TECHNICAL EFFICIENCY AND ELASTICITY OF INPUT SUBSTITUTION IN THE CANADIAN FOOD MANUFACTURING INDUSTRY

by

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ABSTRACT

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The purpose of this study is to estimate technical efficiency and the elasticity of input substitution between factors in production in the Canadian food manufacturing industry. First, the estimated mean technical efficiency of the Canadian food manufacturing industry is 87.5%. Secondly, based on the estimates of Hicks and Morishima elasticities of complementarity measures, capital and labour are substitutes, whereas the capital and energy are complements to each other. Given estimates of technical efficiency, there is only modest scope for increasing aggregate productivity through improvement in technical efficiency. One implication of the findings in the study is that innovation policy that encourages investments in innovation may increase aggregate productivity growth.
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Chapter 1- Introduction

Food processing is among Canada’s leading manufacturing employer and accounts for 236,000 jobs. The food processing industry is also the second-largest manufacturing industry overall by revenue. However, the industry has recently experienced a considerable change in terms of the policy governing the food processing sector, as there has been a rise in energy costs and minimum wages. Both these factors might impact the orientation of the industry and in turn, have a bearing on the efficiency and ease of substitution between the factors of production. To explore this, I intend to formulate the motivation and list down the research questions, purpose, objectives of the undertaken empirical study. Lastly, I provide the structure of the thesis.

1.1 Motivation

Exploring sources of productivity change may help to identify Canada’s food processing drivers of growth and based on those drivers develop policies to lessen the productivity gap with other countries (Hamit-Haggar (2009)). One of the critical drivers of productivity is technical efficiency (Farrell (1957); Forsund and Hjalmasson (1974); Fried et al., (1993); and Kumbhakar and Lovell (2000); Lundvall and Battese (2000); and Nikaido (2004)). Technical efficiency for a firm implies the ability to produce maximum output production with minimum input usage or minimum input usage for a given a level of output production; thus, it is a crucial component which impacts the productivity and its growth. Furthermore, as productivity growth reflects the standard of living in an economy, thus technical efficiency has importance to the long-term policy framing in agricultural, services as well as the manufacturing industry.
There has been ample research on the technical efficiency of the Canadian dairy industry (Mbaga et al. (2003); Hailu et al. (2005); Slade and Hailu (2016); Dayananda (2016); Hailu and Deaton (2016); and Larue et al. (2017)). However, I have scant evidence of the technical efficiency research on the Canadian food manufacturing industry, including Hamit-Haggar (2009), who stated that technical efficiency of the Canadian food, beverage and tobacco industry had declined from 96.10% in 1990 to 92.10% in 2005.

Recently, Lai (2015) and Piedrahita (2016) decomposed the productivity growth for the Canadian manufacturing sector. Where Zili (2015), using the Canadian macro-data, found out full technical efficiency of the food manufacturing sector. While Piedrahita (2016) deemed that the technical efficiency of the food manufacturing sector is 100% from 2004 onwards, but various sub-sectors have varied results over the period (Piedrahita, 2016). These facts certainly need further inspection, as technical efficiency was not the focus of these past researches.

Despite technical efficiency’s importance to the Canadian economy, there is limited literature focusing on the nation’s food processing industry. Research involving the productivity of the Canadian food processing sector typically do so at a national level using an inter-industry comparison across manufacturing sectors (Hamit-Haggar (2009)). However, the production technologies in different manufacturing sectors are significantly heterogeneous. Therefore, the productivity or efficiency measures in other manufacturing industries may not be useful to interpolate in the food processing industry.

Furthermore, previous research has primarily focussed on the technical efficiencies in other countries for the food processing industries (e.g., Coelli et al. (2003); Aedo et al. (2011); Rodamanee and Huang (2013); Ndicu (2015); Rezitis and Kalantzi (2016) and Kapya (2016)).
In the wake of too much ambiguity over the technical efficiency results from these studies, I intend to use the translog production function approach using the stochastic frontier analysis. Thus, my research aims to get a robust estimate of the technical efficiency on provincial and subsector level data of the Canadian food manufacturing industry and comparing those results with its American counterparts.

