity on the translog and the GL cost functions, Ryan and Wales (2000) propose a method to impose it locally, at a chosen reference point. They show that their procedure of curvature imposition does not destroy the flexibility property of the functional forms and it leads to satisfaction of curvature property at all data points for their data set. Since they do not find any impact on productivity estimates they conclude that the effect of imposing concavity is limited, in their case, only to the price responses. However, the productivity literature does not provide any guidance on the selection of appropriate flexible functional forms once they satisfy all theoretical regularity conditions (see Feng and Serletis, 2008).

In this paper I provide empirical evidence that imposing local concavity on the translog and the GL cost functions affects the productivity estimates, in addition to its effect on the elasticity estimates which has attracted the attention in the literature thus far. In doing so, I employ three well-known locally flexible functional forms — the translog, the GL, and the NQ cost functions, and present an empirical comparison and evaluation of the effectiveness of these cost functions in providing total factor productivity (TFP) estimates when they satisfy all theoretical regularity conditions.[2] I use the difference in TFP estimates, with and without curvature constraint, as a criterion for comparing performances of different functional forms. In estimating the models I utilize manufacturing KLEM (capital, labour, energy, and material) data covering the period from 1961 to 2003 for Canada and the U.S.. Moreover, I follow Ryan and Wales (2000) to impose local curvature conditions on the translog and the GL models, and for the NQ I impose global curvature conditions following Diewert and Wales (1987).

While comparing the functional forms in providing TFP estimates, I provide examples of all three possible scenarios: First, the cases where all three regularity conditions are satisfied without curvature being imposed; second, the cases where curvature conditions are not satisfied even with local curvature being imposed; finally, the cases where imposing curvature resulted in the satisfaction of regularity conditions. I also provide substitution and price elasticity estimates of factors of production in the U.S. and Canadian manufacturing industries.

Feng and Serletis (2008) estimate TFP in the U.S. manufacturing industry using four flexible functional forms. In addition to the three functional forms that I use in this study, they also estimate the asymptotically ideal model (AIM) cost function. Although they impose concavity on the three locally flexible functional forms using the same techniques that I use in this study, only the NQ model satisfies curvature conditions. As a result, they provide a comparison between the NQ and the AIM cost functions — the only models that satisfy all regularity conditions. Using a smoothed Fisher TFP index as the benchmark they conclude that the AIM, with curvature imposed, performs better in estimating TFP. However,

[2] Fisher et al. (2001) provide an empirical evaluation of the performances of eight flexible functional forms in the context of consumer demand.

there is not a single case where concavity is satisfied without curvature being imposed and as a result they are unable to analyze this aspect. Moreover, since they fail to include the translog and the GL functional forms in the analysis they could not analyze the impact of local curvature imposition. Based on a different criterion I provide comparisons between all three locally flexible functional forms that I consider in this study. I also compare the effects of local and global curvature imposition while Feng and Serletis (2008) evaluate the effect of global curvature imposition. My estimation results provide me the opportunity to analyze all three possible scenarios, mentioned earlier, which is not the case in Feng and Serletis (2008).

My empirical findings support the result provided by Feng and Serletis (2008) that imposing local curvature conditions on the translog and the GL does not always assure theoretical regularity conditions at all data points in the sample. Moreover, using the estimation results I show that when curvature condition is met by imposition, the NQ model performs better in providing TFP estimates than the translog and GL models, at least for my data sets. However, the GL model performs equally well when all regularity conditions are satisfied without curvature being imposed. My findings also provide evidence that local curvature imposition on the translog and the GL models affect the productivity estimates. Based on my results I argue that since concavity is not guaranteed in the translog and the GL models even with curvature being imposed, functional forms with global curvature conditions appear to be a better choice for econometric productivity estimation.

The rest of the paper is organized as follows. Section 3.2 reviews the theoretical background on different approaches to productivity measurement. Section 3.3 presents the functional forms and relevant techniques for imposing curvature conditions while Section 3.4 discusses the index number techniques used in this study. Section 3.5 describes the data sets and outlines the empirical estimation strategies. Section 3.6 reports the estimation results, and finally, Section 3.7 concludes.

3.2 Theoretical Background

3.2.1 Productivity Measurement

Recent shift in attention to the rate and biases of technical change has put the econometric approach to productivity measurement in the forefront of empirical productivity analysis even though the most commonly utilized approach is the index number technique.[3] See, for example, Acemoglu (2002a,b, 2007), Jaffe et al. (2003), Jin and Jorgenson (2010) for different applications of the biases of technical change. As opposed to the index number approach, it is ideal to have a productivity measure that would also shed some light on the production structure, for example, the factor biases and the elasticities of factor substitution. Accurate information on these estimates is vital for policy making, in particular energy policies. See, for example, León-Ledesma et al. (2010) for a discussion on the importance of parameters of the elasticity of substitution and the direction of technical change. In what follows, I briefly discuss the index number and the econometric approaches to productivity measurement.[4]

With the index number approach, the difference between the rate of change of output and a share weighted index of rates of change in inputs provides a measure of the rate of technical change,

$$\frac{\partial y/\partial t}{y} - \sum_{i=1}^{n} s_i \frac{\partial x_i/\partial t}{x_i}, \tag{3.1}$$

where inputs $\mathbf{x} \geq 0$ are used to produce output y, and $s_i \equiv \frac{p_i x_i}{C}$ is the share of input x_i in total cost C.

[3] See Hulten (2001) for a discussion on the historical development of quantitative analysis of productivity. For a brief discussion on various approaches to productivity measurement see Feng and Serletis (2008). Using simulation Van Biesebroeck (2007) provides a discussion on the robustness of productivity estimates obtained by different measurement approaches. Also for a comparison of growth accounting approaches in measuring TFP, see Norsworthy (1984).

[4] As in Feng and Serletis (2008), this section builds heavily on standard notations in the literature, mainly from Berndt (1991).

The econometric approach typically involves estimating a production or cost function which then is differentiated with respect to time. Technical change is associated with any temporal shift in the production or cost frontier, and under constant returns to scale both production and cost function approaches would yield equivalent results. With the cost function approach the existence of a cost function,

$$C = C(\mathbf{p}, y, t), \tag{3.2}$$

that relates the vector of factor prices $\mathbf{p}$, output y, and a summary of the state of technology t with total cost C, is assumed.[5] It is a solution to the following cost minimization problem

$$\min_{\mathbf{x}} \mathbf{px} \quad s.t. \quad y \leq f(\mathbf{x}, t),\, \mathbf{x} \geq \mathbf{0},$$

and is the corresponding dual of the following strictly monotonic, strictly quasi-concave, and continuously twice differentiable production function,

$$y = f(\mathbf{x}, t), \tag{3.3}$$

which transforms a vector of inputs $\mathbf{x} \geq \mathbf{0}$ into output y. To be able to successfully represent the underlying production process in (3.3), the cost function (3.2) must be nonnegative, non-decreasing in y and $\mathbf{p}$, and linear homogeneous and concave in $\mathbf{p}$. Under constant returns to scale, equation (3.2) becomes

$$C(\mathbf{p}, y, t) = yc(\mathbf{p}, t), \tag{3.4}$$

where c is the corresponding unit cost function. Invoking Shephard's Lemma yields

[5]For notational simplicity I suppress the time subscripts.

the optimal factor demand equations,

$$x_i = \partial C(\mathbf{p}, y, t)/\partial p_i, \quad i = 1, ..., n. \tag{3.5}$$

Rate of technical change in the cost function approach is measured in the following way,

$$TFP = -\frac{\partial \ln C(\mathbf{p}, y, t)/\partial t}{\partial \ln C(\mathbf{p}, y, t)/\partial \ln y}, \tag{3.6}$$

where $\partial \ln C(\mathbf{p}, y, t)/\partial t$ represents the rate of cost diminution and $\partial \ln C(\mathbf{p}, y, t)/\partial \ln y$ represents the inverse of rate of returns to scale which equals to unity under constant returns to scale,

$$TFP = -\frac{\partial \ln C(\mathbf{p}, y, t)}{\partial t} = -\frac{\partial C(\mathbf{p}, y, t)/\partial t}{C}. \tag{3.7}$$

Hence, an upward shift in the production function is equal to an equivalent downward shift in the cost function under constant returns to scale. We can easily obtain the TFP estimates by estimating the parameters of C once we assume the specific functional form for C in (3.2).

The effects of technological change on factor use, which is often referred to as the input bias due to technical change, can also be measured as follows

$$\tau_i = \frac{\partial \ln x_i(\mathbf{p}, y, t)}{\partial t}. \tag{3.8}$$

They provide us with the information about how the usage of inputs changes as a result of technical change and reflect that part of changes in input use which is not due to output change or to factor substitution as a result of relative change in factor prices. With regards to the direction of bias, if $\tau_i > 0$ (< 0), then technical change is factor i using (saving).

Furthermore, for the dual cost function in (3.2) factor substitution can also be calculated using the Morishima elasticities of substitution (see Blackorby and

Russell, 1989),

$$\sigma_{ij}^{m}(\mathbf{p}, y, t) = \frac{p_j C_{ij}(\mathbf{p}, y, t)}{C_i(\mathbf{p}, y, t)} - \frac{p_j C_{jj}(\mathbf{p}, y, t)}{C_j(\mathbf{p}, y, t)}, \tag{3.9}$$

where the i and j subscripts refer to the first and second partial derivatives of equation (3.4) with respect to the corresponding input prices. A positive (negative) σ_{ij}^{m} indicates that input j is a Morishima substitute (complement) for input i. Moreover, the input price elasticities are computed as

$$\eta_{ij} = \frac{\partial \ln x_i(\mathbf{p}, y, t)}{\partial \ln p_j} = \frac{\partial x_i(\mathbf{p}, y, t)}{\partial p_j} \frac{p_j}{x_i(\mathbf{p}, y, t)}. \tag{3.10}$$

The relationship between the price and substitution elasticities can be postulated as,

$$\sigma_{ij}^{m} = \eta_{ij} - \eta_{jj}. \tag{3.11}$$

3.2.2 Curvature Conditions

A crucial requirement about the cost function is that it must be concave in prices. Necessary and sufficient condition for concavity is that the Hessian matrix of the cost function be negative semi-definite. To check for concavity, eigenvalues of the estimated Hessian matrix of the cost functions are computed at each point in the sample space. Morey (1986) provides an excellent overview of the curvature conditions and checking process for empirical applications of different flexible functional forms.

As mentioned earlier, curvature properties are often violated in empirical applications of flexible functional forms. A number of studies report that the estimated functional forms fail to satisfy this property. See, for example, Wills (1979), Slade (1989), Diewert and Wales (1987), Delorme and Lester (1990), Barnett and Serletis (2008). One way to deal with these violations is to perform some simple checking procedures. For example, Caves et al. (1980) check whether the parameter generating positive own price elasticity is significantly different from a value of the parameter generating non-positive elasticity estimate. Another simple procedure is adopted by Slade (1989) which involves checking whether the concavity violations occurred by chance. This procedure uses a technique developed by Geweke (1986) and involves Monte Carlo simulation method to generate replications of the estimated coefficients from a multivariate normal distribution.

The other available option is to impose local or global curvature restrictions. Curvature restrictions are imposed in many different contexts. For applications, in consumer theory, see, for example, Ryan and Wales (1998), Moschini (1999), in case of production theory, see Gallant and Golub (1984), Terrell (1996), and Ryan and Wales (2000), and in the context of GNP functions, see Kohli (1992). Global curvature restrictions can be imposed using Cholesky decomposition on the NQ cost function without destroying its flexibility property. For a discussion on the restrictions and implementation technique, see Diewert and Wales (1987) and Wiley et al. (1973). However, imposing global restrictions on the translog and the GL cost functions destroys their flexibility property.

Instead of imposing global concavity, Ryan and Wales (2000) propose a method to impose it locally at a chosen reference point. Using the same dataset as Diewert and Wales (1987), they show that their procedure of imposing local curvature guarantees concavity at the data point where it is imposed without destroying the flexibility of the functional form. Although imposing concavity on a single observation does not guarantee concavity for other data points, they hope that a judicious choice of point of imposition may lead to satisfaction of concavity at most or all data points. This procedure of local curvature imposition provides the expected concavity coverage for their data set; however, this result is not universal. Other techniques for imposing local curvature conditions include the general computational methods used by Lau (1978) and Gallant and Golub (1984), and the Bayesian approach used by Chalfant and Wallace (1992), Terrell (1996), and Griffiths et al. (2000).

In what follows, I take the econometric approach to productivity measurement for three Canadian and two U.S. energy intensive industries and provide a comparison between three widely used locally flexible cost functional forms — the translog, the GL, and the NQ cost functions. For all cost functional forms, I assume cross-equation symmetry restrictions, linear homogeneity in prices as well as constant returns to scale in the production process as a maintained hypothesis. Obviously one can test for whether these assumptions actually hold.

3.3 Locally Flexible Functional Forms

3.3.1 The Translog Cost Function

If we assume that the unit cost function in (3.4) takes the translog functional form (Christensen et al., 1971, 1973), then we get

$$\begin{aligned}\ln C(\mathbf{p}, y, t) = \beta_0 + \ln y + \sum_{i=1}^{n} \beta_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \beta_{ii} [\ln p_i]^2 + \\ \frac{1}{2} \sum_{i \neq j}^{n} \sum_{j=1}^{n} \beta_{ij} \ln p_i \ln p_j + \sum_{i=1}^{n} \beta_{it} t \ln p_i + \beta_t t + \frac{1}{2} \beta_{tt} t^2.\end{aligned} \tag{3.12}$$

Together with the assumption of symmetry — that is, $\beta_{ij} = \beta_{ji}$ — homogeneity of degree one in prices imposes the following constraints

$$\sum_{i=1}^{n} \beta_i = 1, \quad \sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \beta_{ij} = \sum_{i=1}^{n} \beta_{it} = 0. \tag{3.13}$$

The corresponding factor cost share equations are

$$s_i = \frac{p_i x_i}{C} = \beta_i + \beta_{ii} \ln p_i + \sum_{j \neq i}^{n} \beta_{ij} \ln p_j + \beta_{it} t. \tag{3.14}$$

Equation (3.14) imposes another adding-up restriction, $\sum_{i=1}^{n} s_i = 1$, which already holds through the assumption of linear homogeneity in prices. It is to be noted that as all parameters of the share equations are also present in the cost function we can directly estimate (3.12). However, joint estimation of (3.12) and (3.14) as a system of equations reduces possible high degree of multicollinearity in the independent variables, and increases efficiency and degrees of freedom available.

However, as mentioned earlier, in empirical applications failure of the translog to satisfy the regularity conditions is very common. To overcome this problem local concavity can be imposed at a chosen reference point following the route suggested by Ryan and Wales (2000). Diewert and Wales (1987) show that the Hessian of the translog cost function will be negative semidefinite, providing $C(\mathbf{p}, y, t) > 0$, if and only if the following matrix is negative semidefinite

$$\mathbf{H} = \mathbf{B} - \mathbf{S}^n + \mathbf{S}\mathbf{S}' \tag{3.15}$$

where $\mathbf{B} = [\beta_{ij}]$ is the $n \times n$ symmetric matrix of β_{ij}, $\mathbf{S} = [s_1, ..., s_n]'$ is the vector of input shares, and $\mathbf{S}^n$ is the $n \times n$ diagonal matrix of input shares.

To impose local concavity, equation (3.12) is rewritten as,

$$\begin{aligned} \ln C(\mathbf{p}, y, t) =& \beta_0 + \ln y + \sum_{i=1}^{n} \beta_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n} \beta_{ii}[\ln p_i]^2 + \frac{1}{2}\sum_{i \neq j}^{n}\sum_{j=1}^{n} \beta_{ij} \ln p_i \ln p_j + \\ & \sum_{i=1}^{n} \beta_{it} t \ln p_i + \beta_t[t - t^*] + \frac{1}{2}\beta_{tt}[t - t^*]^2, \end{aligned} \tag{3.16}$$

where t^* is the chosen reference point — that is, the point of imposition of local concavity — where all prices are normalized to one. The corresponding input share equations are

$$s_i = \beta_i + \beta_{ii} \ln p_i + \sum_{j \neq i}^{n} \beta_{ij} \ln p_j + \beta_{it}[t - t^*]. \tag{3.17}$$

Normalizing all input prices to one at t^* makes $s_i = \beta_i$ for all i at this data point.

The ij^{th} element of $\mathbf{H}$ evaluated at t^* is

$$\mathbf{H}_{ij} = \beta_{ij} + \beta_i\beta_j - \beta_i\delta_{ij} \qquad i, j = 1, ..., n, \tag{3.18}$$

where $\delta_{ij} = 1$ if $i = j$ and 0 otherwise. Curvature is imposed at the reference point, t^*, by setting $\mathbf{H} = -\mathbf{A}\mathbf{A}'$, where $\mathbf{A}$ is a lower triangular matrix with elements a_{ij} for $i \geq j$ and 0 elsewhere. Now solving for $\mathbf{A}$ in (3.18) gives us

$$\beta_{ij} = -(\mathbf{A}\mathbf{A}')_{ij} + \beta_i\delta_{ij} - \beta_i\beta_j \qquad i, j = 1, ..., n, \tag{3.19}$$

where $(\mathbf{A}\mathbf{A}')_{ij}$ is the ij^{th} element of $\mathbf{A}\mathbf{A}'$.

Equation (3.19) gives us the following relationships, in the case of four factors:

$$\begin{aligned}
\beta_{11} &= -\,a_{11}^2 + \beta_1 - \beta_1^2, & \beta_{12} &= -\,a_{11}a_{21} - \beta_1\beta_2,\\
\beta_{13} &= -\,a_{11}a_{31} - \beta_1\beta_3, & \beta_{14} &= -\,a_{11}a_{41} - \beta 1\beta_4,\\
\beta_{22} &= -\,(a_{21}^2 + a_{22}^2) + \beta_2 - \beta_2^2, & \beta_{23} &= -\,(a_{21}a_{31} + a_{22}a_{32}) - \beta_2\beta_3,\\
\beta_{24} &= -\,(a_{21}a_{41} + a_{22}a_{42}) - \beta_2\beta 4, & \beta_{33} &= -\,(a_{31}^2 + a_{32}^2 + a_{33}^2) + \beta_3 - \beta_3^2,\\
\beta_{34} &= -\,(a_{31}a_{41} + a_{32}a_{42} + a_{33}a_{43}) - \beta_3\beta_4, & \beta_{44} &= -\,(a_{41}^2 + a_{42}^2 + a_{43}^2 + a_{44}^2) + \beta_4 - \beta_4^2.
\end{aligned}$$

Replacing the elements of $\mathbf{B} = [\beta_{ij}]$ in (3.16) and (3.17) by the above relationships and estimating a_{ij} will ensure that the translog cost function will be concave at the normalization point t^*, and may also encompass concavity at other data points in the sample. However, this replacement makes the system of equations nonlinear in parameters a_{ij}.

Equation (3.7) yields the rate of technical change for the translog as

$$TFP = -\frac{\partial \ln C(\mathbf{p}, y, t)}{\partial t} = -\left(\beta_t + \beta_{tt}t + \sum_{i=1}^{n}\beta_{it}\ln p_i\right). \tag{3.20}$$

Moreover, following Jin and Jorgenson (2010), I decompose the rate of technical change into autonomous and induced technical change components. Together, the first two parts on the right hand side, which depends only on changes in the level of technology, gives us the rate of autonomous technical change. The last part on the right hand side of (3.20), which depends on the prices as well as the biases of technical change, measures the contribution to rate of productivity growth due to the biased effect of technical change and the change in relative input prices. I refer to this as the rate of induced technical change. A fall in the price of energy, for example, will accelerate the rate of technical change if the bias of technical change is energy using; however if the bias is energy saving it will reduce the rate of technical change.

Own- and cross-price elasticities are calculated as

$$\eta_{ij} = \frac{\widehat{\beta}_{ij} + \widehat{S}_i \widehat{S}_j}{\widehat{S}_i}, \qquad \text{for } i \neq j, \tag{3.21}$$

$$\eta_{ii} = \frac{\widehat{\beta}_{ii} + \widehat{S}_i^2 - \widehat{S}_i}{\widehat{S}_i}, \qquad i, j = 1, ..., n, \tag{3.22}$$

where all other factor prices and output are fixed while the Morishima elasticities are obtained by using (3.11).

3.3.2 The Generalized Leontief Cost Function

If we choose the functional form in (3.4) to be the GL cost function (Diewert and Wales, 1987), we get

$$C(\mathbf{p}, y, t) = y \left(\sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} (p_i p_j)^{\frac{1}{2}} + \sum_{i=1}^{n} \beta_{it} p_i t + \sum_{i=1}^{n} \gamma_{it} p_i t^2 \right), \tag{3.23}$$

where $\beta_{ij} = \beta_{ji}$. Using (3.5) we get the corresponding optimal input-output demand equations as follows,

$$a_i = \frac{x_i}{y} = \sum_{j=1}^{n} \beta_{ij} p_j^{\frac{1}{2}} p_i^{-\frac{1}{2}} + \beta_{it} t + \gamma_{it} t^2, \qquad i = 1, ..., n. \tag{3.24}$$

There is no intercept term in (3.23) due to the assumption of constant returns to scale and hence all the parameters in (3.23) can be obtained by estimating only (3.24). When $i = j$ in (3.24), β_{ii} becomes a constant term in the i^{th} input-output equation and if $\beta_{ij} = 0$ for all $i, j, i \neq j$, (3.24) becomes independent of relative input prices and all the cross-price elasticities become zero.

Necessary and sufficient condition for concavity is that the Hessian matrix of (3.23) be negative semi-definite. The elements of the Hessian matrix for (3.23) are as follows

$$\begin{aligned} \mathbf{H}_{ij} &= \frac{1}{2}\beta_{ij}(p_i p_j)^{-\frac{1}{2}} && i \neq j \\ &= -\frac{1}{2}\sum_{j \neq i}^{n} \beta_{ij}(p_j/p_i)^{\frac{1}{2}}(1/p_i) && i = j. \end{aligned} \tag{3.25}$$

Following Ryan and Wales (2000), I reparametrize equation (3.23) to impose local concavity. First, I set $\sum_{k=1}^{n} \beta_{ik} = 0$ for all i, and then I add $(\sum_{i=1}^{n} p_i d_i)y$ to the right hand side of (3.23) which will introduce n new parameters. Therefore, the new set of input-output demand equations are

$$a_i = \frac{x_i}{y} = \sum_{j=1}^{n} \beta_{ij} p_j^{\frac{1}{2}} p_i^{-\frac{1}{2}} + \beta_{it} t + \gamma_{it} t^2 + d_i \qquad i = 1, ..., n. \tag{3.26}$$

Second, I normalize all prices and output to one at the reference point and, as a result, the ij^{th} element of $\mathbf{H}$ evaluated at this data point becomes

$$\begin{aligned} \mathbf{H}_{ij} &= \frac{\beta_{ij}}{2} && i \neq j \\ &= -\frac{1}{2}\sum_{j \neq i}^{n} \beta_{ij} = \frac{\beta_{ii}}{2} && i = j. \end{aligned} \tag{3.27}$$

Finally, I set $\beta_{ij} = -(\mathbf{DD}')_{ij}$, where $(\mathbf{DD}')_{ij}$ is the ij^{th} element of $\mathbf{DD}'$, and $\mathbf{D}$ is a lower triangular matrix with elements d_{ij} for $i \geq j$ and 0 elsewhere. This gives us the following relationships between β_{ij} and d_{ij}, in the case of four factors,

$$
\begin{aligned}
\beta_{11} &= -\, d_{11}^2, & \beta_{12} &= -\, d_{11}d_{21}, \\
\beta_{13} &= -\, d_{11}d_{31}, & \beta_{14} &= -\, d_{11}d_{41}, \\
\beta_{22} &= -\, (d_{21}^2 + d_{22}^2), & \beta_{23} &= -\, (d_{21}d_{31} + d_{22}d_{32}), \\
\beta_{24} &= -\, (d_{21}d_{41} + d_{22}d_{42}), & \beta_{33} &= -\, (d_{31}^2 + d_{32}^2 + d_{33}^2), \\
\beta_{34} &= -\, (d_{31}d_{41} + d_{32}d_{42} + d_{33}d_{43}), & \beta_{44} &= -\, (d_{41}^2 + d_{42}^2 + d_{43}^2 + d_{44}^2).
\end{aligned}
\tag{3.28}
$$

Replacing the elements of $\mathbf{B} = [\beta_{ij}]$ in (3.26) by the relationships in (3.28) and estimating d_{ij} will guarantee that the estimated GL cost function will be concave at the normalization point and it may also lead to the satisfaction of concavity at other data points in the sample.

For the GL specification I compute the price elasticities as

$$
\eta_{ij} = \frac{1}{2}\frac{\beta_{ij}(p_i/p_j)^{-\frac{1}{2}}}{a_i}, \qquad \text{for } i \neq j, \tag{3.29}
$$

$$
\eta_{ii} = -\,\frac{1}{2}\frac{\sum_{j\neq i}^{n}\beta_{ij}(p_i/p_j)^{-\frac{1}{2}}}{a_i}. \tag{3.30}
$$

The Morishima elasticities are computed using equation (3.11).

3.3.3 The Normalized Quadratic Cost Function

If we consider the functional form in (3.4) to be the NQ cost function (Diewert and Wales, 1987), we get

$$
C(\mathbf{p}, y, t) = y\left[\sum_{i=1}^{n}\beta_i p_i + \frac{1}{2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}p_ip_j}{\sum_{i=1}^{n}\theta_i p_i} + \sum_{i=1}^{n}\beta_{it}p_it + \sum_{i=1}^{n}\gamma_{it}p_it^2\right], \tag{3.31}
$$

where $\beta_{ij} = \beta_{ji}$. Equation (3.31) can be rewritten as

$$
C(\mathbf{p}, y, t) = y\left[\sum_{i=1}^{n}\beta_i p_i + g(\mathbf{p}) + \sum_{i=1}^{n}\beta_{it}p_it + \sum_{i=1}^{n}\gamma_{it}p_it^2\right], \tag{3.32}
$$

where $g(\mathbf{p}) \equiv \frac{\mathbf{p}'\mathbf{B}\mathbf{p}}{2\boldsymbol{\theta}'\mathbf{p}}$. $\mathbf{B} \equiv [\beta_{ij}]$ is a $n \times n$ symmetric matrix, and $\boldsymbol{\theta} = [\theta_1, ..., \theta n] > \mathbf{0}$ is a vector of nonnegative constants, not all equal to zero. Usually $\boldsymbol{\theta}$ is predetermined, and I set θ_i equal to the sample average values of the respective inputs. In order to identify all parameters in the model, n extra restrictions on the elements of $\mathbf{B}$ are imposed as

$$\mathbf{B}\mathbf{p}^* = \mathbf{0}, \tag{3.33}$$

for some chosen $\mathbf{p}^* > \mathbf{0}$.

Application of (3.5) yields the following system of n equations

$$\frac{x_i}{y} = \beta_i + \sum_{j=1}^{n} \beta_{ij} \frac{p_i}{\sum_{i=1}^{n} \theta_i p_i} - \frac{1}{2}\theta_i \left(\sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \frac{p_i}{\sum_{i=1}^{n} \theta_i p_i} \frac{p_j}{\sum_{j=1}^{n} \theta_j p_j} \right) + \beta_{it} t + \gamma_{it} t^2. \tag{3.34}$$

Equation (3.34) can also be expressed as

$$\frac{x_i}{y} = \beta_i + \frac{\sum_{j=1}^{n} \beta_{ij} p_i}{\boldsymbol{\theta}'\mathbf{p}} - \frac{\theta_i}{2} \frac{\mathbf{p}'\mathbf{B}\mathbf{p}}{(\boldsymbol{\theta}'\mathbf{p})^2} + \beta_{it} t + \gamma_{it} t^2. \tag{3.35}$$

Furthermore, I assume $\mathbf{p}^* = \mathbf{1_n}$ which, in terms of (3.33), implies $\sum_{j=1}^{n} \beta_{ij} = 0$. With these n restrictions on matrix $\mathbf{B}$ and after denoting $w_i = \frac{p_i}{\sum_{j=1}^{n} \theta_i p_i}$, the system of factor demand equations (3.34), in the case of four factors, can be expressed as,

$$\begin{aligned} \frac{x_1}{y} = {} & \beta_{11}\Big[(w_1 - w_4) - \frac{\theta_1}{2}(w_1 - w_4)^2\Big] + \beta_{12}\Big[(w_2 - w_4) - \theta_1(w_1 - w_4)(w_2 - w_4)\Big] \\ & + \beta_{13}\Big[(w_3 - w_4) - \theta_1(w_1 - w_4)(w_3 - w_4)\Big] + \beta_{22}\Big[\frac{\theta_1}{2}(w_2 - w_4)^2\Big] \\ & + \beta_{23}\Big[-\theta_1(w_2 - w_4)(w_3 - w_4)\Big] + \beta_{33}\Big[-\frac{\theta_1}{2}(w_3 - w_4)^2\Big] + \beta_1 + \beta_{1t} t + \gamma_{1t} t^2, \end{aligned} \tag{3.36}$$

$$
\begin{aligned}
\frac{x_2}{y} &= \beta_{11}\Big[-\frac{\theta_2}{2}(w_1-w_4)^2\Big] + \beta_{12}\Big[(w_1-w_4) - \theta_2(w_1-w_4)(w_2-w_4)\Big] \\
&\quad + \beta_{13}\Big[-\theta_2(w_1-w_4)(w_3-w_4)\Big] + \beta_{22}\Big[(w_2-w_4) - \frac{\theta_2}{2}(w_2-w_4)^2\Big] \\
&\quad + \beta_{23}\Big[(w_3-w_4) - \theta_2(w_3-w_4)(w_2-w_4)\Big] + \beta_{33}\Big[\frac{\theta_2}{2}(w_3-w_4)^2\Big] \\
&\quad + \beta_2 + \beta_{2t}t + \gamma_{2t}t^2, \qquad (3.37)
\end{aligned}
$$

$$
\begin{aligned}
\frac{x_3}{y} &= \beta_{11}\Big[-\frac{\theta_3}{2}(w_1-w_4)^2\Big] + \beta_{12}\Big[-\theta_3(w_1-w_4)(w_2-w_4)\Big] \\
&\quad + \beta_{13}\Big[(w_1-w_4) - \theta_3(w_1-w_4)(w_3-w_4)\Big] + \beta_{22}\Big[\frac{\theta_3}{2}(w_2-w_4)^2\Big] \\
&\quad + \beta_{23}\Big[(w_2-w_4) - \theta_3(w_2-w_4)(w_3-w_4)\Big] + \beta_{33}\Big[(w_3-w_4) - \frac{\theta_3}{2}(w_3-w_4)^2\Big] \\
&\quad + \beta_3 + \beta_{3t}t + \gamma_{3t}t^2, \qquad (3.38)
\end{aligned}
$$

$$
\begin{aligned}
\frac{x_4}{y} &= \beta_{11}\Big[-(w_1-w_4) - \frac{\theta_4}{2}(w_1-w_4)^2\Big] + \beta_{12}\Big[-(w_2-w_4) - \theta_4(w_1-w_4)(w_2-w_4)\Big] \\
&\quad + \beta_{13}\Big[-(w_3-w_4) - \theta_4(w_1-w_4)(w_3-w_4)\Big] + \beta_{22}\Big[(w_2-w_4) - \frac{\theta_4}{2}(w_2-w_4)^2\Big] \\
&\quad + \beta_{23}\Big[(w_2-w_4) - (w_3-w_4) - \theta_4(w_1-w_4)(w_3-w_4)\Big] \\
&\quad + \beta_{33}\Big[(w_3-w_4) - \frac{\theta_4}{2}(w_2-w_4)^2\Big] + \beta_4 + \beta_{4t}t + \gamma_{4t}t^2. \qquad (3.39)
\end{aligned}
$$

Estimates of β_i, β_{it}, and the elements of matrix $\mathbf{B}$, except for the parameters $\beta_{i4}\,(i = 1, 2, 3, 4)$, are obtained by estimating the system of input-output equations (3.36)–(3.39). β_{i4} can then be recovered from the imposed restrictions.

Global concavity for the NQ cost function requires that the estimated $\mathbf{B}$ matrix is negative semidefinite provided that $\boldsymbol{\theta} > \mathbf{0}$ — see Diewert and Wales (1987) for a detailed discussion. However, in empirical applications the estimated $\mathbf{B}$ matrix may not be negative semidefinite and if this turns out to be the case, Diewert and Wales (1987) show that global concavity on the NQ can be imposed without destroying its flexibility by using the technique suggested by Wiley et al. (1973).

To impose global concavity I set

$$\mathbf{B} = -\mathbf{A}\mathbf{A}',$$

where $\mathbf{A}$ is a lower triangular matrix, with elements a_{ij} for $i \geq j$ and 0 elsewhere, that satisfies

$$\mathbf{A}'\mathbf{p}^* = \mathbf{0}_n.$$

This gives us the following relationships between β_{ij} and a_{ij},

$$\begin{aligned}
\beta_{11} &= -\, a_{11}^2, & \beta_{12} &= -\, a_{11}a_{21}, \\
\beta_{13} &= -\, a_{11}a_{31}, & \beta_{22} &= -\, (a_{21}^2 + a_{22}^2), \\
\beta_{23} &= -\, (a_{21}a_{31} + a_{22}a_{32}), & \beta_{33} &= -\, (a_{31}^2 + a_{32}^2 + a_{33}^2).
\end{aligned} \tag{3.40}$$

Finally, I replace the elements of $\mathbf{B}$ in the system of input-output equations (3.36)–(3.39) by the relationships in (3.40) and estimate a_{ij} which ensures global concavity for the NQ function in (3.31). This replacement makes the system of input-output equations nonlinear in parameters a_{ij}.

For the NQ specification the price elasticities have the following expressions,

$$\eta_{ii} = \left[\frac{\beta_{ii} \sum_{j=1}^n \theta_j p_j - 2\theta_i \sum_{j=1}^n \beta_{ij} p_j + 2\theta_i^2 g(\mathbf{p})}{\left[\sum_{j=1}^n \theta_j p_j\right]^2} \right] \frac{p_i y}{x_i}, \tag{3.41}$$

$$\eta_{ij} = \left[\frac{\beta_{ij} \sum_{j=1}^n \theta_j p_j - \theta_i \sum_{i=1}^n \beta_{ij} p_j - \theta_j \sum_{j=1}^n \beta_{ij} p_j + 2\theta_i \theta_j g(\mathbf{p})}{\left[\sum_{j=1}^n \theta_j p_j\right]^2} \right] \frac{p_j y}{x_j}, \tag{3.42}$$

and the Morishima elasticities can then be computed using (3.11).

3.4 Index Number Techniques

I also calculate the productivity growth in my sample industries using two widely used index number techniques: the Tornqvist index and the Fisher ideal index. Results from the index number techniques can be used to check the performance of the flexible functional forms. The Tornqvist index is the discrete approximation of equation (3.1), and the rate of technical change is calculated as follows

$$\ln y_t - \ln y_{t-1} - \sum_{i=1}^{n} \frac{1}{2}(s_{it} + s_{it-1})(\ln x_{it} - \ln x_{it-1}). \tag{3.43}$$

Equation (3.43) can also be written as

$$\ln \prod_{i=1}^{n} \left[\frac{(y/x_i)_t}{(y/x_i)_{t-1}} \right]^{\frac{1}{2}(sx_{it}+sx_{it-1})}. \tag{3.44}$$

The advantage of using the Tornqvist index is that it is exact for the linear homogeneous translog aggregator function (see Diewert, 1976a). However, in practice estimates of technical change obtained from the two approaches can be markedly different (Slade, 1986, 1989). Obviously one can think of the possibility of using a bilateral Tornqvist index (see Caves et al., 1982) to compare the productivity performances of Canadian and U.S. industries. However, to implement this we require time series data that have been constructed in a consistent way across industries and countries which is not the case with the data sets used in this study. See Keay (2003) for such comparisons between U.S. and Canadian industries and also for the data requirements to do so.

With the Fisher ideal index, first the Fisher ideal quantity index for inputs is calculated as,

$$I^t = \left[\frac{\sum_{j=1}^{n} p_j^t x_j^t}{\sum_{j=1}^{n} p_j^t x_j^{t-1}} \frac{\sum_{j=1}^{n} p_j^{t-1} x_j^t}{\sum_{j=1}^{n} p_j^{t-1} x_j^{t-1}} \right]^{1/2}, \tag{3.45}$$

and then the quantity index for the single output is calculated as $Q^t = y^t/y^{t-1}$.

Finally, the Fisher ideal total factor productivity index is computed as

$$\frac{Q^t}{I^t} - 1.$$

I also obtain a smoothed Fisher ideal index of total factor productivity, following Feng and Serletis (2008), by regressing the raw total factor productivity index on a constant and a time trend, and then calculating the fitted values.[6]

3.5 Data and Estimation Strategy

3.5.1 Data

In this study I use two different data sets that cover the period from 1961 to 2003 for the Canadian and U.S. manufacturing industries. Data for the Canadian manufacturing industries come from annual Canadian KLEMS database developed by the "Industry Multifactor Productivity Program" of Statistics Canada — see Baldwin et al. (2007) for a detailed description on the methodology used to construct this database.[7] Among the Canadian manufacturing industries I consider primary metal (NAICS 331), cement (NAICS 32731), and paper (NAICS 322) manufacturing industries in my sample.[8] The Canadian KLEMS data set contains annual information on chained Fisher quantity and price indexes for capital, labour, energy, material and services together with the information on quantity index of gross output as well as their nominal values.

The Jorgenson (2008) KLEM database, developed by Dale W. Jorgenson, and described in Jorgenson et al. (2000), provides the sample data for the U.S. manufacturing industries. The database is a combination of industry data collected

[6]TFP estimates obtained from the smoothed Tornqvist index are almost identical to that obtained from the smoothed Fisher ideal index, and are not reported for brevity.

[7]Dissou and Ghazal (2010) utilize this dataset to examine energy substitutability in the primary metal and cement industries.