The ability to substitute between the factors of production without compromising on the output and the efficiency in production is also an important concept, technically known as ‘elasticity of substitution’. This concept gained momentum after the 1973 global oil crisis when manufacturing firms heavily reliant on oil supply looked to shift from expensive oil (energy) to other forms of factors of production following the “theory of induced innovation” (Hicks (1932)). Thus, the elasticity of substitution is another critical economic indicator which may affect the manufacturing sector’s productivity growth (Berndt and Christensen (1973); Griffin and Gregory (1976); Fuss (1977); Pindyck (1979); Magnus (1979); and Andrikapoulous (1989).

With most of the early substitution studies post 1973 oil crisis focussed on the US industry, including Berndt and Christensen (1973), which used the time series analysis. These studies also did cross-country analysis using pooled data, including Griffin and Gregory (1976) and Pindyck (1979). Magnus (1979) focussed on the inter factor substitution possibilities in the Netherlands, whereas Fuss (1977) and Andrikapoulous (1989) focussed on the Canadian industry. Similarly, there is also a lack of elasticity of substitution studies in the context of Canadian food manufacturing industries as previous literature has looked upon the food manufacturing sector of various other countries. The prevalent literature is contextually different (Ball and Chambers (1982); Lopez (1984); Huang (1991); Ahmed et al. (1993); Goodwin and Brester (1995); Nguyen and Streitweiser (1999); Alarcon (2005) and Hailu et al.,
2010). Most of these studies focus on the US food industry apart from Lopez (1984). Thus, I cannot use these findings in the recent context of Canadian food manufacturing industry.

It is also hypothesised that the rise in the minimum wages in Canada will affect the inter-factor substitution and in turn, may affect the efficiency and productivity levels of the food processing industry as well. To estimate the impact of minimum wages on firm profitability, Draca et al. (2011) studied the introduction of a UK national minimum wage. Draca et al. (2011) showed that minimum wages raise wages and significantly reduce profitability. It is consistent with a model where wage gains from minimum wages map directly into profit reductions. Recently, Alvarez and Fuentes (2018) studied the minimum wage and productivity of Chilean manufacturing firms. They show that the minimum wage increases in Chile in the ’90s is partially accountable for the slowdown in firm productivity.

In a similar vein, Riley et al. (2015) explored the national minimum wage in Britain and identified the effects of minimum wages on productivity. Riley et al., (2015) stated that firms responded to these increments in labour costs by raising their labour productivity and suggested that these productivity changes did not lead to a reduction in firms' workforce. In short, the researchers have pointed out that productivity increases can result due to fall in employment due to the minimum wage, as enterprises adopt more capital-intensive production technologies.

It is also proposed that the rise in electricity (energy) costs in recent times in Canada will also impact the factor substitution within the industry. Fuss (1977) explained that substantial inter-fuel substitution is possible in Canadian manufacturing. While relatively recent analysis by Andrikapoulos et al. (1989) showcased the increased substitutability between energy and capital measures. However, of late little attention has been given to factor demands in the
Canadian food-manufacturing industry at its sub-sector levels. Therefore, our research results are imperative. The rise in the minimum wages and electricity cost might also lead to lower technical efficiency and elasticity of substitution, which in turn would likely reduce the global competitiveness of Canadian processed food products. In a way, it could also impact Canada’s primary agriculture industry because the food processing industry is the largest destination for Canadian raw agricultural produce (AAFC, 2015).

To sum up, this thesis is motivated by a lack of information about technical efficiency and the elasticity of factor substitution and the link between the two in the Canadian food processing industry. This thesis will not only document the food processing sector’s technical efficiency and factor substitution performance but will also identify the link between them with the ultimate objective of improving the competitiveness of the industry.

1.2 Research question

Rising input cost could impact on the food manufacturing sector’s competitiveness and efficiency. The extent to which this may happen will depend on the ability of various industries within a sector to substitute from higher-cost inputs to lower-cost inputs, and its ability to maintain efficiency in the process. Whether or not the industry can substitute between inputs is at the heart of this study. This study seeks to understand this issue better by trying to answer the question “Do technical efficiency affects the factor substitution in the food manufacturing industry?”
1.3 Purpose

The purpose of this study is to examine the technical efficiency and elasticity of factor substitution and the relationship between the two in the food manufacturing industry. However, as I do not have information on the input prices, thus I am using the primal model to estimate the elasticity of complementarity to study factor substitutions.