[8]The industries are at the L-level of aggregation in the North American Industry Classification System 2012.

from the U.S. Bureau of Labor Statistics (BLS) and the U.S. Bureau of Economic Analysis (BEA). It contains information on value and the price of output together with information on the values and prices for four inputs — capital, labour, energy, and material — for thirty-five U.S. industries covering the period from 1960 to 2005. The industries generally correspond to the 2-digit sectors in the Standard Industrial Classification (SIC) system.[9] In this study, I consider two of the thirty-five U.S. manufacturing industries — 'primary metal' and 'paper and allied' — which roughly match with two of the Canadian industries in my sample and I also match the time period with the period covered in the Canadian KLEMS database.

Table 3.1 provides a summary of descriptive statistics for selected variables in all industries during the study period used in this study. The variables are self-explanatory. Summary statistics include mean and standard deviation of output along with that of the prices, quantities and cost shares of four inputs. Average annual growth rates of inputs, output, and input prices for all industries are presented in Table 3.2.

3.5.2 Estimation

For the translog specification, I perform joint estimation of the cost function (3.12) and the share equations (3.14) as a system of equations. Error disturbances, $\mathbf{v}_t$, which are assumed to have a multivariate normal distribution with zero mean and constant covariance over time are added to the set of equations in the system. I use the iterative Zellner's technique for Seemingly Unrelated Regression (SUR) to estimate the system of equations. However, to avoid the problem of singularity I arbitrary delete the material share equation. Parameter estimates of the

[9] Young (2013), for example, uses this dataset to provide U.S. industry level estimates of the elasticity of substitution between labour and capital. He describes one major desirable feature of the U.S. KLEM database that it includes quality-adjusted labour services that combine data on individuals from the U.S. Census and Current Population Survey (CPS) after controlling for different qualities of labour.

deleted material share equation are obtained by using the linear homogeneity and symmetry restrictions.

For the GL and the NQ specifications I only estimate the system of input-output equations (3.24) and (3.34), respectively, since the cost functions do not contain any additional information in both cases. All four input-output equations are used for the iterative SUR estimation. In estimating the NQ model for Canadian industries I normalize inputs prices in the first year to one. However, for the U.S. industries normalization is not required as input prices are equal to one for the base year (1996) in the data set.

If estimated models fail to satisfy the curvature condition, I follow the procedures explained in Section 3.3 to impose concavity. For the translog and the GL models, I follow the route suggested by Ryan and Wales (2000) to impose local concavity. It is important to note that the point of concavity imposition is arbitrary. If imposition of local concavity at all reference points fails to provide the expected concavity coverage at all sample points, then I choose the data point that provides the lowest number of curvature violations as the best approximation point and report results for that. For the NQ model I follow the technique described in Diewert and Wales (1987) to impose global concavity. For all three functional forms, imposing curvature conditions transforms the linear system of equations into a nonlinear one in parameters. Thus I use the nonlinear iterative SUR technique to estimate the systems restricted for concavity.

To verify whether the economic theoretical regularity conditions are satisfied by the estimated models I perform checks on positivity, monotonicity, and concavity. I evaluate fitted values of the cost function at each observation as a check for whether the estimated cost function is strictly positive. For monotonicity, I check whether the estimated input demand functions are all strictly positive at all data points. Necessary and sufficient condition for concavity is that the Hessian matrix of the cost function be negative semi-definite, and a real symmetric matrix will be negative semi-definite if it has non-positive eigenvalues. To check for the curvature condition, I compute eigenvalues of the estimated Hessian matrix of the cost function at each point in the sample space.

Although the full basic models are presented in Section 3.3, I test for the presence of technical change in all three functional forms using the likelihood ratio test. Since constant returns to scale are built in the datasets used in this study, test for the presence of returns to scale is ruled out. Moreover, in the translog model I test for the presence of neutral technical change. Finally, inclusion of the squared term of time trend is also tested for each model.

3.6 Result

3.6.1 Theoretical Regularity

Results from the likelihood ratio tests are presented in Table 3.3. Possibility of no technical change is rejected at 1% level of significance for all industries in the sample. In the translog model, the possibility of neutral technical change is also rejected for all industries. However, for the Canadian cement industry in the translog model and for the Canadian paper industry in the GL and the NQ models I fail to reject the null hypothesis of no squared time trend at 1% level of significance.

Tables 3.4–3.9 present results from estimating the translog, the GL, and the NQ models with and without curvature conditions. All models satisfy positivity and monotonicity at all data points in the sample when curvature conditions are not imposed. However, results for the concavity condition are not quite satisfactory. Counts on the incidence of curvature violations are reported in the tables. When curvature conditions are not imposed only the GL model satisfies concavity at all data points for three out of the five sample industries. The translog and the NQ models violate curvature conditions in all cases.

Results from estimating the models with curvature conditions being imposed are also reported in Tables 3.4–3.9. For the translog and the GL models, imposing curvature conditions does not completely eliminate curvature violations in all cases. For example, in the translog model for the Canadian metal and paper industries and in the GL model for the U.S. metal industry it fails to completely eliminate curvature violations. On the other hand, imposing global curvature conditions on the NQ reduces curvature violations to zero, as expected, in all cases.

Feng and Serletis (2008) find the performances of the translog and the GL models as poor when curvature conditions are being imposed on these models, and since both models fail to meet the curvature condition they do not provide productivity estimates based on these models. In this study, I present a more comprehensive case in the sense that my results include examples where imposing concavity on the translog and the GL models does successfully reduce curvature violations to zero. For example, in both the translog and the GL models for the Canadian cement industry it reduces curvature violations to zero. Moreover, the GL cost function satisfies all regularity conditions even without curvature being imposed for the Canadian metal and paper industries, for example.

In what follows, I discuss the productivity and elasticity estimates only for those industries where the model satisfies all economic regularity conditions.

3.6.2 Productivity Estimates

Tables 3.10–3.12 report average total factor productivity measures estimated with all three functional forms used in this paper. With the translog model, for the Canadian cement industry as well as for both U.S. metal and paper industries, imposing curvature restrictions result in the satisfaction of all regularity conditions. However, the difference in TFP estimates, with and without curvature conditions, for these industries are noticeable in Table 3.10. Moreover, this discrepancy is also present in the estimates of autonomous and biased technical change. Given the importance of the rate and biases of technical change it is highly desirable that we get accurate estimates of those parameters. Results for the GL model in the case of Canadian cement industry, presented in Table 3.11, exhibit similar difference in TFP estimates with and without curvature being imposed. It can be seen more vividly in Figure 3.1 which provides year-by-year TFP estimates for the Canadian cement industry estimated by the GL model with and without curvature being imposed.

The NQ model, on the other hand, performs better than the translog and the GL models when curvature condition is being imposed. Average TFP estimates for the NQ model are reported in Table 3.12. TFP estimates with curvature imposed are almost identical to the ones without curvature being imposed. Year-by-year TFP estimates for this model are presented in Figures 3.2 and 3.3. It can be seen that the TFP estimates obtained from the restricted (for curvature) and unrestricted models are almost identical.

Figures 3.4 and 3.5 plots year-by-year TFP estimates from the NQ model, together with the productivity measures obtained from the Tornqvist, Fisher, and smoothed Fisher ideal indexes. Estimates from the GL model, when all economic regularity conditions are satisfied without curvature being imposed, are also included. The Tornqvist and the Fisher ideal indexes produce similar TFP estimates and for U.S. industries they are virtually identical. Productivity estimates from the NQ and GL models exhibit similar patterns during the sample period. Furthermore, both series of the GL and NQ estimates follow the smoothed Fisher ideal index very closely. Feng and Serletis (2008) use this criterion in evaluating the performance of NQ and AIM functional forms in providing TFP estimates. However, there is no theoretical correspondence of the smoothed Fisher Ideal index with the NQ or the AIM functional forms, although the correspondence between the Tornqvist index and the translog functional forms is well known (Diewert, 1976b). If we consider the benchmark adopted by Feng and Serletis (2008), both the NQ (with curvature being imposed) and the GL (without curvature being imposed) functional forms perform equally well in providing TFP estimates.

3.6.3 Elasticity Estimates

Tables 3.13–3.16 present own and cross price elasticities of factor demand along with the Morishima elasticities for my sample industries in U.S. and Canada. I calculate elasticities at the middle year of the sample period. Although not reported here for brevity, I also compute the elasticities when curvature conditions are not imposed. In most of the cases they follow closely to the ones reported in the tables. In general, elasticity estimates obtained from the NQ model are smaller in absolute terms than the ones obtained from the GL and translog models.

Estimated own price elasticities of demand in all cases have the correct sign. For all industries in the sample I find the derived factor demands inelastic as the estimated own price elasticities are below one in absolute terms. However, one particular feature of the own price elasticity estimates from the GL and the NQ models is worth mentioning. Feng and Serletis (2008) find that own price elasticity estimates in the NQ model for U.S. manufacturing do not show variations over time and Diewert and Lawrence (2002), who first identified the issue, term this as 'the problem of trending elasticities'. However, my findings on own price elasticities for my sample industries do not show any lack of variation, and more interestingly they show more variation than the ones I estimate with the GL model. Figure 3.6 plots the own price elasticities for the U.S. paper industry, for example.

Estimates for the Morishima elasticities of substitution are mostly positive for all pairs of inputs in all industries. This suggests that the inputs are mostly substitutes in all industries. However, few exceptions are worth mentioning. For example, estimates of σ^m_{MK} in the Canadian cement industry and σ^m_{LK} and σ^m_{KL} in the U.S. metal and paper industries, respectively, are negative in the NQ model while they are positive in the GL model.

3.7 Conclusion

In this paper I provide an empirical comparison and evaluation of three widely used locally flexible cost functional forms — the translog, the GL, and the NQ — in providing TFP estimates once they satisfy the economic theoretic regularity conditions. In doing so, I take the econometric approach to productivity measurement and generate estimates of total factor productivity for two U.S. industries — primary metal and paper — along with three Canadian industries — primary metal, cement, and paper — covering the period of 1961 to 2003. Moreover, I impose curvature restrictions on the functional forms once the estimated models fail to satisfy the curvature condition. In particular, for the translog and the GL models I impose local concavity according to the way suggested by Ryan and Wales (2000) while for the NQ model I impose global concavity following the route suggested by Diewert and Wales (1987).

Estimation results for the sample industries provide me the opportunity to cover all possible cases one might encounter in terms of curvature violations while estimating these three locally flexible functional forms: (i) curvature conditions are satisfied without curvature restrictions being imposed, (ii) curvature conditions are satisfied when curvature restrictions are imposed, and (iii) curvature conditions are not satisfied even with curvature restrictions being imposed. Findings reveal evidences of concavity violations even with curvature being imposed locally for the translog and the GL models. However, curvature violations reduce to zero for the NQ model when concavity is imposed globally.

When all economic regularity conditions are satisfied with curvature being imposed, my results suggest that the NQ model performs better than the other two models in providing TFP estimates. Estimates of productivity from the unrestricted and the restricted NQ models are almost identical. However, the GL cost function performs equally well when all the regularity conditions are satisfied without curvature being imposed. Based on the evidences provided in this study I argue that since desired curvature coverage is not guaranteed in the translog and the GL models and local curvature imposition on these functional forms affects the productivity estimates, functional forms with global curvature conditions appear to be a better choice for econometric productivity estimation.

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Table 3.1: Summary Statistics: Mean and Standard Deviation (in parenthesis): 1961–2003

	Canada			U.S.	
Variables	Cement	Metal	Paper	Metal	Paper
Price of Capital	37.29 (29.13)	35.77 (28.56)	54.40 (42.17)	0.58 (0.28)	0.61 (0.27)
Price of Labour	51.30 (30.81)	52.29 (34.15)	50.10 (32.28)	0.64 (0.34)	0.63 (0.37)
Price of Material	57.20 (31.25)	60.11 (30.34)	58.72 (31.15)	0.67 (0.30)	0.63 (0.31)
Price of Energy	46.81 (33.20)	55.85 (34.74)	44.98 (33.31)	0.65 (0.35)	0.64 (0.36)
Quantity of Capital	96.78 (15.37)	84.44 (20.75)	90.39 (30.60)	18137.85 (2594.18)	16793.13 (6717.58)
Quantity of Labour	82.92 (11.11)	101.51 (10.97)	102.34 (18.79)	39062.33 (8707.00)	32187.82 (3843.13)
Quantity of Material	59.43 (16.16)	60.97 (20.66)	63.14 (23.86)	106246.30 (14826.51)	68784.46 (18347.83)
Quantity of Energy	110.56 (26.27)	86.40 (16.93)	92.01 (14.18)	11827.48 (2643.29)	5770.94 (1017.06)
Cost Share of Capital	17.54 (3.17)	9.03 (2.97)	16.08 (6.08)	9.52 (1.52)	13.29 (1.70)
Cost Share of Labour	24.38 (1.54)	20.16 (2.52)	22.67 (3.53)	20.86 (1.47)	25.55 (1.89)
Cost Share of Material	51.17 (2.39)	63.00 (1.84)	51.97 (3.40)	63.38 (1.08)	56.57 (1.33)
Cost Share of Energy	6.91 (1.18)	7.81 (1.57)	9.27 (2.00)	6.24 (1.25)	4.59 (0.96)
Output	65.99 (15.20)	64.08 (19.21)	71.78 (19.44)	172455.70 (24263.58)	123955 (32039.78)

Note: Annual data: 1961–2003.

Table 3.2: Average Annual Growth Rates: 1961–2003

	Canada			U.S.	
	Cement	Metal	Paper	Metal	Paper
Price of Capital	5.80	4.63	2.10	3.62	2.14
Price of Labour	5.30	5.42	5.45	4.42	5.13
Price of Material	4.20	3.94	4.00	3.34	3.54
Price of Energy	6.37	5.40	6.59	4.37	4.54
Quantity of Capital	0.94	1.79	2.09	1.00	3.11
Quantity of Labour	1.56	0.68	1.15	-.52	0.81
Quantity of Material	3.04	2.96	3.21	0.50	1.94
Quantity of Energy	0.20	1.58	1.11	-.13	1.15
Output	2.67	2.72	2.31	0.61	2.09

Note: Annual data: 1961–2003.

Table 3.3: Test Statistics for Likelihood Ratio Tests

	Canada			U.S.	
Functional Form	Cement	Metal	Paper	Metal	Paper
No Technical Change					
TL	72.62	152.39	127.12	77.63	160.88
GL	124.84	185.23	179.20	101.04	248.86
NQ	138.10	160.68	200.64	105.23	206.22
No Squared Term of Time					
TL	2.17*	42.13	8.71	33.91	28.64
GL	22.23	45.00	11.80*	66.53	97.00
NQ	29.76	44.68	10.85*	62.43	92.39
Neutral Technical Change					
TL	15.12	78.82	78.56	52.24	117.85

Notes: Test for the possibility of no technical change involves five restrictions in the translog, $\beta_t = \beta_{tt} = \beta_{it} = 0$, for $i = 1, ..., n-1$, and eight restrictions in both the GL and the NQ models, $\beta_{it} = \gamma_{it} = 0$, for $i = 1, ..., n$. Test for the possibility of neutral technical change in the translog imposes three restrictions, $\beta_{it} = 0$, for $i = 1, ..., n-1$. Again, test for the inclusion of squared time trend involves one parameter restriction in the translog, $\beta_{tt} = 0$, and in both the GL and the NQ models it involves four restrictions, $\gamma_{it} = 0$, for $i = 1, ..., n$. In all cases, $prob > \chi^2 = 0.0000$ except for the cases identified with *. For the Canadian Paper industry, in case of GL $prob > \chi^2 = 0.0189$, and in case of NQ $prob > \chi^2 = 0.0283$, while for the Canadian Cement industry, in TL $prob > \chi^2 = 0.1406$.

Table 3.4: Translog Parameter Estimates For Canadian Industries

Parameter	Cement		Metal		Paper	
	Curvature Not Imposed	Local Curvature Imposed	Curvature Not Imposed	Local Curvature Imposed	Curvature Not Imposed	Local Curvature Imposed
β_0	-.2068 (.012)	2.7101 (.009)	1.6140 (.014)	4.6604 (.005)	1.1430 (.015)	5.6763 (.017)
β_k	.2133 (.007)	.2121 (.002)	.1001 (.003)	.0938 (.002)	.1498 (.007)	.2133 (.012)
β_l	.2238 (.007)	.2453 (.002)	.2792 (.009)	.2041 (.002)	.3800 (.010)	.1632 (.004)
β_e	.0857 (.006)	.0492 (.001)	.1056 (.006)	.0582 (.001)	.1244 (.007)	.0997 (.003)
β_{kk}	.0815 (.006)	—	.0441 (.002)	—	.0765 (.004)	—
β_{ll}	.0919 (.013)	—	.0842 (.012)	—	.1943 (.015)	—
β_{ee}	.0486 (.004)	—	.0493 (.006)	—	.0495 (.005)	—
β_{kl}	-.0402 (.003)	—	-.0223 (.002)	—	-.0234 (.001)	—
β_{ke}	-.0270 (.003)	—	-.0057 (.002)	—	-.0119 (.001)	—
β_{le}	-.0304 (.005)	—	.0190 (.005)	—	-.0013 (.004)	—
β_{kt}	-.0006 (.000)	-.0006 (.000)	.0006 (.000)	.0006 (.000)	.0006 (.000)	.0007 (.000)
β_{lt}	.0001 (.000)	.0001 (.000)	-.0029 (.000)	-.0028 (.000)	-.0049 (.000)	-.0039 (.000)
β_{et}	-.0007 (.000)	-.0007 (.000)	-.0007 (.000)	-.0006 (.000)	-.0004 (.000)	-.0004 (.000)
β_t	-.0044 (.000)	-.0035 (.000)	.0077 (.001)	.0024 (.001)	-.0003 (.001)	-.0069 (.001)
β_{tt}	—	—	-.0007 (.000)	-.0007 (.000)	-.0002 (.000)	-.0002 (.000)
a_{kk}	—	.2903 (.009)	—	.2019 (.006)	—	.3028 (.018)
a_{kl}	—	-.0303 (.012)	—	.0191 (.008)	—	-.0297 (.016)
a_{ll}	—	.3222 (.019)	—	-.2968 (.019)	—	.0618 (.018)
a_{ke}	—	.0508 (.009)	—	.0038 (.009)	—	-.0310 (.006)
a_{le}	—	.0436 (.013)	—	.1097 (.015)	—	-.1983 (.015)
a_{ee}	—	-.0000 (2.02)	—	-.0000 (8.28)	—	-.0001 (.000)
Curvature Violations	11	0	15	3	43	3
Log likelihood	537.62	537.14	545.05	543.20	522.56	517.63

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.5: Translog Parameter Estimates For U.S. Industries

Parameter	Metal		Paper	
	Curvature Not Imposed	Local Curvature Imposed	Curvature Not Imposed	Local Curvature Imposed
β_0	-.0464 (.012)	.0141 (.007)	.1181 (.010)	.0368 (.006)
β_k	.0779 (.003)	.0712 (.002)	.0827 (.002)	.1047 (.001)
β_l	.2580 (.010)	.2649 (.005)	.2755 (.009)	.2963 (.004)
β_e	.0704 (.003)	.0669 (.002)	.0648 (.002)	.0564 (.001)
β_{kk}	.0403 (.004)	—	.0770 (.004)	—
β_{ll}	.1851 (.035)	—	-.0183 (.026)	—
β_{ee}	.0684 (.006)	—	.0406 (.003)	—
β_{kl}	.0022 (.006)	—	.0616 (.007)	—
β_{ke}	-.0223 (.003)	—	-.0116 (.002)	—
β_{le}	-.0466 (.011)	—	.0098 (.007)	—
β_{kt}	.0009 (.000)	.0007 (.000)	.0020 (.000)	.0017 (.000)
β_{lt}	-.0017 (.000)	-.0020 (.000)	-.0009 (.000)	-.0012 (.000)
β_{et}	-.0003 (.000)	-.0004 (.000)	-.0007 (.000)	-.0008 (.000)
β_t	.0113 (.001)	.0063 (.001)	-.0116 (.000)	-.0086 (.001)
β_{tt}	-.0006 (.000)	-.0005 (.000)	.0004 (.000)	.0005 (.000)
a_{kk}	—	.1984 (.007)	—	.1830 (.009)
a_{kl}	—	-.1266 (.045)	—	.1167 (.036)
a_{ll}	—	.1705 (.123)	—	.4347 (.033)
a_{ke}	—	.1239 (.022)	—	.0324 (.014)
a_{le}	—	.0039 (.072)	—	-.0816 (.020)
a_{ee}	—	.0000 (3.56)	—	.0000 (5.67)
Curvature Violations	28	0	43	0
Log likelihood	562.45	546.48	603.30	589.67

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.6: GL Parameter Estimates For Canadian Industries

Parameter	Cement		Metal	Paper
	Curvature Not Imposed	Local Curvature Imposed	Curvature Not Imposed	Curvature Not Imposed
β_{kl}	-.1861 (.048)	—	-.0830 (.038)	-.0258 (.011)
β_{km}	-.2340 (.102)	—	.0770 (.022)	.0635 (.009)
β_{ke}	.6909 (.103)	—	.1511 (.055)	.0238 (.024)
β_{kt}	-.0191 (.007)	-.0269 (.009)	.0204 (.005)	.0036 (.002)
γ_{kt}	-.0002 (.000)	.0000 (.000)	-.0006 (.000)	—
β_{kk}	1.8184 (.124)	—	1.0591 (.050)	1.0982 (.053)
β_{lm}	1.5267 (.150)	—	-.0224 (.062)	-.0072 (.069)
β_{le}	-.0576 (.081)	—	.4923 (.086)	.4384 (.034)
β_{lt}	-.0040 (.003)	-.0273 (.004)	-.0125 (.004)	-.0164 (.001)
γ_{lt}	.0000 (.000)	.0003 (.000)	-.0004 (.000)	—
β_{ll}	-.0948 (.181)	—	1.8487 (.103)	1.4791 (.096)
β_{me}	.0524 (.164)	—	.2914 (.050)	.1117 (.038)
β_{mt}	-.0267 (.004)	-.0135 (.002)	.0063 (.001)	.0069 (.000)
γ_{mt}	.0006 (.000)	.0004 (.000)	-.0001 (.000)	—
β_{mm}	-.1489 (.170)	—	.5685 (.051)	.5582 (.055)
β_{et}	-.0241 (.009)	-.0283 (.008)	.0237 (.008)	-.0128 (.001)
γ_{et}	-.0002 (.000)	-.0001 (.000)	-.0007 (.000)	—
β_{ee}	1.7650 (.302)	—	.4530 (.183)	.9523 (.116)
d_k	—	1.8569 (.094)	—	—
d_{kk}	—	.5854 (.069)	—	—
d_{km}	—	.1858 (.099)	—	—
d_{kl}	—	.1396 (.116)	—	—
d_l	—	1.6205 (.033)	—	—
d_{ll}	—	.3011 (.325)	—	—
d_{lm}	—	.1178 (.176)	—	—
d_m	—	.9087 (.023)	—	—
d_{mm}	—	.0008 (.089)	—	—
d_e	—	2.7003 (.065)	—	—
Curvature Violations	43	0	0	0
Log likelihood	184.88	184.48	237.95	280.0

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.7: GL Parameter Estimates For U.S. Industries

Parameter	Metal		Paper
	Curvature Not Imposed	Local Curvature Imposed	Curvature Not Imposed
β_{kl}	-.0145 (.021)	—	-.0632 (.012)
β_{km}	.1269 (.019)	—	.1379 (.017)
β_{ke}	-.0013 (.007)	—	-.0074 (.005)
β_{kt}	.0007 (.000)	.0007 (.001)	.0009 (.000)
γ_{kt}	.0000 (.000)	.0000 (.000)	.0000 (.000)
β_{kk}	-.0305 (.011)	—	.0293 (.007)
β_{lm}	.2917 (.069)	—	.2533 (.042)
β_{le}	.0195 (.020)	—	.0128 (.011)
β_{lt}	-.0019 (.001)	-.0040 (.001)	-.0096 (.000)
γ_{lt}	.0001 (.000)	.0000 (.000)	.0002 (.000)
β_{ll}	-.0535 (.078)	—	.1770 (.043)
β_{me}	-.0304 (.023)	—	.0068 (.014)
β_{mt}	.0092 (.001)	.0073 (.001)	.0028 (.001)
γ_{mt}	-.0002 (.000)	-.0002 (.000)	-.0001 (.000)
β_{mm}	.1846 (.077)	—	.1504 (.053)
β_{et}	.0016 (.000)	.0019 (.000)	.0003 (.000)
γ_{et}	-.0001 (.000)	-.0001 (.000)	-.0001 (.000)
β_{ee}	.0803 (.013)	—	.0410 (.008)
d_k	—	.0648 (.004)	—
d_{kk}	—	.3086 (.019)	—
d_{km}	—	-.2921 (.077)	—
d_{kl}	—	-.0371 (.080)	—
d_l	—	.2915 (.008)	—
d_{ll}	—	-.2079 (.058)	—
d_{lm}	—	.2246 (.063)	—
d_m	—	.5688 (.008)	—
d_{mm}	—	.0001 (.564)	—
d_e	—	.0603 (.001)	—
Curvature Violations	43	1	0
Log likelihood	561.69	561.39	644.86

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.8: NQ Estimates For Canadian Industries

Parameter	Cement		Metal		Paper	
	Curvature Not Imposed	Global Curvature Imposed	Curvature Not Imposed	Global Curvature Imposed	Curvature Not Imposed	Global Curvature Imposed
β_{kk}	33.235 (13.6)	—	-35.699 (4.37)	—	-13.136 (3.86)	—
β_{kl}	-46.001 (14.8)	—	51.998 (8.28)	—	-.9588 (5.73)	—
β_{ke}	109.38 (19.3)	—	99.102 (16.2)	—	-5.6413 (17.0)	—
β_{ll}	-73.020 (29.7)	—	-88.273 (11.7)	—	-39.915 (10.0)	—
β_{le}	-2.7645 (19.1)	—	58.524 (9.61)	—	50.311 (7.30)	—
β_{ee}	-139.69 (27.9)	—	-186.88 (21.5)	—	-45.212 (21.3)	—
β_{kt}	-.0136 (.009)	-.0115 (.008)	.0049 (.006)	.0241 (.007)	.0051 (.003)	.0036 (.002)
γ_{kt}	-.0003 (.000)	-.0003 (.001)	-.0004 (.000)	-.0007 (.001)	—	—
β_{k}	1.8719 (.086)	1.8695 (.074)	1.3074 (.049)	1.2005 (.060)	1.1388 (.059)	1.1499 (.058)
β_{lt}	-.0227 (.004)	-.0181 (.006)	-.0018 (.005)	-.0008 (.006)	-.0164 (.001)	-.0166 (.001)
γ_{lt}	.0003 (.000)	.0002 (.001)	-.0006 (.000)	-.0006 (.000)	—	—
β_{l}	1.6577 (.035)	1.6471 (.039)	2.1718 (.047)	2.1671 (.050)	1.7896 (.040)	1.7895 (.037)
β_{mt}	-.0249 (.004)	-.0294 (.008)	.0092 (.001)	.0098 (.002)	.0082 (.000)	.0075 (.000)
γ_{mt}	.0005 (.000)	.0006 (.001)	-0001 (.000)	-.0001 (.000)	—	—
β_{m}	.9593 (.033)	.9559 (.042)	.8160 (.012)	0.8117 (.015)	.6903 (.007)	.6868 (.008)
β_{et}	-.0241 (.008)	-.0259 (.008)	.0402 (.010)	.0138 (.008)	-.0169 (.002)	-.0157 (.001)
γ_{et}	-.0002 (.000)	-.0001 (.001)	-.0012 (.000)	-.0006 (.000)	—	—
β_{e}	2.5201 (.077)	2.5391 (.076)	1.3875 (.087)	1.5420 (.074)	1.7348 (.039)	1.7433 (.039)
a_{kk}	—	5.5786 (1.26)	—	5.9888 (.729)	—	3.3611 (.891)
a_{kl}	—	3.4976 (4.04)	—	-4.9476 (2.67)	—	2.1987 (1.37)
a_{ke}	—	-11.749 (1.85)	—	-2.4875 (1.89)	—	-2.8631 (1.83)
a_{ll}	—	-10.440 (2.52)	—	-6.5599 (.913)	—	-6.4141 (.580)
a_{le}	—	-3.1756 (4.54)	—	9.2811 (1.02)	—	7.4143 (.822)
a_{ee}	—	.0000 (1.00)	—	.0000 (2.84)	—	-.0000 (2.18)
Curvature Violations	43	0	43	0	43	0
Log likelihood	178.68	175.09	244.0	237.16	262.76	260.85

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.9: NQ Estimates For U.S. Industries

Parameter	Metal		Paper	
	Curvature Not Imposed	Global Curvature Imposed	Curvature Not Imposed	Global Curvature Imposed
β_{kk}	-10112.5 (1694.0)	—	-4772.5 (510.6)	—
β_{kl}	-3973.5 (1790.2)	—	-3193.0 (770.7)	—
β_{ke}	-517.34 (710.0)	—	-233.79 (349.7)	—
β_{ll}	-33785.1 (5671.9)	—	-11157.3 (2244.8)	—
β_{le}	3648.8 (1739.7)	—	1090.5 (679.7)	—
β_{ee}	457.53 (1070.1)	—	-803.89 (397.4)	—
β_{kt}	.0013 (.001)	.0012 (.000)	.0003 (.000)	.0003 (.000)
γ_{kt}	.0000 (.000)	.0000 (.000)	.0000 (.000)	.0000 (.000)
β_{k}	.0757 (.008)	.0754 (.008)	.1044 (.003)	.1042 (.003)
β_{lt}	-.0033 (.001)	-.0032 (.001)	-.0103 (.001)	-.0103 (.001)
γ_{lt}	.0001 (.000)	.0001 (.000)	.0002 (.000)	.0002 (.000)
β_{l}	.2481 (.013)	.2474 (.015)	.3889 (.007)	.3991 (.007)
β_{mt}	.0085 (.001)	.0083 (.001)	.0026 (.001)	.0026 (.001)
γ_{mt}	-.0002 (.000)	.0002 (.000)	-.0001 (.000)	-.0001 (.000)
β_{m}	.5836 (.016)	.5874 (.015)	.5467 (.011)	.5468 (.013)
β_{et}	.0015 (.000)	.0016 (.000)	.0004 (.000)	.0004 (.000)
γ_{et}	-.0001 (.000)	-.0001 (.000)	-.0001 (.000)	-.0001 (.000)
β_{e}	.0687 (.004)	.0656 (.003)	.0529 (.002)	.0527 (.003)
a_{kk}	—	101.03 (8.71)	—	69.074 (4.40)
a_{kl}	—	38.959 (20.9)	—	46.292 (14.4)
a_{ke}	—	7.0168 (7.27)	—	3.4175 (5.89)
a_{ll}	—	-152.67 (28.5)	—	79.915 (22.7)
a_{le}	—	23.441 (16.7)	—	-15.684 (10.9)
a_{ee}	—	.0000 (5.70)	—	-23.387 (9.92)
Curvature Violations	43	0	43	0
Log likelihood	562.84	562.63	644.08	644.02

Notes: Annual data: 1961–2003. Standard errors of the parameter estimates are reported in parenthesis. Positivity and monotonicity violations are 0 in each case.

Table 3.10: Average Annual Rates of Technical Change (%) Using translog

	Autonomous Technical Change		Biased Technical Change		Total Technical Change	
	Curvature Not Imposed	Curvature Imposed	Curvature Not Imposed	Curvature Imposed	Curvature Not Imposed	Curvature Imposed
Canada						
Cement	0.44	0.35	-0.06	0.02	0.38	0.37
U.S.						
Metal	0.17	0.18	-0.01	0.08	0.16	0.26
Paper	0.20	0.21	-0.01	0.07	0.19	0.28

Notes: Annual data: 1961–2003. All theoretical regularity conditions are satisfied in each case when curvature being imposed.

Table 3.11: Average Annual Rates of Technical Change (%) Using GL

	Curvature Not Imposed	Local Curvature Imposed
Canada		
Cement	1.12	1.44
Paper	0.28	—
Metal	1.00	—
U.S.		
Paper	0.17	—

Notes: Annual data: 1961–2003. All theoretical regularity conditions are satisfied in each case when curvature being imposed.

Table 3.12: Average Annual Rates of Technical Change (%) Using NQ

Curvature	Canada			U.S.		Curvature
Restrictions	Cement	Metal	Paper	Metal	Paper	Violation
No	1.42	1.23	0.69	0.16	0.20	Yes
Yes	1.42	1.20	0.69	0.16	0.20	No

Notes: Annual data: 1961–2003. Positivity and monotonicity violations are 0 in each case.

Table 3.13: Price Elasticities for the Canadian Industries

Factor i	Model	Price Elasticities η_{Ki}	η_{Li}	η_{Mi}	η_{Ei}
Cement					
(K)	NQ	-.047	-.036	-.091	.058
	GL	-.248	-.020	-.039	.074
	TL	-.159	-.048	.086	-.148
(L)	NQ	-.048	-.264	.346	.067
	GL	-.034	-.098	-.035	.055
	TL	-.112	-.432	.243	.012
(M)	NQ	-.064	-.169	-.533	.069
	GL	-.043	-.022	-.106	.045
	TL	.396	.475	-.440	.600
(E)	NQ	-.014	.131	.278	-.194
	GL	.326	.139	.180	-.175
	TL	-.125	.004	.111	-.465
Metal					
(K)	NQ	-.007	.001	-.006	.002
	GL	-.190	-.005	.009	.012
	TL	-.364	-.032	.056	.009
(L)	NQ	.014	-.124	-.086	.168
	GL	-.085	-.144	-.010	.157
	TL	-.083	-.435	.092	.440
(M)	NQ	.011	-.028	-.058	.054
	GL	.088	-.007	-.161	.104
	TL	.437	.279	-.144	-.023
(E)	NQ	-.030	.151	.150	-.223
	GL	.186	.156	.162	-.273
	TL	.010	.188	-.003	-.426
Paper					
(K)	NQ	-.011	-.011	.005	.009
	GL	-.037	-.006	.025	.007
	TL	-.208	.004	.040	.008
(L)	NQ	-.057	-.144	-.031	.133
	GL	-.013	-.137	-.004	.173
	TL	.009	-.210	.051	.197
(M)	NQ	-.017	-.012	-.020	.014
	GL	.037	-.003	-.080	.050
	TL	.191	.113	-.143	.248
(E)	NQ	.056	.166	.046	-.156
	GL	.012	.146	.059	-.230
	TL	.008	.094	.053	-.452

Notes: Annual data: 1961–2003. Elasticities are calculated at the middle year of the sample period.

Table 3.14: Morishima Elasticities for the Canadian Industries

Factor i	Model	Morishima Elasticities			
		σ_{Ki}	σ_{Li}	σ_{Mi}	σ_{Ei}
Cement					
(K)	NQ	—	.010	-.044	.105
	GL	—	.229	.209	.323
	TL	—	.112	.246	.012
(L)	NQ	.216	—	.610	.330
	GL	.063	—	.063	.153
	TL	.320	—	.675	.444
(M)	NQ	.470	.702	—	.602
	GL	.063	.084	—	.151
	TL	.836	.916	—	1.04
(E)	NQ	.180	.325	.472	—
	GL	.501	.314	.355	—
	TL	.340	.469	.575	—
Metal					
(K)	NQ	—	.008	.001	.009
	GL	—	.185	.199	.202
	TL	—	.332	.420	.373
(L)	NQ	.138	—	.038	.292
	GL	.059	—	.133	.301
	TL	.353	—	.527	.875
(M)	NQ	.069	.030	—	.112
	GL	.249	.154	—	.265
	TL	.582	.424	—	.121
(E)	NQ	.193	.374	.373	—
	GL	.460	.429	.436	—
	TL	.436	.614	.423	—
Paper					
(K)	NQ	—	.000	.016	.020
	GL	—	.030	.062	.044
	TL	—	.212	.248	.216
(L)	NQ	.086	—	.113	.276
	GL	.123	—	.133	.310
	TL	.220	—	.261	.407
(M)	NQ	.003	.008	—	.034
	GL	.118	.078	—	.131
	TL	.334	.256	—	.391
(E)	NQ	.212	.322	.201	—
	GL	.243	.376	.289	—
	TL	.460	.546	.505	—

Notes: Annual data: 1961–2003. Elasticities are calculated at the middle year of the sample period.

Table 3.15: Price Elasticities for the U.S. Industries

		Price Elasticities			
Factor i	Model	η_{Ki}	η_{Li}	η_{Mi}	η_{Ei}
Metal					
(K)	NQ	-.048	-.136	.158	-.011
	GL	-.557	.016	.046	-.020
	TL	-.362	.069	.039	-.218
(L)	NQ	-.122	-.381	.368	.017
	GL	.077	-.085	.033	-.015
	TL	.404	-.171	.000	.241
(M)	NQ	-.091	.487	-.675	.109
	GL	.529	.077	-.088	.049
	TL	.497	.001	-.125	.444
(E)	NQ	.189	.030	.148	-.114
	GL	-.048	-.007	.010	-.013
	TL	-.539	.101	.086	-.466
Paper					
(K)	NQ	-.168	-.059	.173	.016
	GL	-.281	-.112	.110	-.058
	TL	-.189	-.084	.090	-.058
(L)	NQ	-.071	-.031	.045	.030
	GL	-.269	-.422	.227	.112
	TL	-.320	-.667	.375	.491
(M)	NQ	-.059	.046	-.328	.077
	GL	.585	.505	-.344	.060
	TL	.568	.619	-.456	-.057
(E)	NQ	.274	.044	.110	-.123
	GL	-.036	.029	.007	-.115
	TL	-.059	.132	-.009	-.376

Notes: Annual data: 1961–2003. Elasticities are calculated at the middle year of the sample period.