1.4 Research objective

1. To implement translog production function and based on its parameter estimates, computing the elasticity of complementarity performance.

2. Based on the translog production function, calculate technical efficiency in the Canadian food processing sector, and understand how technical efficiency varies across provinces, sub-sectors, and time.

3. To explore the link between the technical efficiency and elasticity of complementarity.

1.5 Structure of this Study

Chapter Two provides a brief overview of the Canadian food processing industry. Chapter Three provide reviews of the literature on technical efficiency and elasticity of substitution in the food manufacturing industry. Chapter Four introduces the conceptual framework used to estimate technical efficiency and elasticity of substitution. Chapter Five shows the empirical model used to calculate technical efficiency and the elasticity of substitution. Chapter Six provides the source and description of the data. Chapter Seven and
eight reports result and discussion for the Canadian and the U.S. food processing industry.

Chapter nine concludes the thesis with a summary discussion and possible future extensions.
Chapter 2- Industry Background

This chapter looks at the industry of interest, i.e. the food manufacturing industry of Canada, and its micro-level composition constituting various sub-sectors in the industry. The chapter flows from industry background and gravitates towards the factor of changes, which in turn are the main reasons for this econometric inquiry. The main factor of changes includes the rise in electricity costs as well as a hike in the minimum wages. Both these inputs are vital factors in the production cycle of the manufacturing industry. This chapter aims to draw attention to the economic importance of the food manufacturing industry and the core intuition behind the empirical study.

2.1 Background of the Canadian Food Manufacturing Industry

Canada’s food and beverage manufacturing sector (NAICS 311 and 312) accounts for 1.68% of national GDP and 15.93% of total manufacturing GDP. The food processing sector is Canada’s second-largest manufacturing industry in terms of shipments having a valuation of about CAN$105.5 billion in 2014. The sector employs about 246,000 Canadians and supplies 75% of processed food products in Canada (AAFC, 2014). There are about 6,500 food processing establishments in Canada. Ninety per cent of these firms have fewer than 100 workers, while nine per cent has between 100 and 500 workers, and only one per cent have more than 500 workers.
Ontario and Quebec account for about 65% of food processing sector sales, followed by British Columbia and Alberta accounting 21%, while the remaining provinces have a smaller combined share of 14% (AAFC, 2014). Based on figure 2.1, I can see that bakeries and tortilla manufacturing and the beverage manufacturing were the sub-sectors which had the highest number of establishments in the Canadian food processing industry.

There are regional differences in the importance of various sub-sectors. Meat is the significant food industry sub-sector in Quebec, Ontario, Alberta, and British Columbia; grain and oilseed milling are the largest food industry sub-sector in Manitoba and Saskatchewan; seafood is the most significant part of the industry in Atlantic Canada.

Ontario is Canada's largest food processing sector, and sixth most significant in North America, employing about 94,000 people, and with manufacturing revenues totalling CAN$35 billion, and almost 25 per cent of the province’s food manufacturing businesses are based in
rural Ontario, wherein the inputs are primarily obtained from the Ontario’s farming community growing more than 200 agricultural commodities (OMAFRA, 2013).

Ontario’s agri-food sector includes firms of varying scale, ranging from small scale domestically oriented firms to large scale globally oriented companies. The Ontario food processing sector, has become the nation’s largest, chiefly because of lower overall costs and lower provincial corporate taxes in food processing compared to the U.S. and other regions in Canada (Piedrahita, 2016). Taken together, lower costs and taxes might have led to the rise of comparative advantages in the Ontario food processing sector and its growth (Piedrahita, 2016).

After the collapse of the Canadian loonie in 2014, the Canadian food product exports depressed in the year 2018, with volumes estimated to have grown by a meagre 0.1 per cent. However, the recent free trade agreements, such as the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP) and the Comprehensive Economic and Trade Agreement (CETA), are facilitating newer export destinations for Canadian food processors.

Similarly, the signing of the new Canada–U.S.–Mexico Agreement (CUSMA) has removed the uncertainty about access to Canada’s largest export market. These developments are supporting the industry’s bright export outlook (Conference Board of Canada, 2019). Between 2012 and 2015, 94% of Canadian exports of processed foods were to the United States, so the proliferation of free trade agreements provides an opportunity for the agri-food industry to enhance its global competitiveness (Piedrahita, 2016).

Key challenges facing the food processing industries include rising prices of agricultural commodities, as well as the recent rise in prices of factors of production including the energy (electricity) as well as labour wages, environmental regulations, overseas competition and the
volatility in the exchange rate. Also, the trend of the diminishing trade balance after 2000 in the Canadian food processing industry could point towards lacking competitiveness in the domestic food industry (Seguin and Sweetland, 2014). Hence, to face increasingly competitive global and domestic environment; processing firms have undergone structural as well as operational reforms. Therefore, in Alberta, Saskatchewan, Manitoba and Nova Scotia there have been many new plant openings, whereas there has been a downscaling of operations in Ontario and Quebec resulting in plants being shut down, displaced or reorganised (Sparling and LeGrow, 2014).

In short, the food processing industry constitutes a significant market for the domestic farming sector and, hence, the success of the agriculture sector depends on the advances in the food processing industry. Therefore, the expansion of domestic food processing is an essential element in the AAFC (Agriculture and Agri-food Canada) strategy, as they have a strong focus on trade, setting a target of CAN$75 billion in agriculture and food exports by 2025.

**2.2 Increase in labour wages**

In 2017, the Government of Ontario passed legislation to increase the minimum wage from CAN$11.60 per hour to CAN$14 per hour (w.e.f. Jan 1, 2018), and it is tipped to stay at this level for the forthcoming year as well. This rise has represented as one of the steepest rises in the minimum wage in the history of wage hikes for the province. Resultantly, it may also impact the wages across sectors and especially the food manufacturing industry. Hence, it is of utmost importance for firms to track the rising costs in the face of the apparent wage hikes, to be sustainable and profitable at the same time.
I recognise that minimum wages do not apply to all waged employment. There is, however, a relationship between the minimum wage and median wage, expressed as a ratio that economists sometimes refer to as the “Kaitz index” (Dube, 2014; Cass, 2016). The index is expressed as a number between 0 and 1, consists of the ratio of the minimum wage to the median wage. As the Kaitz Index gets higher, there are adverse impacts on the employment front (Rutkowski, 2003).

Data from the Organisation for Economic Co-operation and Development (OECD) shows that the Kaitz index equal to 0.5 is generally the norm in developed countries. As of May 2017, the values of the Kaitz index for Canadian provinces ranged from a low of 0.46 in Saskatchewan to a high of 0.60 in Prince Edward Island. The country’s larger provinces are hovering around
the 0.5 standards. At the moment, Ontario’s Kaitz index is 0.5, however, as per the recent rise in the minimum wages in the province of Ontario to CAN$14/hour in the year 2018, the Kaitz index for Ontario is expected to shift upwards. Based on the figure 2.2, I can also compare the minimum to the median wage of other Canadian provinces (including SK= Saskatchewan, BC= British Columbia, NL= Newfoundland and Labrador, ON= Ontario, QC= Quebec, AB= Alberta, MB= Manitoba, NS= Nova Scotia, NB= New Brunswick, and PE= Prince Edward Island), which again brings attention to the rising minimum wages across provinces, and especially for Ontario post-2017.

Given the importance of the wage bill in food manufacturing, expectations for a rising Kaitz index suggests the sector may be put at a competitive disadvantage relative to other jurisdictions where the Kaitz index is lower or falling. Consequently, the concern for cost efficiency of the industry requires attention, as this might lead to structural distortion in the industry, in the form of more labour efficient as well as capital intensive (or automation) options.

2.3 Rise in electricity cost

The recent hike in the Ontario’s electricity prices can be primarily attributed to the “Global Adjustment Fees”, as on average, residential customers and small businesses in Ontario paid about 7.9 cents per kilowatt-hour in Global Adjustment fees last year. This fee stems from the Ontario Green Energy Act. This act was put into motion in 2009, and it intended to expand the province’s use of renewables to promote conservation of energy and is billed to all hydro customers in the province (Jackson et al., 2017).

As a result, a rise in the energy cost structures may also impact the efficiency of the firms, as Ontario historically used to be a jurisdiction with low electricity costs. It was a competitive
advantage in attracting businesses into the province. Recently, Ontario electricity prices have soared, threatening industrial competitiveness, and primarily that of the manufacturing sector for which electricity is a significant input cost. Ontario’s manufacturing sector accounts for almost 40% of Canada’s exports, and between 2005 and 2015, Ontario’s manufacturing output declined by 18% and employment by 28% (Mckitrick and Aliakbari, 2017).