Table 3.16: Morishima Elasticities for the U.S. Industries

Factor i	Model	Morishima Elasticities			
		σ_{Ki}	σ_{Li}	σ_{Mi}	σ_{Ei}
Metal					
(K)	NQ	—	-.089	.206	.037
	GL	—	.573	.603	.537
	TL	—	.431	.401	.144
(L)	NQ	.259	—	.368	.397
	GL	.161	—	.118	.070
	TL	.574	—	.171	.412
(M)	NQ	.584	1.16	—	.783
	GL	.618	.165	—	.137
	TL	.622	.125	—	.568
(E)	NQ	.303	.144	.263	—
	GL	-.035	.006	.023	—
	TL	-.072	.568	.552	—
Paper					
(K)	NQ	—	.109	.341	.184
	GL	—	.169	.391	.223
	TL	—	.105	.279	.131
(L)	NQ	-.039	—	.077	.062
	GL	.154	—	.649	.535
	TL	.347	—	1.04	1.16
(M)	NQ	.269	.374	—	.404
	GL	.929	.849	—	.404
	TL	1.02	1.08	—	.398
(E)	NQ	.397	.167	.233	—
	GL	.079	.144	.122	—
	TL	.317	.508	.367	—

Notes: Annual data: 1961–2003. Elasticities are calculated at the middle year of the sample period.

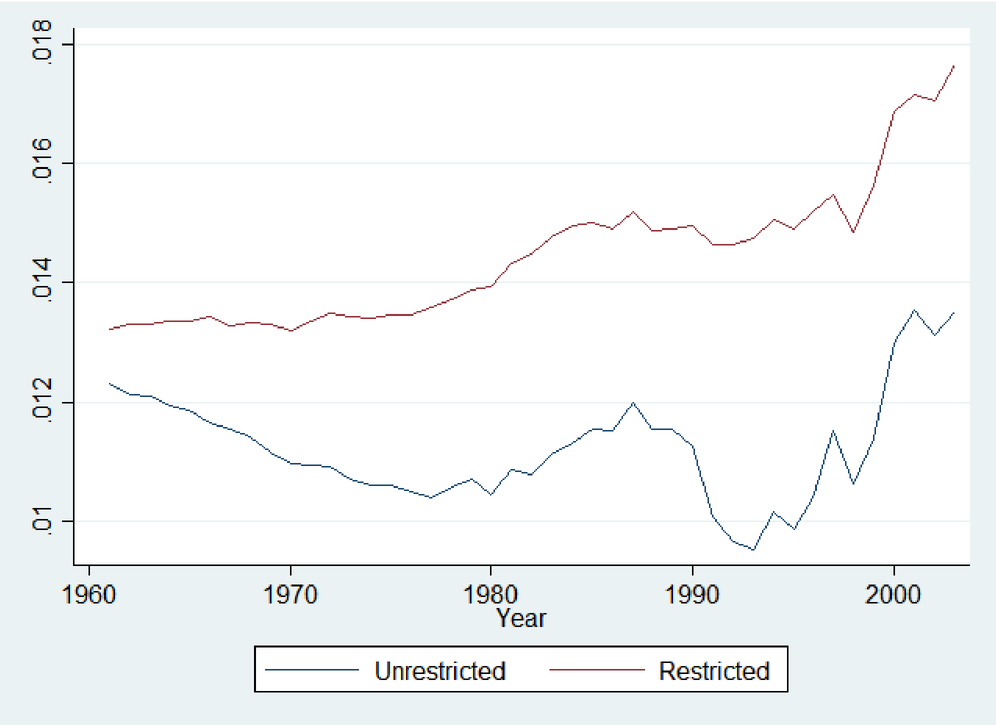
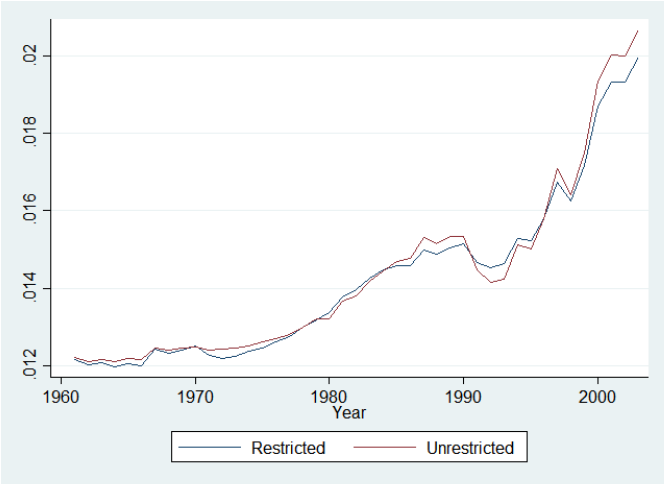
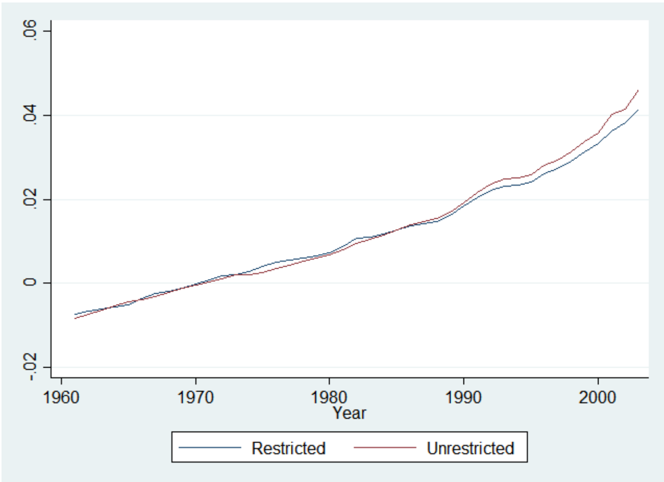


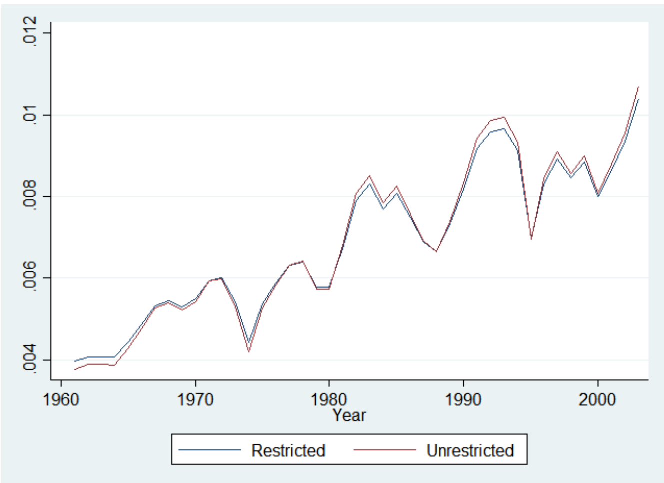
Figure 3.1: Total Factor Productivity in Canadian Cement Industry Using GL



(a) Cement

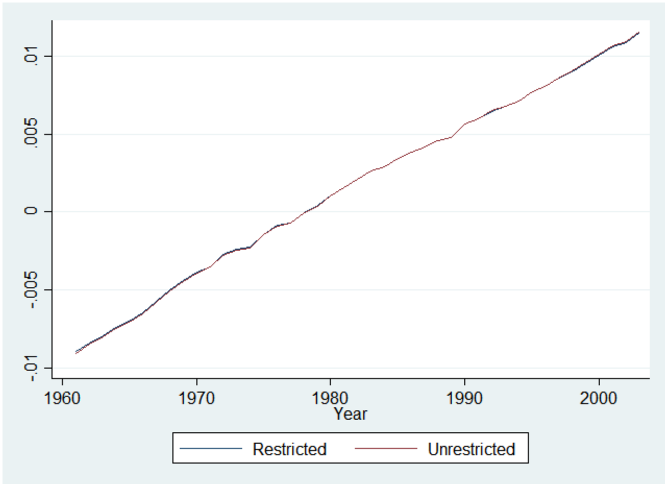


(b) Metal

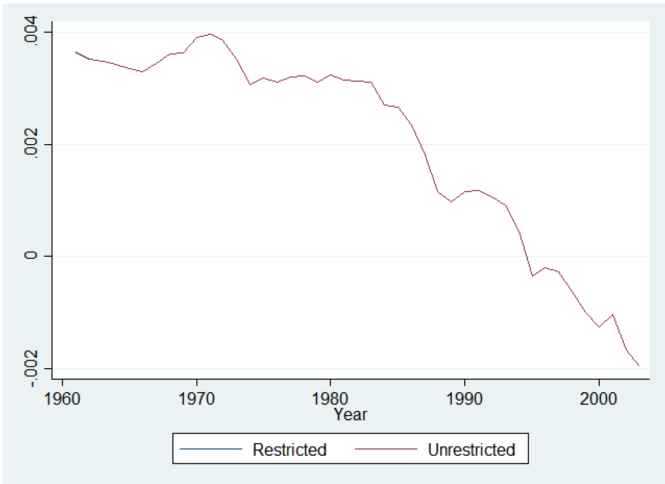


(c) Paper

Figure 3.2: Total Factor Productivity in Canadian Manufacturing Using NQ

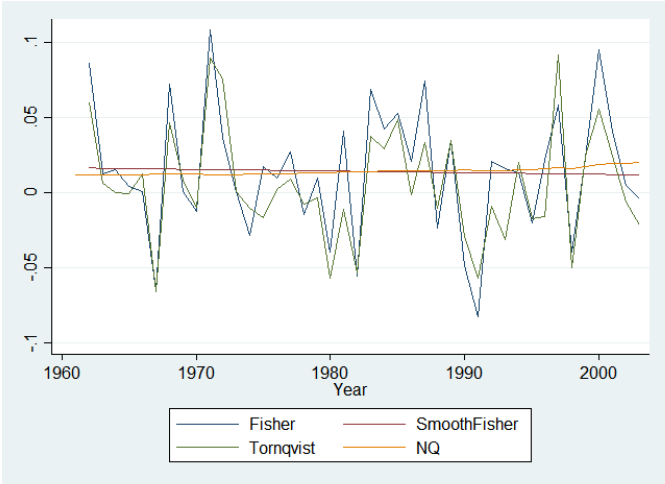


(a) Metal

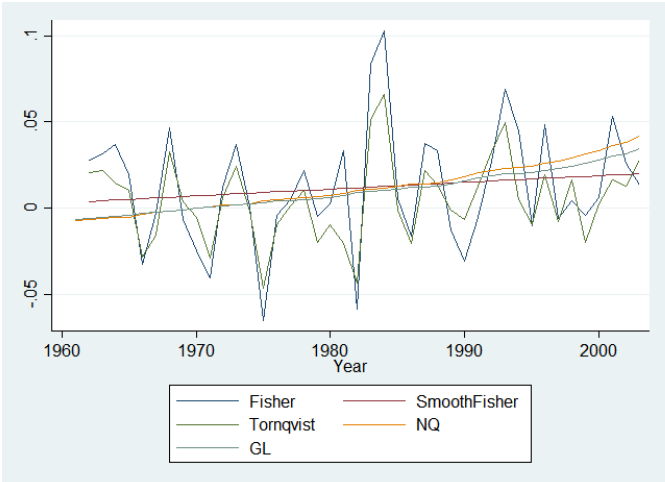


(b) Paper

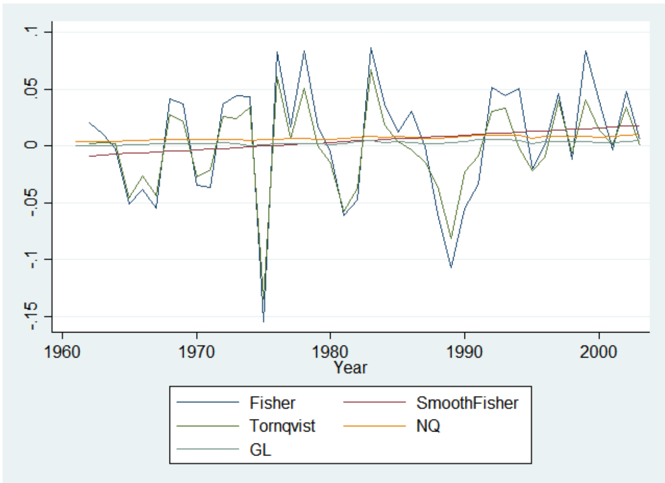
Figure 3.3: Total Factor Productivity in U.S. Manufacturing Using NQ



(a) Cement

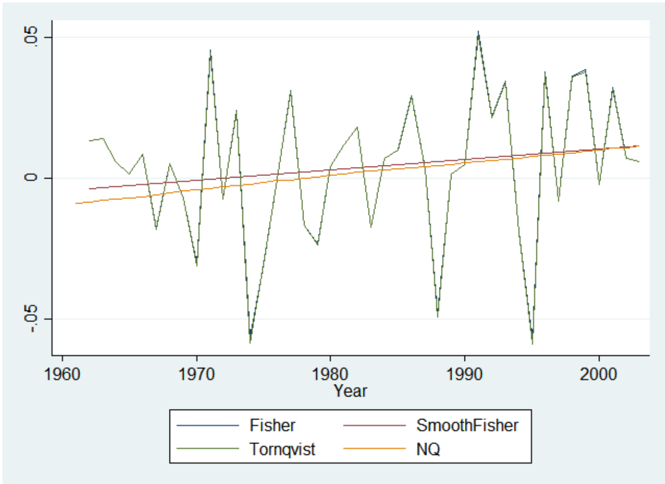


(b) Metal

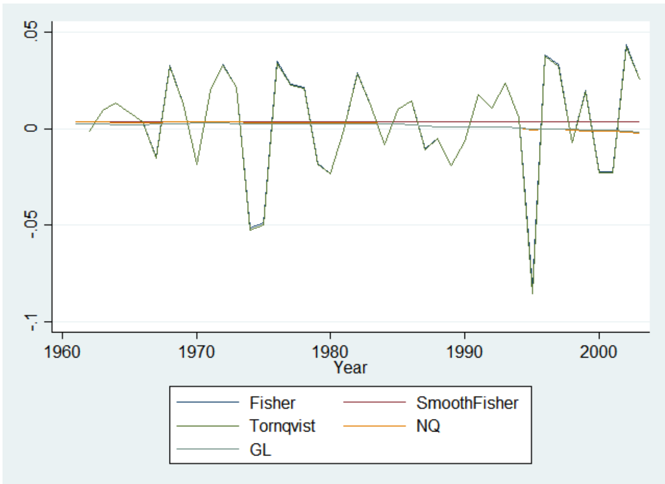


(c) Paper

Figure 3.4: Total Factor Productivity in Canadian Manufacturing

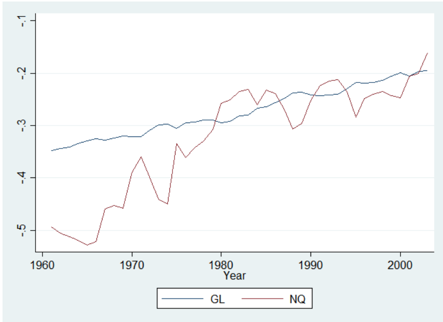


(a) Metal

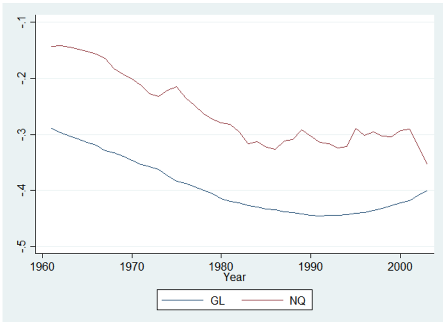


(b) Paper

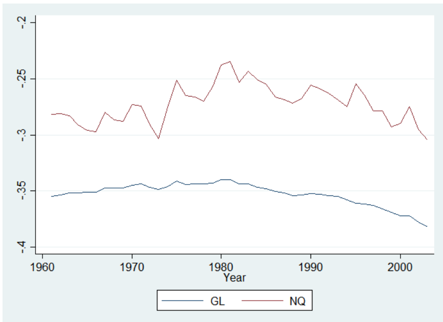
Figure 3.5: Total Factor Productivity in U.S. Manufacturing



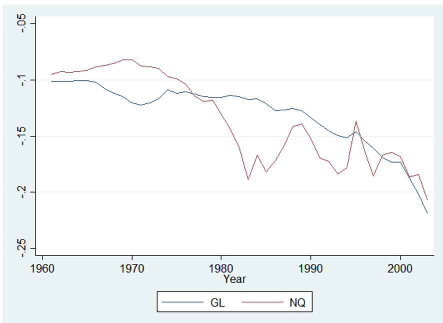
(a) Capital



(b) Labour



(c) Material



(d) Energy

Figure 3.6: Own Price Elasticites in U.S. Paper Industry

Chapter 4

Realized Energy Use Impacts of Energy Standards in Commercial Buildings

4.1 Introduction

While energy efficiency standards and green labels are not typically considered cost-effective policy responses to address pollution externalities, they may be an optimal response to informational market failures that weaken the incentive to invest in energy conservation (Jaffe and Stavins, 1994; Choi, 2010; Stavins, 2011). This latter possibility has been invoked to support a number of regional building energy efficiency and labeling policies in Canada and the U.S. Simulation studies have attributed reductions in energy demand due to energy codes on the order of about 5-8 percent (CEC, 2009; US Department of Energy, 2002b), comparable to the savings from LEED and Energy Star-labelled buildings.[1] As a result, energy standards and green labels are presently widespread policy instruments affecting energy use in the American and Canadian building stocks.[2]

[1]Compared to the average office building in the Energy Information Administration's Commercial Building Energy Consumption Survey, both Energy Star and LEED (Leadership in Energy and Environmental Design) office buildings use approximately 35-40 percent less energy (Turner and Frankel, 2008; EPA, 2006). Buildings constructed in compliance with ASHRAE (American Society of Heating, Refrigeration and Air-Conditioning Engineers) standards 90.1-1999 or 90.1-2004 are estimated to use 40-50 percent less energy (US Department of Energy, 2002a, 2008).

[2]Forty-four U.S. states have adopted the 2006 version of the residential building energy standards or better and forty-seven states have adopted the 2004 version of the commercial building

Simulation studies estimate building code uptake and energy use impacts on the basis of assumptions about cost-effective investments and technical specifications of energy-using technologies. They do not typically account for behavioral characteristics at the building level. Such behavioral responses may include a modest increase in energy demand due to a decrease in the effective price of energy induced by energy efficiency investments, a phenomenon that may be exacerbated by the prevalence of owner-paid utility contracts in renter-occupied space, which results in renters being shielded from energy price volatility (Jacobsen and Kotchen, 2013; Gillingham et al., 2012). As argued by Jessoe et al. (2013), a better understanding of occupant behavior and the mechanisms driving energy use are important for achieving a policy mix that reduces emissions cost-effectively.

Obtaining an accurate estimate of the impact of building energy standards using building-level realized energy use is important not only to assess the ex-post cost-effectiveness of these policies, but also to help improve the behavioral realism in energy-economy models' characterization of energy demand response in energy efficiency policy simulations (Murphy et al., 2007; Rivers and Jaccard, 2006).

This study helps to fill these gaps in our understanding of the impact of energy efficiency policies on energy use in multi-tenanted space. While high frequency data on commercial building energy use and tenancy contract type are not available for Canada, a unique policy adopted by the District of Columbia (DC) in the U.S. has resulted in the availability of detailed data on both these fronts. In addition, buildings constructed in DC have been required to satisfy increasingly stringent mandatory energy standards since the early 1980s (Hadley and Halverson, 1993; US Department of Energy, 2007). Beginning in August 2013, the DC municipal government has made detailed hourly energy use and building characteristic data available as part of its Sustainable DC policy. At present, energy use data for

energy standards or better (US Department of Energy, 2015b). Alberta, British Columbia, Manitoba, Nova Scotia, and Ontario have recently updated their building energy standards, and Saskatchewan is in the process of doing so. Canada's model energy code was updated in 2015.

almost 400 institutional buildings are available. Combining these data with hourly weather data and information on tenancy contract structure obtained from the CoStar Group, I evaluate the impacts of energy standards, tenant-paid utility bills, and Energy Star certification on electricity consumption.