Given the facts, it can also be correlated that the rising electricity prices in Ontario have led to declining output of the manufacturing sector, resulting in downscaling of operation of the firms and in turn, may have caused job losses in the province. Therefore, the decline in the manufacturing output because of rising energy prices is a matter of immense importance and calls for an economic inquiry.

![Comparative growth in electricity prices](image)

**Figure 2.3: Comparison of electricity price changes in Canadian provinces**

*Source: Fraser Institute (2017)*
The electricity price shock in Ontario intensified in 2011. Thus, analysis from 2011 to 2016 is useful to explain price growth. Between 2011 and 2016, electricity prices across Canada increased by about 22 per cent (Mckitrick and Aliakbari, 2017). In a comparison of major provinces, the growth in electricity prices in Ontario and British Columbia was at a higher rate than the national average during the period. Between 2011 and 2016, the electricity prices increased by 48 per cent in Ontario and 30 per cent in British Columbia but decreased in Alberta by nearly 25 per cent (Mckitrick and Aliakbari, 2017). To sum it all up, basis figure 2.3, I can say that rise in the electricity prices in Ontario is the largest in the country, whereas Alberta is the only major province where the electricity prices have decreased over time from 2008-2016.

So, energy can be a significant factor impacting the efficiency of the food processing firms between the Canadian provinces and can also act as a stimulus towards the adoption of higher energy-efficient technologies in the food industry. Therefore, the underlying motivation for our research is to link these two crucial factors (labour and electricity) of production with respect to the efficiency and elasticity of substitution of the food processing sector across the provinces.

2.4 Other factors influencing the food processing industry

Productivity growth is the primary source of economic growth and competitiveness, which corresponds to higher levels of human development indexes. On the other hand, a slowdown in productivity growth may translate to a detrimental impact on the living standards of society. The overall determination of competitiveness of the food processing industry is an amalgam of a variety of characteristics.
These characteristics include the size of and proximity to the major markets for the food processor, the distance to raw materials sources, along with the availability highly qualified personnel at a competitive wage, services and utilities at a competitive rate and the relative cost of all local taxes. Changing demographics and greater access to foreign markets, through international trade agreements are some driving forces that have reshaped the food processing sector in the past.

![Scale of operation (by size)](image)

**Figure 2.4: US-CAN food processing establishment’s scale of operation basis employee count**

*Source: George Morris Centre (2012)*

Other significant factors impacting the level of productivity is the size of the firm, and we know that most of the food processors in Ontario are SMEs (Small and Medium Enterprises). Based on figure 2.4, it is evident is that the Canadian scale of operation is way lower than their US counterparts in the various food manufacturing subsectors. However, based on the “theory of selection and evolution of industry” by Jovanovic (1982), the literature has shown that larger
average plant sizes support higher efficiency and productivity especially in manufacturing industry (Leung et al., 2008), which suggests for economies of production through scale and scope.

![Productivity gap (US and CAN)](image)

**Figure 2.5: US-CAN productivity gap basis revenue per employee**

**Source: George Morris Centre (2012)**

Secondly, there has been a latent need for capital investment in the food processing industry. In the early '90s, the consolidation of food processing sector led to increased capital investment. As a result, sizeable gains in productivity placed Ontario food products in a very competitive position to capitalise international markets (Trant, 1996). However, in the recent past, there has been a decline in the multi-factor productivity of Ontario’s food processing industry. Moreover, as the food processing industry is highly regulated in a competitive environment, with low margins, the need to purchase significant assets is hampered as it is challenging to obtain adequate finances. It is among a significant reason blocking the rise of capital investment in the industry. Therefore, based on figure 2.5, showcases the lagging Canadian productivity with respect to their American counterparts, the reason for this lag can
be linked-to lesser investment in research and development (R&D) in the Canadian food manufacturing plants than their American counterparts (George Morris centre, 2012).

The optimum usage of resources is an appropriate measure for competitiveness (Porter 1990). Therefore, improvement in productivity and efficiency is intended to enhance the competitiveness of Canadian food manufacturing. Also significant is getting to know the underlying sources of changes in productivity for developing future sectoral policy. Therefore, econometric work on production response due to changes in cost stress in the food processing industry is of grave importance.