Using this panel dataset, the analysis takes advantage of detailed building and tenant-level characteristics and the heterogeneity in the building age distribution, resulting in buildings constructed before and after mandatory energy standards came into effect. My empirical strategy compares the response of energy consumption to weather shocks in buildings constructed before and after the code change, with interaction terms for buildings with tenant-paid utilities and Energy Star labels. Estimation results suggest that in commercial buildings constructed under a code, electricity consumption is lower by about 0.48 kWh per cooling degree hour. When tenants pay for their own utilities, consumption is lower by 0.82 kWh per cooling degree hour. Moreover, the Energy Star effect is a 0.31 kWh reduction per cooling degree hour.

To the best of my knowledge, no other study has looked at the effect of energy efficiency standards on realized hourly energy use at the account level in multi-tenanted commercial spaces. Studies at the building level typically assume that all tenants in a given building behave homogeneously and aggregate their electricity use, despite the possibility that individual tenants may react differently to the same weather shocks. Accounting for this heterogeneity in occupant behaviour in multi-tenanted space requires controlling for the tenant-level durable goods stock, as well as the behavioural characteristics of tenants. Following Gilbert and Zivin (2014), I employ a distinct methodology to infer tenant characteristics by taking advantage of hourly variation in energy use and hourly variation in temperature.[3]

Although a handful of studies have attempted to estimate the impact of build-

[3]Gilbert and Zivin (2014) examine the impact of intermittent billing on residential electricity consumption in Escondido, California. According to their results, following the receipt of a bill households reduce electricity consumption by 0.6-1 percent.

ing energy efficiency standards on realized energy use in residential buildings (see Levinson, 2014; Aroonruengsawat et al., 2012; Jacobsen and Kotchen, 2013, for example), thus far only one study, Papineau (2014b), has investigated this for commercial buildings. For the residential sector, while Aroonruengsawat et al. (2012) and Jacobsen and Kotchen (2013) find significant reductions in electricity consumption, Levinson (2014) does not find any significant effect in California as a result of the adoption of building standards. In commercial buildings Papineau (2014b) finds an 11 percent reduction in aggregate commercial electricity use due to the adoption of building standards.

This paper builds on the prior literature and makes several distinct contributions. First, it is the first study that estimates the impact of building standards, tenant-paid utility bills, and Energy Star labels on realized electricity consumption in commercial buildings, using physical and behavioural characteristics at the account level. Second, it uses a unique dataset that involves high frequency energy consumption data which allows an investigation of consumer responses to hourly weather shocks. To the best of my knowledge, no other study has used electricity consumption data at this frequency to estimate the individual effects of building standards, tenancy contracts, and Energy Star labels.[4] Third, the hourly consumption data allows us to quantify whether building energy standards, contract type and Energy Star labels deliver their maximum savings when marginal electricity prices are at their peak. I do this by comparing the hourly savings profile from each policy to the average hourly marginal price profile of DC's electric utility, the Potomac Eectric Power Company (PEPCO). Fourth, the estimation framework used in this paper differs from the existing literature in that it accounts for behavioural characteristics of tenants, inferred from the rich variation in electricity use and temperature.

The rest of the paper is organized as follows. Section 4.2 provides a brief review

[4]See Jessoe and Rapson (2014) for a discussion on the importance of high frequency electricity consumption data.

of some relevant literature. Section 4.3 presents the empirical model. Section 4.4 outlines the data sources and describes the methodology used to construct the dataset. In Section 4.5, I present estimation results. Section 4.6 reports further robustness checks. Finally, Section 4.7 adds some concluding remarks.

4.2 Literature Review

Energy efficiency and energy conservation have always played a central role in national and regional energy and environmental policies. Several studies have assessed the outcomes of energy efficiency and energy conservation policies in the buildings sector (Auffhammer et al., 2008; Horowitz, 2004; Arimura et al., 2012). Qiu (2014) examines the rebound effects of the adoption of several energy efficiency measures in U.S. commercial buildings. She estimates a 35 percent reduction in electricity use as a result of using at least one of eight energy efficient technologies in commercial buildings.[5] See Gillingham et al. (2009) for a discussion on the economics of energy efficiency and conservation in buildings and appliances and a review of related empirical literature.

Building energy efficiency codes have become a key instrument in implementing climate change policies, yet a significant portion of the work evaluating the effectiveness of building energy efficiency codes are *ex ante* engineering studies on energy savings using simulation modeling. Simulation studies typically assume that the standards are close to perfectly enforced, which may not always be realistic (Jaffe and Stavins, 1995), and as mentioned earlier, they do not account for the behavioral responses of tenants. A small number of studies have examined the *ex post* effectiveness of building energy standards in reducing realized energy demand. See Levinson (2014) for an excellent review of methodologies and empir-

[5]The eight energy efficient building technologies that she considers are: energy management and control systems (EMCS), economizer cycles, variable air volume (VAV) system, electronic blast, specular reflector, skylight/atrium, sensor on lighting, and compact fluroscent bulbs.

ical findings in recent studies. Findings suggest that the realized energy savings fall short of engineers' estimates. For example, when California introduced and implemented building codes in 1978, they were expected to reduce residential electricity consumption by 80 percent for buildings constructed after 1990. Levinson (2014) investigates whether this expectation has become a reality and finds little or no evidence of significant reduction of energy use in newer buildings. Moreover, Metcalf and Hassett (1999) find that the realized savings of insulation installation is 9 percent as opposed to the 50 percent savings predicted by a simulation model.

Although a few studies have attempted to assess the impact of building standards on realized energy use in residential buildings[6] (see Levinson, 2014; Aroonruengsawat et al., 2012; Jacobsen and Kotchen, 2013, for example), to the best of my knowledge, Papineau (2014b) is the only study that examines the realized energy effect of building standards in commercial buildings. Papineau (2014b) estimates the impact of U.S. state-level building energy standards on realized electricity use in commercial buildings. Using annual data from 1993–2010, she finds that in states induced by EPAct to adopt an energy standard where all new nonresidential construction was erected under a standard, electricity consumption per service worker is lower by about 13 percent, and total commercial electricity consumption is lower by 11 percent.

Levinson and Niemann (2004) and Kahn et al. (2014) address the effect of rental contract type on energy consumption. Levinson and Niemann (2004) estimate energy use for utilities-included rental contracts in the U.S., and find that the utilities-included apartments consume relatively more energy. However, their estimation framework does not take building codes into account. In a more recent study, Kahn et al. (2014) explore the dynamics of electricity consumption in commercial buildings by examining the role of structural quality, human capital, and tenancy contract structures. Using monthly electricity consumption data from a

[6] A set of other studies examine the determinants of energy consumption in residential buildings. See Brounen et al. (2012), Costa and Kahn (2011), Hojjati and Wade (2012), for example.

California electric utility they investigate how electricity consumption differs across a sample of commercial buildings with differing contract structures and building vintages. They find that newer buildings with utilities-included contracts consume relatively more electricity on hot days. However, this behavioural response of tenants, along with large scale adoption of electronic appliances, leads to a positive correlation between commercial building quality and electricity consumption.

4.3 Empirical Strategy

To investigate the impact of energy efficiency standards on energy usage in institutional buildings, I adopt a simple framework that considers the key determinants of electricity consumption, Y_{it}, for an account i in a building at time t,

$$Y_{it} = f(C_i, U_i, \mathbf{S_i}, \mathbf{X_{it}}, W_t) \tag{4.1}$$

where C_i denotes the presence of an energy efficiency standard and it takes a value of 1 if the building is constructed under any building code regime and 0 otherwise. U_i is an indicator variable reflecting whether the tenant faces any incremental cost of electricity consumption, identified by the tenant rental contract structure, and it takes a value of 1 if the tenant is responsible for the payment of their own energy consumption, and 0 if energy bills are included in the rent. The vector $\mathbf{S}_i$ represents the structural characteristics of the building, such as building size, number of stories, number of elevators, and construction material. $\mathbf{X}_{it}$ represents tenant specific characteristics, such as the individual requirements to heat and cool the space, and appliances or equipments used by the tenant. It also includes the behavioural aspect of individual tenant. For example, the tenant's electricity use may be driven by habit or high adjustment costs. Finally, W_t represents the weather conditions which drive changes in the use of heating and cooling mechanisms to maintain indoor comfort.

In order to examine the relationship in (4.1) the following model is estimated:

$$Y_{it} = \alpha Bcode_i + \beta Ctype_i + \mathbf{Z_i'}\Psi_z + \gamma_{c,h}[CDH_t^2, HDH_t^2] + \mathbf{Z_i'} \times [CDH_t, HDH_t]\Psi_{c,h} + \alpha_{c,h}Bcode_i \times [CDH_t, HDH_t] + \beta_{c,h}Ctype_i \times [CDH_t, HDH_t] + \Lambda_i + \Pi_{hwm} + \varepsilon_{it} \tag{4.2}$$

where Y_{it} denotes electricity consumption (in kWh) for account i at hour t. $Bcode_i$ is the binary variable representing the existence of energy efficiency standards when the building, related to account i, was built. The binary variable $Ctype_i$ indicates whether the tenant with account i directly pays for electricity use or it is included in the rent. Variables CDH_t and HDH_t are cooling and heating degree hours, which indicate and measure the extent to which indoor air conditioning and heating, respectively, are required due to outdoor climatic conditions. CDH_t is the difference between actual temperature and 65^o Fahrenheit at each hour t, if outdoor temperature is above 65^o Fahrenheit. HDH_t is the difference between 65^o Fahrenheit and actual temperature at each hour t, if outdoor temperature is below 65^o Fahrenheit. The vector $\mathbf{Z_i}$ consists of account specific covariates which include structural characteristics of the building as well as behavioral characteristics of the tenant related to account i. The covariates included in $\mathbf{Z_i}$ are described in Section 4.4.

The Λ_i term controls for time-invariant account specific characteristics, and Π_{hwm} captures time fixed effects — hour, weekday, and month — controlling for unobservable shocks that apply homogeneously to all accounts.

Equation (4.2) allows tenants, who pay electricity bills separately, to behave differently in reaction to outdoor temperature conditions by interacting contract type with cooling and heating degree hours. Moreover, it also allows the interaction between account specific characteristics and weather, which facilitates varying tenant reaction to outdoor weather conditions in terms of air conditioning and heating requirements based on their individual behavioral characteristics and the structural characteristics of the building they live in.

While the empirical framework includes the response of energy consumption to weather conditions, it does not explicitly consider the other dynamic factor, business cycle, that is commonly assumed to play a role in affecting energy consumption at the building level. Typically, unemployment rate and building occupancy rate are the two business cycle variables linked to electricity consumption at the building level. It is expected that the unemployment rate and occupancy rate decline during recessions, causing reductions in electricity consumption for buildings. For studies with data spanning decades or at least several years, and that includes tenants from retail business or private industries, for example, unemployment rate and occupancy rates for buildings become critical factors in determining electricity consumption. Since the present study covers only institutional buildings over a period of one year, and the occupancy rates in the sample buildings are almost 100 percent, occupancy rate and unemployment rate are not included in the empirical framework.

4.4 Data

The dataset used in this study contains information on hourly tenant-level electricity consumption (in kWh) and hourly outdoor temperature for municipal buildings in Washington DC, for the period of January 2013 to January 2014. It also contains the precise location of the building, several building-level characteristics, information on monthly gas use, and tenant rental contract structure. The characteristics of buildings included in the analysis are year built, building size, number of stories, number of elevators, Energy Star score, and construction material. Data on building code, obtained from several different sources, are also included in the analysis.

Table 4.1 provides a summary of descriptive statistics for the variables in the sample, separated by the building code status. Summary statistics include mean, standard deviation as well as the normalized difference for each covariate included in the analysis. Normalized difference for each covariate indicates the degree of overlap among the treatment and control samples, and typically a good overlap has a normalized difference of less than 0.3 (Imbens and Wooldridge, 2009).

In what follows, I briefly describe how the data on building code, electricity consumption, building characteristics, rental contract structure, and weather are utilized to construct the variables used in this study.

4.4.1 Building Code

Information on building code adoptions for commercial buildings in DC were obtained from the online database maintained by the Building Code Assistance Project (BCAP) (BCAP, 2015), BCAP's bi-monthly newsletters, and the online energy codes database of U.S. Department of Energy (DOE) (US Department of Energy, 2015b).[7] While the International Code Council (ICC) and the American Society of Heating, Refrigeration and Air-Conditioning Engineers (ASHRAE) are primarily responsible for managing and updating the model commercial building energy code development process, DOE takes part in the industry processes to revise the model code and evaluates energy and cost savings associated with the revisions.[8] See Papineau (2014b) for a brief description on the historical development of building energy codes in U.S. as well as for the adoption dates of different energy standards in U.S. states.

As there is no national energy code in the U.S., State and local levels of government adopt their own energy standards (US Department of Energy, 2015b). DC adopted the Building Officials and Code Administrators (BOCA) International

[7]In addition to the online database, BCAP's bi-monthly news letter contains current status of the state level energy codes for commercial and residential buildings along with any changes from its previous issue.

[8]However, DOE is responsible for establishing energy efficiency standards for federal buildings and manufactured housing (US Department of Energy, 2015a).

(Version 1990), National Energy Conservation Code, with amendments, as its energy conservation code in 1992. The energy conservation code in DC has been updated regularly.[9] It began the ASHRAE 90.1-1989 adoption process in 1998 and finally officially adopted it effective in October 1999, replacing BOCA-1992. In January 2004, ASHRAE 90.1-1989 was replaced by the 2000 International Energy Conservation Code (IECC) which is a part of the 2000 International Construction Codes package developed by the U.S. regional model code-writing organizations — BOCA, International Conference of Building Officials (ICBO) and Southern Building Code Congress International (SBCCI). A subsequent update was effective in December 2008 when DC adopted ASHRAE 90.1-2007 replacing 2000 IECC, with a one-year transition period when both codes could be used. The current code is the 2013 DC Construction Code, based on ASHRAE 90.1-2007 for commercial buildings, which became effective in March 2014.[10] (BCAP, 1998, 2000, 2004; US Department of Energy, 2015b)

I use the information on commercial building code adoptions in DC to construct a binary variable that captures the effect of building codes (or, equivalently, standards) on energy consumption. As DC adopted its first building energy code in 1992 and since then for any given year DC had a commercial building code in effect, I construct the binary variable "Bcode" that takes a value of 1 for buildings constructed in year 1992 and afterwards, and 0 otherwise.

The use of a binary variable in estimating the effect of building codes on energy consumption has some drawbacks if the sample covers several jurisdictions and the codes vary across jurisdictions in terms of stringency and implementation dates. Another limitation of this approach is that it ignores the diversity in intensity of treatment across jurisdictions as areas may differ in the growth rates of new building construction. Since the present study only includes DC buildings, the

[9] Submission of updated building codes, every three years with the first edition due by January 1, 2010, to the City Council is mandated by the DC Green Building Act of 2006.

[10] For residential buildings, the 2013 DC Construction Code is based on the 2012 IECC.

estimation strategy with the binary variable remains a valid estimation strategy. See Aroonruengsawat et al. (2012) for a brief discussion on this issue.

The stringency of building energy codes has increased over time. However, since the objective is not to capture the effect of code stringency on energy use, but rather to estimate the effect of any existing building code on electricity consumption, I focus on a comparison of mean energy consumption in buildings before and after the mandatory energy standards came into effect, after controlling for other building characteristics.

4.4.2 Electricity

Data on electricity consumption for institutional buildings in Washington DC come from BuildSmart DC — a portal created by the Sustainability and Energy Division of DC's Department of General Services (DGS-SE) in an effort to provide energy usage data in the city's buildings as part of its Sustainable DC policy. The district's electric utility company, Pepco Holdings Inc, daily provides electricity use data, recorded by smart meters, to DGS-SE and are available for 15 minutes interval, at the minimum. In addition to the electricity use data, BuildSmart DC also provides monthly utility billing data on electricity, natural gas, and water along with some data on building characteristics, for example, address, size, type, and Energy Star score. Energy usage data for all public buildings, a total of 354 buildings, are currently available and updated daily. However, energy information for private buildings are not yet available (DDOE, 2015).

I aggregate 15 minutes interval account level electricity consumption data to hourly consumption which serves as the dependent variable in the main analysis. Information on natural gas use from monthly billing data are used to form a binary variable, 'Gas Use', which indicates whether the account uses gas as an energy source. Moreover, the variable 'Energy Star' is constructed by using the actual Energy Star score such that it takes a value of 1 if the Energy Star score is above 75, and 0 otherwise.[11]

4.4.3 Building Characteristics and Tenancy Contract Structure

Data on building hedonic characteristics and information on tenancy contract structure were obtained from the CoStar database, maintained by the CoStar Group. CoStar Group is a private company that primarily operates as a listing service for the U.S. commercial real estate industry, and advertises buildings or commercial spaces available for sale or rent. It has been maintaining an extensive building-level database for U.S. commercial properties since the 1980s.[12] The CoStar database includes information on building location, hedonic characteristics of the building, and tenancy contract structure, along with other detailed information.

Since the objective in this paper is to estimate the effects of building codes, Energy Star status, and tenant rental contract structure on energy use, I supplement the account level electricity consumption data obtained from BuildSmart DC with building characteristics and tenancy contract structure data obtained from the CoStar database. In doing so, I match the addresses of buildings identified in the BuildSmart DC database to the addresses of buildings in the CoStar database. The matching process resulted in 144 accounts in 99 buildings that can be identified in both databases. I also discarded renovated buildings from the analysis using identification from CoStar database, and as a result, finally there were 99 accounts in 81 buildings in the sample for which information on electricity consumption, building characteristics, and tenant rental contract structure could

[11] Energy Star buildings receive a score of 75 or above, they are defined as the 25% most efficient buildings on a 1-100 scale.

[12] The CoStar and other databases maintained by the CoStar Group have recently been widely used in other studies. See, for example, Papineau (2014a,b, 2015), Kahn et al. (2014), Eichholtz et al. (2010, 2013). The CoStar database has tracked approximately 4.6 million commercial properties, and has information on the tenancy contract structure for 185,192 commercial buildings across the U.S.

be identified.[13]

Three types of tenant rental contract structure were identified in the CoStar database — triple net, plus electric, and full services gross — where in cases of *triple net* or *plus electric* tenants directly pay for their own utility bills whereas utility bills are included in the monthly rent in case of *full services gross.* Tenants paying for their own utility bills represent almost 50 percent of total lease contracts in the CoStar database. Installation costs of sub-metering and legislative barriers are identified as the major causes for the limited prevalence of this type of contract although it is considered to be superior in motivating tenants to limit energy use. See Papineau (2014b) for a more detailed discussion.

Information on rental contract structure were used in the following way to construct a binary variable that captures the effect of utility contract structure on energy use. The variable of interest, which I define as 'Ctype', takes a value of 1 if the rental contract is *triple net* or *plus electric*, where the tenants directly pay for their electricity bills, and 0 if the bills are included in the rent, i.e., if the contract is *full services gross*.

It can be seen from Table 4.1 that average hourly electricity consumption for accounts in buildings constructed under a building code regime is higher than that of the accounts in buildings built without any code in effect. However, this is expected since the buildings built under a code are larger, on average, and have more stories with more elevators in service. Moreover, the average year built for buildings built before any energy code regime is fairly older compared to the buildings built under a building energy standard regime. It is also not surprising since the overall commercial building stock in the U.S. is fairly old. Energy Information Administration (2015) reports that about half of all U.S. commercial buildings were constructed before 1980, and in 2012 the median age of commercial buildings

[13]Although the CoStar database identifies buildings with renovation, not all types of renovations are subject to a mandatory code update. It was not possible to identify buildings that went through renovations with code update.

was 32 years. Furthermore, almost half of the sample accounts in both treatment and control groups use natural gas.

4.4.4 Weather

Weather data on hourly outdoor temperature come from the National Oceanic and Atmospheric Administration (NOAA), for the Ronald Reagan Washington National Airport weather station. Hourly weather data were also available for Washington Dulles International Airport weather station. However, since Ronald Reagan National Airport is the closest weather station to DC, data were collected only for this station.

Weather data are utilized in two different ways in this study. First, the variables, cooling and heating degree hours, as described in Section 4.3, are constructed using hourly temperature data. Summary statistics for cooling and heating degree hours indicate that the summer temperature goes as high as 95^o Fahrenheit, equivalent to 35^o Celsius, and on colder days it falls as low as 7^o Fahrenheit, equivalent to -7^o Celsius. Second, the hourly electricity consumption data are combined with this hourly temperature data, and following Gilbert and Zivin (2014), I use the hourly variation in temperature and in individual consumption to infer several account-specific characteristics. In doing so I construct five variables, 'Heating Capacity', 'Cooling Capacity', and 'Fit' - to represent account-specific physical characteristics, and 'Pattern', and 'Persist' - to reflect account-specific behavioral characteristics.[14] Summary statistics for these variables are reported under the heading, *Constructed Variables*, in Table 4.1. All of the constructed variables, along with the building characteristics variables, are used in Z_i for estimating equation (4.2).

As mentioned earlier, variation in account-level electricity consumption arises partly from the heterogeneity in appliance use, heating and air conditioning sys-

[14]Further detail on the construction of these variables is discussed below.

tems, and partly from the variation in account-specific energy related preferences. In this study, while the constructed variables that reflect account-specific physical characteristics are meant to proxy for the heating and cooling capacity, the variables that reflect behavioural characteristics are meant to proxy for the account specific sensitivity to temperature fluctuations. The following regression equation is estimated separately for each account to construct the account specific variables - Heating Capacity, Cooling Capacity, Pattern, and Fit:

$$Y_t^i = \sum_{h=1}^{24} \Phi_h^i Hour + \sum_{d=1}^{7} \Phi_w^i Weekday + \sum_{m=1}^{12} \Phi_m^i Month + \lambda_c^i CDH_t + \lambda_h^i HDH_t + \varepsilon_t^i \tag{4.3}$$

As in Gilbert and Zivin (2014), the account specific $\hat{\lambda_c^i}$ and $\hat{\lambda_h^i}$ are the proxies for air conditioning and heating capacities of the respective account, i. A mean of 0.76 for cooling capacity indicates that when temperature is above 65^o, a 1^o increase in outdoor temperature would induce an average of 0.76 kWh increase in electricity consumption for an average account in that particular hour. It is interesting to note that the average cooling capacity is the same across treatment and control groups, and is higher than the average heating capacity, which indicates that electricity is more important in cooling than heating in this region. One possible explanation could be the use of gas for heating in buildings in this region. Summary statistics for the variable 'Gas Use' in Table 4.1 indicates that more than 50 percent of the accounts use gas.

'Fit' captures the explanatory power of the regressors — hourly variation in temperature and different cyclical patterns — in explaining the variation in hourly electricity use for each account, i, and is measured by the R^2 from regression equation (4.3) for each account, i. A mean of 0.88 for both treatment and control groups indicate high explanatory power of the regressors. Moreover, the variable 'Pattern' measures the average variation in electricity consumption during the day for each account, i, and calculated as the percentage difference between the maximum and minimum $\hat{\Phi}_h^i$ for each account, i. A mean of 23.9 for pattern tells us that on average there is a 23.9 percent difference in electricity consumption between the highest and lowest consuming hours.

In order to construct the variable 'Persist', I estimate the following regression separately for each account, i:

$$\%\Delta Y_t^i = \mu_p^i \%\Delta Y_{t-1}^i + \delta_c^i \%\Delta CDH_t + \delta_h^i \%\Delta HDH_t + \varepsilon_t^i \tag{4.4}$$

where $\%\Delta$ refers to percentage change. I refer to the autoregressive coefficient, μ_p^i, which indicates lagged persistence in electricity consumption for each account, as 'Persist'. A high value of persist would imply higher adjustment cost for the consumer, possibly as a result of consumption habits or forced continuous use of appliances. However, a mean of 0.06 for persist does not indicate strong persistence, on average, in energy consumption.

4.5 Results

Table 4.2 presents the results from estimating equation (4.2) with hourly observations. While columns (1) through (5) present results for pooled specifications without account fixed effects, columns (6) and (7) show results from estimating panel specifications. All regressions for which results are reported in Table 4.2 include the quadratic terms of cooling and heating degree hours, and all account specific covariates in $\mathbf{Z}_i$, except for 'Energy Star', which is added only in columns (3), (5), and (7).[15]

The first specification in column (1) is a pooled specification without any fixed effects or the interactions of account covariates and temperature. However, it includes the squared terms of temperature variables and the full set of account

[15] Although clustering of standard errors are often used in empirical studies, the current study does not use this approach.

covariates, except 'Energy Star'. The variables – building code and contract type, which are of particular interest in this case, have their expected signs, and are statistically significant at the 1 percent level. As the estimated specification is in linear form, the estimated coefficients can be interpreted as conditional average effects on hourly electricity consumption. For example, the estimated negative coefficient of building code tells us that if all buildings in DC were built under an active building code, a reduction of 25.42 kWh, on average, could have been realized per hour. A symmetric interpretation applies for the variable labeled as contract type. If all of the tenant rental contracts do not include electricity bills in monthly rents and all tenants pay bills according to their actual electricity use, electricity consumption per hour, on average, would be lower by 16.99 kWh. The rest of the variables have their expected signs.

Column (2) adds hour, weekday, and month fixed effects, all controlling for homogeneous unobservable shocks to electricity consumptions for all accounts. The introduction of time fixed effects does not have a substantial affect on the coefficient estimates, as the coefficients are almost identical to those reported in column (1).

In column (3) I augment the specification in column (2) by including the Energy Star dummy. Inclusion of Energy Star is of particular interest since the realized energy efficiency of Energy Star rated buildings has been a matter of debate (Kahn et al., 2014).[16] The statistically significant estimated coefficient of Energy Star reveals that if all buildings in DC were Energy Star certified, hourly electricity consumption would be lower by 20.30 kWh, on average. In fact, in terms of size, the magnitude of the effect of Energy Star on consumption is greater than the effect of contract type. While the inclusion of Energy Star in the model slightly reduces the size of building code effect, it increases the effect of contract type on consumption. Both variables remain significant at 1 percent level.

[16]Among all U.S. cities DC has the highest number of Energy Star certified buildings (Energy Information Administration, 2016).

Column (4) adds the interactions of account covariates with climatic conditions. Addition of interaction terms between covariates and temperature offers more flexibility in terms of reactions to temperature shocks. For example, interacting contract type with cooling and heating degree hours enables tenants with common building structural characteristics to behave in a heterogeneous way as a response to outdoor temperature variation. Column (5) is the final pooled specification. All coefficient estimates have their expected signs except the interaction between contract type and heating degree hours. The magnitude of the effect of building code is somewhat smaller whereas the effect of Energy Star increases once all covariates and interactions terms are added. However, the coefficient on contract type remains almost identical.

Finally, columns (6) and (7) display results for the panel specifications. While column (6) does not include Energy Star, column (7) presents results for the full specification with all fixed effects and covariates that are considered in this study, and thus it is the preferred specification. The coefficient estimates of interaction terms, temperature with building code and contract type, remain roughly the same in magnitude and sign compared to column (5). However, the coefficient estimate on the interaction between Energy Star and heating degree hour is insignificant. The point estimates for building code interacting with cooling and heating degree hours are -0.48 and -0.41. This suggests that the hourly electricity consumption response to outside weather conditions for an account in a building built under an energy efficiency standard is lower both for air conditioning and heating purposes, compared to an account in a building built without a building code in effect. Moreover, the size of electricity savings for heating and cooling purposes are almost same. For a 1^o increase in outdoor temperature when temperature is above 65^o, electricity consumption per hour is 0.48 kWh lower for an account with building code. This translates into a 0.54 percent reduction in hourly electricity consumption per account, which is a significant reduction once we keep in mind that this is an hourly estimate. In terms of air conditioning need where tenants pay their own utility bills, electricity consumption per account is 0.82 kWh lower in an hour in response to a one unit increase in cooling degree hours. Finally, in Energy Star certified buildings electricity consumption per account per cooling degree hour is 0.31 kWh lower relative to uncertified buildings.

4.6 Robustness

In examining the effect of energy efficiency standards on realized energy use in commercial buildings I use a unique data set and a set of covariates encompassing account-specific physical and behavioral characteristics. I find significant effect of building codes on electricity consumption in commercial buildings. The compelling evidence of the effect of building codes on hourly electricity consumption, presented in Table 4.2, remains robust in sign and significance across various alternative specifications. Moreover, the magnitude of the effect also remains roughly stable. In this section, I conduct two robustness checks on my results. First, I re-estimate the various specifications of equation (4.2) reported in Table 4.2, however, by excluding contract type. Second, I adopt the methodology described in Oster (2015) to check the robustness of my estimated coefficients in Table 4.2.

As mentioned earlier, once a building is constructed under a code, its electricity consumption depends primarily on the building characteristics, for instance, size and age of the building, durable goods stock running on electricity, weather, and the behavioural responses of tenants to outdoor temperature. However, the behavioural responses of tenants might depend on the rental contract type since tenants face differing incentives based on their contract types. Estimation results presented in column (6) of Table 4.2 indicate that the coefficient estimates of building code and its interactions with outdoor temperature variables remain roughly the same when controls for Energy Star are excluded. Nevertheless, it might be desirable to check whether the effect of building code variables remain robust when contract type variables are excluded from the specifications. Results from re-estimating various specifications of equation (4.2) by excluding contract type are reported in Table 4.3. The coefficient estimates of the building code variables remain the same in sign and significance, and roughly the same in magnitude.

Next, using the Oster statistic, I explore the possibility that omitted variables bias could explain away the observed effects. Oster (2015) shows that checking the coefficient movements with added controls is not enough to identify potential omitted variable bias. In order to properly identify the omitted variable bias it is essential to evaluate movements both in coefficient and in R-squared. Coefficient movements are informative about omitted variable bias only if coefficient movements are scaled by movements in R-squared.

Following Oster's suggested procedure I investigate the robustness of my estimated coefficients and present results in Table 4.4. In doing so, I assume equal selection on both observables and unobservables, and select the upper bound of maximum R-squared as one. The coefficient bounds are reported as an identified set estimate in Table 4.4. Bounded coefficient values leading to the same approximate outcome imply the robustness of estimates. It is ideal to have bounds that do not include zero. The identified Oster (2015) coefficient bounds for the reported coefficients, except for the interaction of contract type with heating degree hours, suggest that the unobservable covariates are unlikely to explain away the observed effects. In other words, the reported bounds of the coefficients are leading to similar conclusions compared to the controlled regression, and they do not include zero in the bounds.

4.6.1 Hourly Savings

Figures 4.1, 4.2, and 4.3 present the hourly electricity savings estimates in summer months, by cooling degree hour, for building codes, contract type, and Energy

Star labels, respectively. All three policies achieve peak consumption savings at approximately 2pm. Figure 4.5 presents the average hourly marginal price of electricity at DC's electric utility (PEPCO), in the summer months of May to October, as these months have positive cooling degree hours (Figure 4.4). Prices peak at 5pm, 3 hours after peak savings from the three variables of interest. Nevertheless, at 2pm prices are climbing steeply, and stand at 75 percent of their 5pm peak.

4.7 Conclusion

Building energy codes have become a primary instrument in national and regional policies aiming to improve energy efficiency and reduce CO_2 emissions in building stocks through energy conservation. While buildings in the U.S. represent almost 72 percent of total electricity consumption and are responsible for approximately 40 percent of carbon dioxide (CO_2) emissions (PNNL, 2014), commercial buildings are responsible for one-fifth of energy consumption and almost 40 percent of electricity consumption (US Department of Energy, 2011). The importance of the commercial sector as a major consumer of electricity is even more prominent in DC where the commercial sector consumes 76 percent of electricity sales and 65 percent of total energy consumption. However, this is not surprising given the large concentration of government buildings and museums in the DC building stock (Energy Information Administration, 2016). Despite this significant importance, studies on the role of energy codes, tenancy structure, and Energy Star labels in the dynamics of realized energy consumption in commercial buildings are sparse.

In this paper I provide novel insights on the realized energy use impacts of energy efficiency standards in commercial buildings. In doing so, I capitalize on newly available high frequency data for municipal buildings in DC in the U.S. Combined with hourly weather data and detailed building characteristics, I use account level hourly electricity consumption to estimate the effect of building code on realized electricity use. Moreover, I also examine how different contractual structures of tenants' utility bill payments and Energy Star labels affect the electricity consumption in a unified empirical framework. Examining the impact of various tenancy contract structures on electricity use is particularly important once we recognize the price inelastic demand of energy for this sector (Levinson and Niemann, 2004). My estimation results suggest a 0.48 kWh reduction in hourly electricity use in buildings with energy efficiency standards. In addition, I also find that rental contract structures where tenants directly pay their utility bills induce a 0.82 kWh electricity saving per account-hour during hotter days, whereas Energy Star labels induce a 0.31 kWh hourly reduction in electricity use. The estimated impacts prove robust in sign and significance. Finally, comparing the peak hourly savings from all three policies to the peak hourly price of electricity in the summer months, I find that prices peak three hours after peak policy savings.

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Table 4.1: Summary Statistics

	Building Code = 0 (N= 696926)				Building Code = 1 (N= 141600)				Norm. Diff.
	Mean	Std.	Min	Max	Mean	Std.	Min	Max	
Observed Variables									
Electricity Consumption (kWh)	53.7	92.3	0.00	857.2	89.3	112.5	0.00	817.0	0.24
Rentable Building Area (sq ft in 000s)	78.3	159.9	0.95	563.1	143.6	139.8	6.11	341.9	0.30
Year Built	1949	32	1880	1990	2007	4.47	1993	2013	1.81
Tenancy Contract Type	0.05	0.22	0	1	0.06	0.24	0	1	0.03
Number of Elevators	0.05	0.62	0	7	1.13	2.34	0	6	0.44
Number of Stories	2.71	2.60	1	11	4.44	2.96	1	8	0.43
Energy Star	0.10	0.29	0	1	0.19	0.39	0	1	0.18
Construction Material	0.70	0.45	0	1	0.38	0.48	0	1	-0.48
Gas Use	0.57	0.49	0	1	0.56	0.50	0	1	-0.01
Cooling Degree Hours	4.61	7.07	0.00	30.0	4.53	7.02	0.00	30.0	-0.01
Heating Degree Hours	11.9	13.6	0.00	58.0	12.1	13.7	0.00	58.0	0.01
Constructed Variables									
Heating Capacity	0.14	0.69	-3.99	3.54	0.58	0.84	-0.55	2.51	0.40
Cooling Capacity	0.76	1.32	-1.33	7.78	0.76	2.84	-4.60	7.47	0.00
Fit	0.88	0.18	0.04	0.99	0.88	0.09	0.69	0.98	0.02
Persist	0.06	0.18	-0.46	0.61	0.12	0.14	-0.10	0.39	0.26
Pattern	21.1	43.2	0.03	252.9	58.5	57.6	1.13	193.8	0.51

Notes: The normalized difference is calculated as $\frac{\bar{X}_1-\bar{X}_0}{\sqrt{S_1^2+S_2^2}}$, where $\bar{X}_i$ is the mean of the covariate for each treatment status, $i = 0, 1$, and S_i^2 is the sample variance of X_i. It measures the degree of overlap for each covariate across building code regimes of treatment samples.

Table 4.2: Results with Tenant Contract Type

	Electricity Consumption in kWh						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Building Code	-25.42***	-25.03***	-23.69***	-21.67***	-19.93***		
	(0.280)	(0.275)	(0.276)	(0.435)	(0.435)		
Contract Type	-16.99***	-16.76***	-18.08***	-15.92***	-17.62***		
	(0.437)	(0.430)	(0.430)	(0.788)	(0.787)		
Building Code X CDH				-0.374***	-0.504***	-0.481***	-0.483***
				(.0381)	(.0381)	(.0331)	(.0331)
Building Code X HDH				-0.260***	-0.336***	-0.408***	-0.408***
				(.0194)	(.0194)	(.0170)	(.0170)
Contract Type X CDH				-1.088***	-0.956***	-0.806***	-0.817***
				(.0715)	(.0714)	(.0604)	(.0604)
Contract Type X HDH				0.437***	0.514***	0.468***	0.467***
				(.0366)	(.0366)	(.0311)	(.0311)
Energy Star			-20.30***		-21.05***		
			(0.395)		(0.675)		
Energy Star X CDH					-0.372***		-0.314***
					(.0576)		(.0481)
Energy Star X HDH					-.0488*		-.0089
					(.0295)		(.0247)
Hour Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Temperature X Covariates	No	No	No	Yes	Yes	Yes	Yes
Account Fixed Effects	No	No	No	No	No	Yes	Yes
Energy Star	No	No	Yes	No	Yes	No	Yes
Observations	838,526	838,526	838,526	838,526	838,526	838,526	838,526
R-squared (within)	0.515	0.531	0.533	0.576	0.578	0.167	0.167

Notes: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include the building covariates and the squared terms of cooling and heating degree hours.

Table 4.3: Results without Tenant Contract Type

	Electricity Consumption in kWh						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Building Code	-23.64***	-23.27***	-21.86***	-19.95***	-18.10***		
	(0.276)	(0.272)	(0.273)	(0.430)	(0.431)		
Building Code X CDH				-0.412***	-0.549***	-0.463***	-0.464***
				(.0380)	(.0380)	(.0331)	(.0331)
Building Code X HDH				-0.303***	-0.384***	-0.416***	-0.416***
				(.0193)	(.0193)	(.0170)	(.0170)
Energy Star			-19.31***		-20.85***		
			(0.395)		(0.675)		
Energy Star X CDH					-0.352***		-0.298***
					(.0576)		(.0481)
Energy Star X HDH					-.0608**		-.0214
					(.0295)		(.0247)
Hour Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Temperature X Covariates	No	No	No	Yes	Yes	Yes	Yes
Account Fixed Effects	No	No	No	No	No	Yes	Yes
Energy Star	No	No	Yes	No	Yes	No	Yes
Observations	838,526	838,526	838,526	838,526	838,526	838,526	838,526
R-squared (within)	0.514	0.530	0.532	0.575	0.577	0.166	0.166

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include the building covariates and the squared terms of cooling and heating degree hours.