Henceforth, the purpose of this thesis is to examine the technical efficiency and elasticity of factor substitution in the food processing industry of Canada, comparing results with the US data, primarily focusing on the respective sub-sectors and the provinces/states along the time horizon of the study.

Finally, the growth in the food processing industry brings overall development in the economy as it establishes a vital synergy between the two main pillars of economy, agriculture and manufacturing industry. This thesis is an attempt to identify constraints that may create hurdles in the path of development of food processing sector in Canada.

**Summary**

At the time when food processors faced significant challenges such as rising input prices and higher concentration amongst food retailers, real revenue increased slightly over the past 20 years. Additionally, increased global competition and the appreciation of the Canadian dollar led to a decline in trade balance over time. Maintaining competitiveness in domestic and global
markets despite these challenges could be achieved with higher efficiency and ease of substitution between the factors of production. Identifying the bottlenecks and narrowing the gap between provinces and sub-sectors could improve the standing of Canada’s food processing sector.
Chapter 3- Review of Literature

There have been ample studies focusing on the broader productivity analysis and factor substitutions in developed and developing countries for various industries. This section primarily takes into consideration relevant studies that have been conducted in the food processing industry. Specifically, the literature cited here gives a brief snapshot of the results of the analysis focussed on the technical efficiency, and the elasticity of factor substitution.

3.1 Efficiency

Efficiency reflects the firm’s ability to maximise outputs given inputs (output-oriented) or minimise inputs used in the production for a given level of output production (input-oriented). The efficiency measurement of a firm or industry is useful for policymakers to help them know how much output increase can happen given the same usage of input levels and increasing input usage efficiency (Farrell, 1957). Further, Farrell (1957) suggested that the efficiency of a firm has two components, the technical and allocative efficiency.

The efficiency of a firm is a relative concept that compares the values of observed output and input (Fried et al., 1993). Wherein the technical efficiency compares the ratio of observed to maximum attainable output from a given input quantity, so a technically efficient firm aims to produce the maximum output, given the level of input usage and the available technology (Amaza and Maurice, 2005). Alternatively, the allocative efficiency of a firm aims at choosing an optimal combination of inputs with a given set of input prices (Daraio and Simar, 2007). Thus, the allocative efficiency point is the point where the producer equates the price of the input to the marginal value product of the input. Therefore, the overall economic efficiency is
the product of technical and allocative efficiency and occurs when a firm combines the inputs in the least possible combination to produce maximum output (Chukwuji et al., 2006).

Therefore, knowing the determinants of technical efficiency for a firm or industry is vital, so that they can execute policies that could improve their efficiency levels. The technical efficiency levels rely on a gamut of factors as explained by Hossain and Karunaratne (2004), Pavcnik (2002), and Aggrey, Eliab and Joseph, (2010). Along with these, there are also firm-level factors that may affect the levels of technical efficiency, including kind of ownership, the age of a given firm and firm size (Pitt and Lee, 1981). Economic efficiency aims at the production of given outputs at minimum cost, or the proper utilisation or allocation of inputs and outputs to maximise profits (Kumbhakar and Lovell, 2000). Therefore, efficiency analysis can provide valuable information for enhancing the performance of the sector (Fried et al., 1993).

3.2 Measurement of Technical Efficiency

The efficiency estimation can be classified into the following approaches: parametric, non-parametric and semi-parametric estimation. The non-parametric efficiency estimation technique uses the data envelopment analysis (DEA), which may not account for the stochastic nature of production. The benefits of the non-parametric approach are that it does not require the specification of a functional form. Moreover, the efficiency is referenced such that all deviations from the optimum output are attributed to inefficiency. This approach has been considered less appropriate by some authors due to the inherent stochasticity in production. As per Markovits-Somogyi et al., (2011), the non-parametric (DEA) approach has drawbacks including the sensitivity of the efficiency estimates to outliers as well as the potential bias in the
estimated efficiency arising from the exclusion of potentially more efficient decision-making units. However, the approach has been widely used in the context of agricultural production and other fields (ex. Coelli et al. (2002); and Rezitis and Kalantzi (2016)).