Table 4.4: Robustness: Oster (2015)

	Uncontrolled		Controlled		Identified Set Estimate	
	Coeff.	R-squared	Coeff.	R-squared	Lower Bound	Upper Bound
Building Code	20.37	0.015	-19.93	0.578	-50.15	-19.93
Building Code X CDH	-0.019	0.032	-0.504	0.578	-0.878	-0.504
Building Code X HDH	0.174	0.015	-0.336	0.578	-0.718	-0.336
Contract Type	15.53	0.002	-17.62	0.578	-41.89	-17.62
Contract Type X CDH	-1.428	0.002	-0.956	0.578	-0.956	-0.611
Contract Type X HDH	1.388	0.015	0.513	0.578	-0.142	0.513

Figure 4.1: Treatment Effect in Summer Months - Building Codes, By Cooling Degree Hour

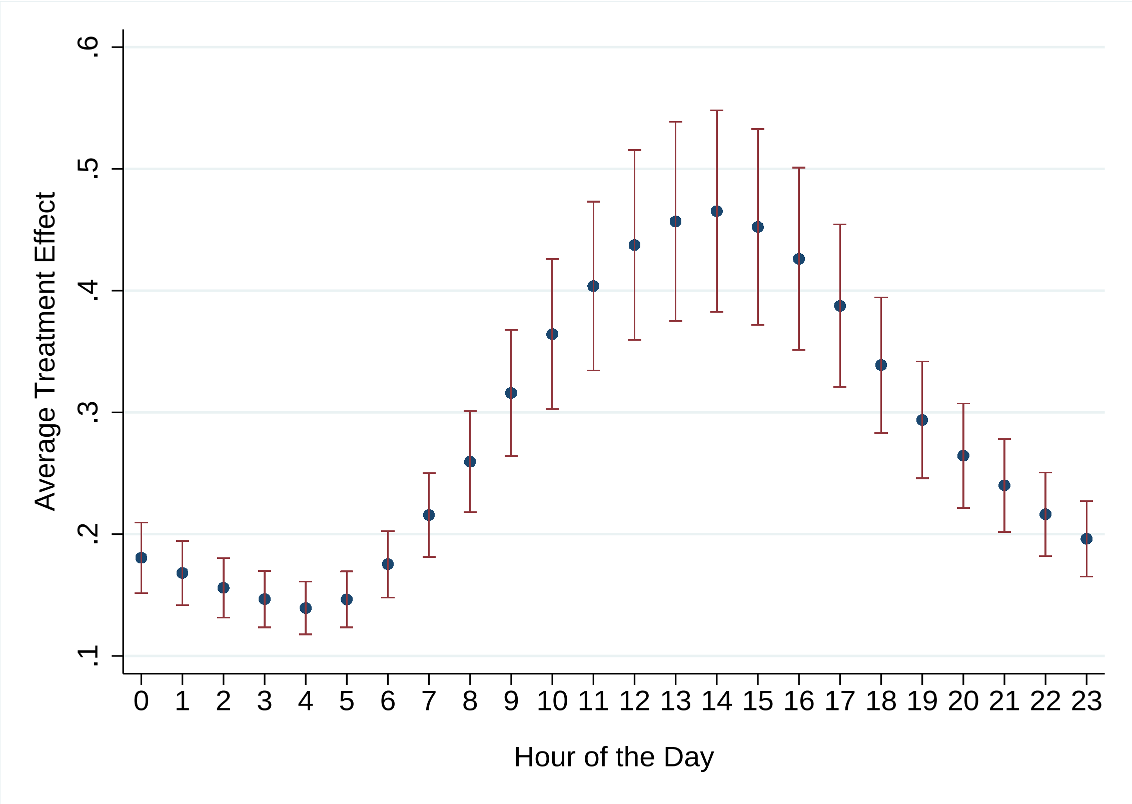


Figure 4.2: Treatment Effect in Summer Months - Tenant-Paid Contract, By Cooling Degree Hour

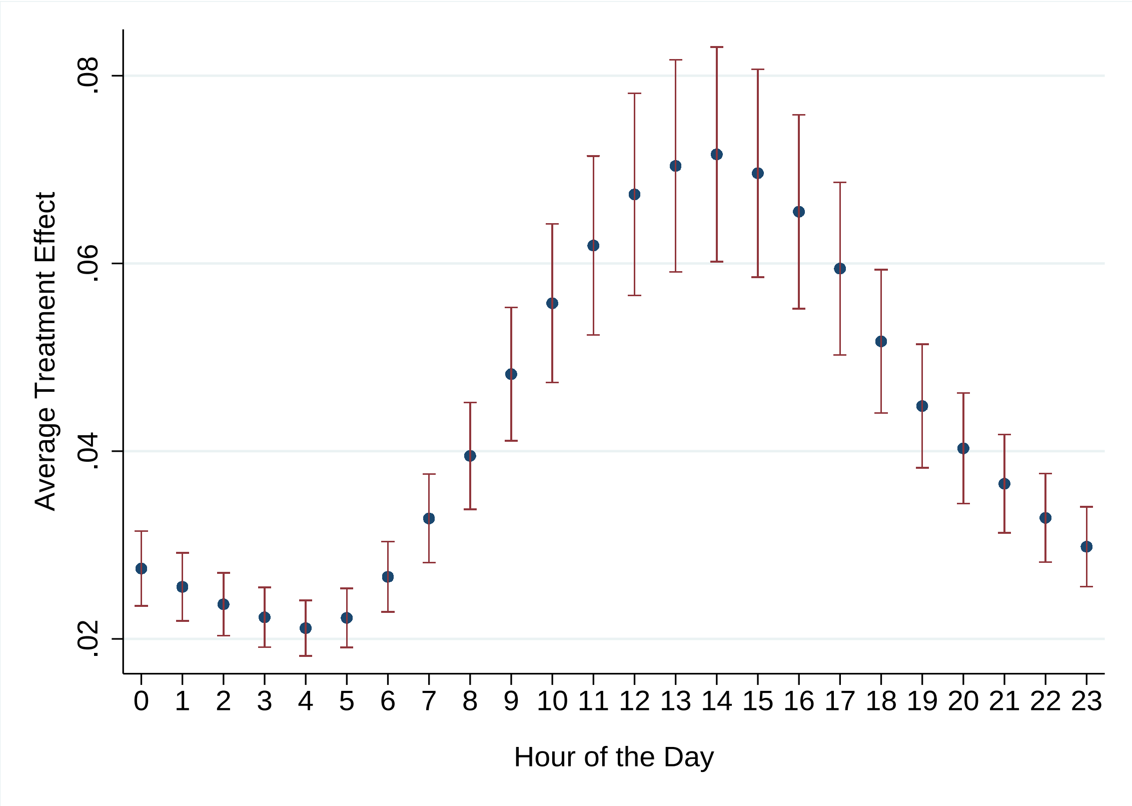


Figure 4.3: Treatment Effect in Summer Months - Energy Star, By Cooling Degree Hour

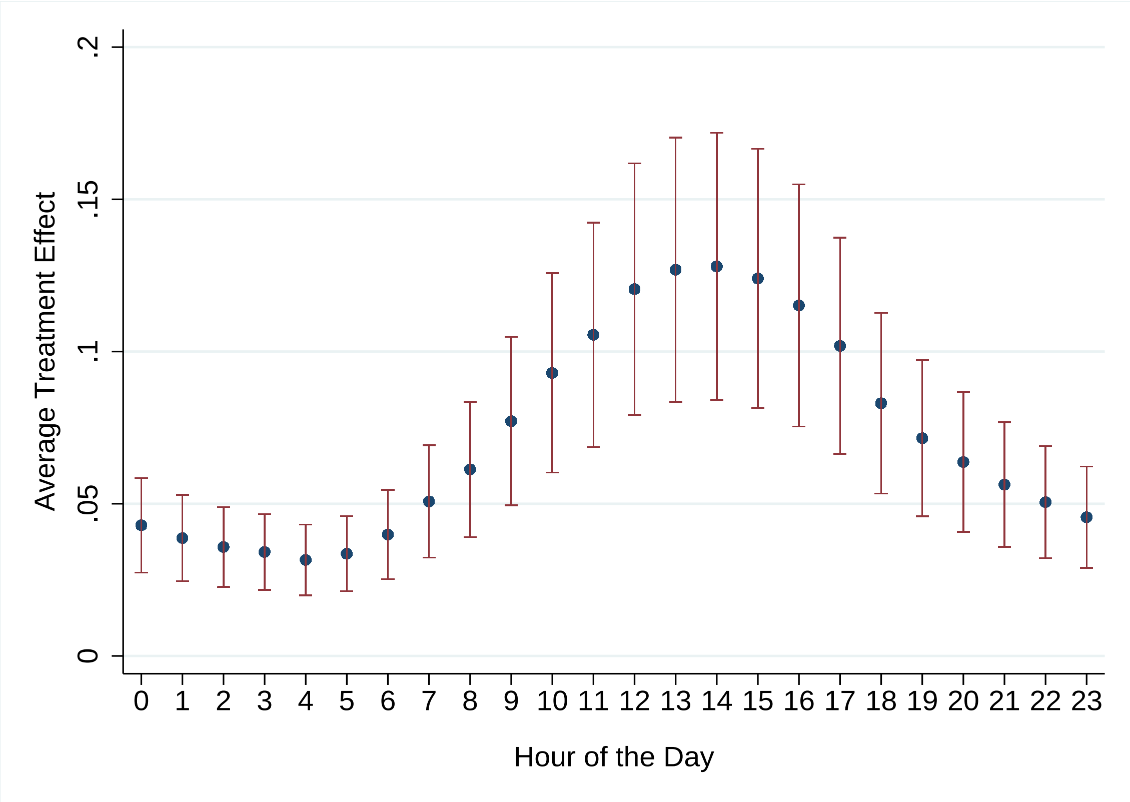


Figure 4.4: Average Hourly Summer Temperature

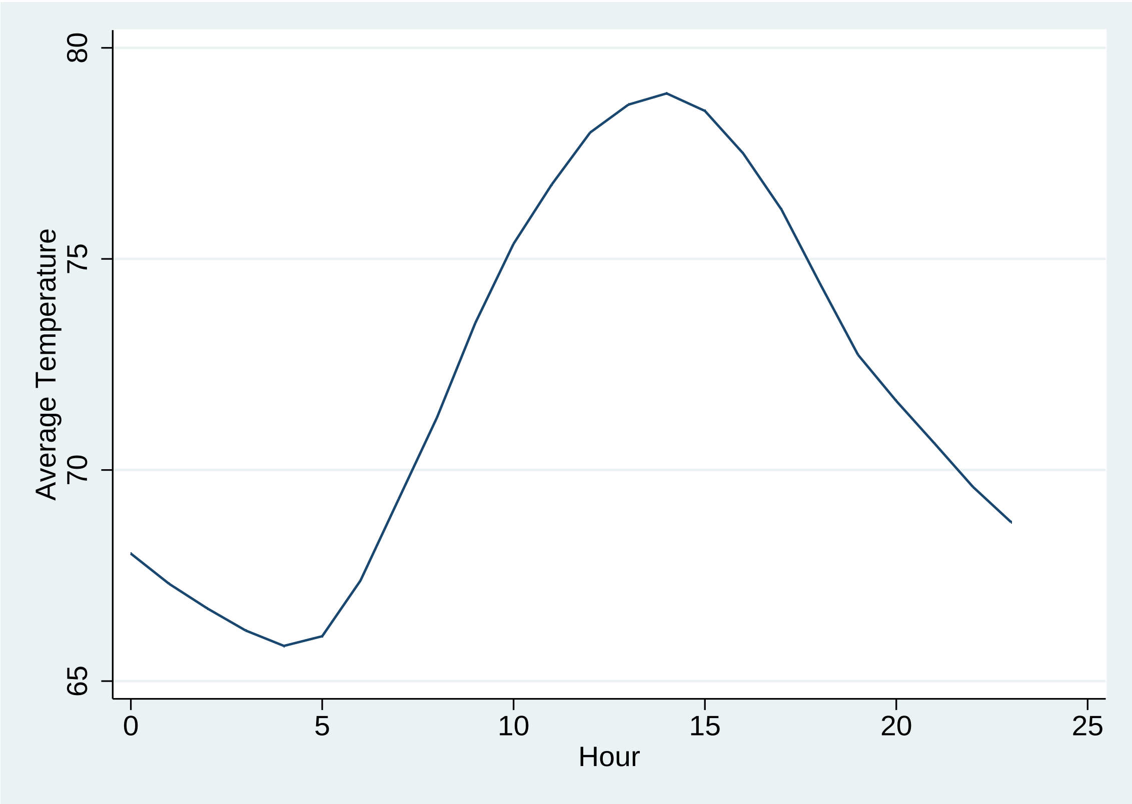
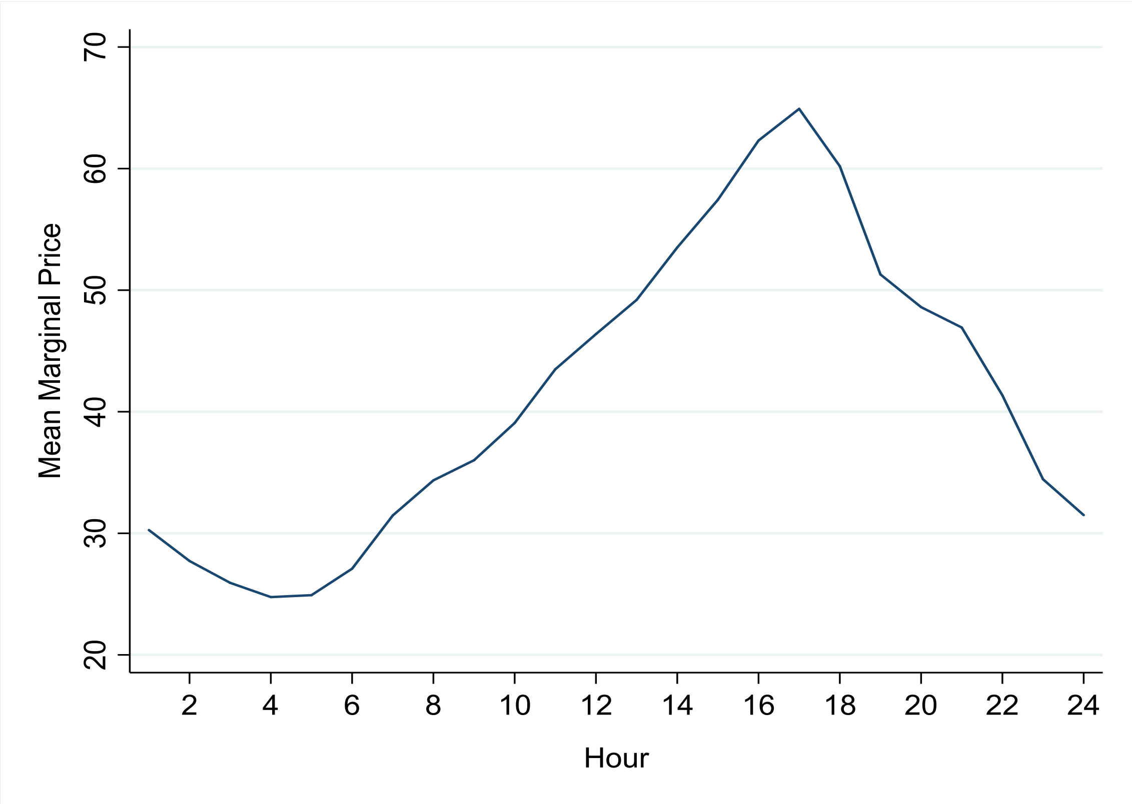


Figure 4.5: Average Hourly Summer Price (PEPCO)



Chapter 5

Conclusion

There are three essays in this thesis. In the first essay, I investigate the existence of productivity convergence in regional pulp and paper industries of U.S. and Canada. In doing so, I analyze the productivity performance of the pulp and paper industries in Canada and the U.S. over the period extending from 1971 to 2005 by taking advantage of regional disaggregated data on four Canadian provinces — Alberta, British Columbia (BC), Ontario, and Québec — and on four U.S. states — Georgia, Illinois, Maine, and Washington. The use of regional disaggregated data allows me to investigate whether the regional industries within a country follow a uniform path over the course of time. Moreover, this also allows me to investigate the presence of convergence in terms of total factor productivity in the pulp and paper industry. I supplement the North American regional level data with national data for two Nordic countries — Finland and Sweden. The inclusion of Finland and Sweden is justified in the sense that this gives me the opportunity to compare performances of the North American regions with those of others who are competing with them in the global market. Based on my results I find evidence in favour of the catch-up hypothesis among the regional pulp and paper industries of U.S. and Canada in my sample. The growth performance is at the advantage of Canadian provinces relative to their U.S. counterparts. However, it is not good enough to surpass the growth rates of this industry in the two Nordic countries.

In the second essay I provide an empirical comparison and evaluation of three widely used locally flexible cost functional forms — the translog, the GL, and the NQ — in providing TFP estimates once they satisfy the economic theoretic regularity conditions. In particular, I provide empirical evidence that imposing local concavity on the translog and the GL cost functions affects the productivity estimates, in addition to its effect on the elasticity estimates which has attracted the attention in the literature thus far. In doing so, I take the econometric approach to productivity measurement and generate estimates of total factor productivity for two U.S. industries — primary metal and paper — along with three Canadian industries — primary metal, cement, and paper — covering the period of 1961 to 2003. Moreover, I impose curvature restrictions on the functional forms once the estimated models fail to satisfy the curvature condition. My estimation results suggest that the NQ model performs better than the other two models in providing TFP estimates once regularity conditions are satisfied with curvature conditions being imposed. Estimates of productivity from the unrestricted and the restricted NQ models are almost identical. However, the GL cost function performs equally well when all the regularity conditions are satisfied without curvature being imposed. Based on the evidences provided in this study I argue that since desired curvature coverage is not guaranteed in the translog and the GL models and local curvature imposition on these functional forms affects the productivity estimates, functional forms with global curvature conditions appear to be a better choice for econometric productivity estimation.

The last essay of my thesis provides novel insights on the realized energy use impacts of energy efficiency standards in commercial buildings. In doing so, I capitalize on newly available high frequency data for municipal buildings in DC in the U.S. Combined with hourly weather data and detailed building characteristics, I use account level hourly electricity consumption to estimate the effects of building energy standards, contractual structure of utility bill payments, and energy star labeling on realized electricity use. Examining the impact of various tenancy contract structures on realized electricity use is particularly important once we recognize the price inelastic demand of energy for this sector. My estimation results suggest that in commercial buildings constructed under a code, electricity consumption is lower by about 0.48 kWh per cooling degree hour. Moreover, when tenants pay for their own utilities, consumption is lower by 0.82 kWh per cooling degree hour. The Energy Star effect is a 0.31 kWh reduction per cooling degree hour. Furthermore, the estimated impacts prove robust in sign and significance.