In terms of the parametric efficiency approaches, the stochastic frontier analysis (SFA) is used most often. It was developed independently by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The stochastic frontier analysis (SFA) accounts the stochasticity of the production process and models efficiency as a function of factors that limit the attainment of maximum output. The SFA is based on the principle that maximum output may be unattainable due to inefficiency. SFA decomposes the error term into random effect that factors in the measurement errors and other factors beyond the control of the firm in a non-negative error term that measures inefficiency (which can also be called as the systematic deviation from the production frontier). Authors have widely used this approach. A third approach to the efficiency estimation is the semi-parametric approach which has aspects of both the parametric and non-parametric approaches. This approach is less commonly adopted and hence, was not considered in the current study.

In order to choose between the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) approaches empirically, Hjalmarsson et al. (1996) did a comparative study based on 15 Columbian cement plants data between 1968 and 1988. They found higher efficiency score estimation in the SFA approach than the DEA approach. As only SFA accounts for exogenous or stochastic effects; consequently, SFA leads to higher efficiency estimates than DEA (Hjalmarsson et al., 1996; Reinhard et al., 2000). The stochastic frontier method is also referred to as “composite error model”, it has the advantage of taking into account the random error and the distribution of the inefficiency component, which allows for richer specifications.
and hypothesis testing. Thus, based on comparisons of the methodologies, I am proposing to use the SFA method for this analysis.

3.3 Previous studies on the technical efficiency in the food manufacturing industry

While broader literature on the efficiency and productivity exists, including various manufacturing sectors of the global economy, in terms of the global food processing, there is a growing body of literature focused on efficiency analysis, including Coelli et al. (2003), who used the stochastic input distance function approach (Cobb-Douglas form) and studied the cost efficiency (including both technical and allocative efficiency) of the Indian dairy processing industry.

Aedo et al. (2011) using the translog production function approach for the stochastic frontier analysis (SFA) indicated the drivers of the technical efficiency on the Chilean agribusiness sector. Rodamanee and Huang (2013) using the data envelopment analysis, examined the technical efficiency of the Thai food manufacturing industry. In a similar mould, Ndicu (2015) used the Cobb-Douglas production function for the stochastic frontier approach and revealed the factors which influence the technical performance of the firms in the agro-processing industry in Kenya. Similarly, Kapya (2016) used the data envelopment analysis and showed the firm technical efficiency and its drivers in Zambia’s agro-processing industry. Rezitis and Kalantzi (2016) used the data envelopment analysis and assessed the technical efficiency of the Greek food manufacturing industry.

There has been abundant research on the technical efficiency of the Canadian dairy industry (Mbaga et al. (2003); Hailu et al. (2005), Slade and Hailu (2016); Dayananda (2016);
Hailu and Deaton (2016); and Larue et al. (2017)). However, there is a dearth of evidence of technical efficiency studies focussing on the Canadian food processing industry, including Hamit-Haggar (2009), who using parametric approach evaluated Canadian manufacturing industries’ multifactor productivity growth and investigated the sources for productivity growth over the period 1990-2005. The focus of the study was total factor productivity growth, technological changes and efficiency changes for the broader Canadian manufacturing industries. The study stated that the technical efficiency dropped from 96.10% in 1990 to 92.10% in 2005 for the food, beverage and tobacco industry.

Recently, Lai (2015) and Piedrahita (2016) decomposed the productivity growth for the Canadian manufacturing sector using the non-parametric (data envelopment analysis) and parametric approach (ordinary least squares), respectively. Lai (2015), using macro-data, explored that capacity under-utilisation is the prominent reason for Atlantic and Prairie Provinces’ productivity growth slowdown and found out full technical efficiency of the food manufacturing sector. Later, Piedrahita (2016), using micro-data, found that there is a gradual fall in multi-factor productivity, technical change as well as scale efficiency in the food manufacturing plants. The technical efficiency of the food manufacturing sector is deemed 100% from 2004 onwards, but various sub-sectors have varied results over the period (Piedrahita, 2016).

Both studies suggest that the food processing industry is technically efficient, a claim which certainly needs further examining. Technical efficiency was not the focus of these earlier studies, and this evidence does not consider the impact of technical efficiency levels on the sensitivity of the elasticity of substitution between the inputs, and vice versa. Therefore, this pertinent question can be addressed through our research findings.
3.4 Elasticity of factor substitution

Food-processing technologies require heavy usage of factors of production, primarily capital, labour, energy and materials. One of our chief reasons to undertake this research is that the changes in an input price have significant effects not only on demand for that input but also on the utilisation rates of other primary factors of production in the manufacturing industry. Thus, the elasticity of substitution is another critical economic indicator which may affect the manufacturing sector’s productivity growth (Berndt and Christensen (1973); Griffin and Gregory (1976); Fuss (1977); Pindyck (1979); Magnus (1979); and Andrikapoulous (1989)).

However, the directions of these effects depend upon the technical relationships among the various factors. Thus, evidence of these relationships undoubtedly has significant economic policy implications. Therefore, to make decisions in terms of resource usage, food manufacturers need information on the nature of industrial demand for factor inputs. To illustrate, I use the concept of elasticity of substitution, which measures the percentage change in the ratio of inputs used in response to a percentage change in their prices. It measures the substitutability between factors of production, i.e. how easy it is to substitute one input for the other input without affecting the output levels. However, in our case, as I am assuming the multi-factor (more than two factors) substitution in the industry, hence I intend to explain factor demands and their interdependent relationships between various factors of production.

3.5 Previous studies on the elasticity of substitution in the food manufacturing industry

Several studies have analysed the demand for production factors in various sectors of developed economies. Ball and Chambers (1982), using the cost function approach, studied the factor substitution between the factors of production including; capital equipment, labour,
energy, intermediate materials, and capital structures in the US meat products industry using the Allen, Morishima and Shadow elasticities of substitution.

Focusing on the Canadian food processing sector, Lopez (1984), using a profit function, studied the supply response and investment, and results suggest the extent of substitution between labour, energy, intermediate materials and capital in the short as well as the long run. Similarly, Huang (1991), using the cost function approach, showed the extent of substitution between capital, labour and energy in the U.S. food-manufacturing industry using the Allen and Morishima elasticity of substitution measures.

In the same vein, Goodwin and Brester (1995), using the translog cost function approach, indicated the ability of factor substitution between labour, capital, food materials, energy and other inputs in the U.S. food and kindred products industry using the Morishima elasticity of substitution. Nguyen and Streitweiser (1999), using translog production function model, focus on the factor substitution between capital, labour, energy and materials in the US manufacturing, but the analysis also included some of the food processing subsectors using the Allen, Morishima and the Shadow elasticity of substitution measures.

Similarly, Alarcon (2005), using the translog production function model, studied the factor substitution for labour, capital and material inputs in the Spanish food industry using the Morishima and Shadow elasticity of substitution. Hailu et al. (2010), using the translog cost function approach, explored the effects of relative price and health information on derived demand for sweeteners in the U.S. food processing industry and suggested for the substitution possibilities among various factors of production including cane, corn, material, capital, labour, and energy using the Allen as well as Morishima elasticity of substitution measures. These
studies have explored the structural shift in factor demands, including an assessment of elasticities of factor substitution.

3.6 Link between Technical Efficiency and Factor Substitution

As per my knowledge, there is no established link between the technical efficiency and the elasticity of substitution in the context of the food manufacturing industry. Thus, I hope to integrate these two separate bodies of literature into our research. The link between the technical efficiency and the elasticity of substitution is followed as per the seminal works of Arrow et al. (1961), and Sato (1977). Both Arrow et al. (1961) and Sato (1977) used the constant elasticity of substitution (CES) production function and debated over the elasticity of substitution values for capital and labour relationship. Arrow et al. (1961) showed that the elasticity of substitution is less than one, whereas Sato (1977) stated that the elasticity of substitution is more than one. Based on these values of elasticities of substitution, they ranked the labour efficiency across countries.

Other recent evidence of the efficiency and factor substitution include Christopoulos and Tsionas (2002), who using the translog cost function, studied the link between allocative efficiency and the capital and energy substitution in the Greek manufacturing sector. Similarly, Burki and Khan (2004), using the translog cost function, studied the effect of allocative efficiency on the resource allocation and the energy substitution in the Pakistani manufacturing sector. In a similar vein, Khiabani and Hasani (2010), using the translog cost function, studied the effect of technical and allocative efficiency on the factor substitution in the Iranian manufacturing sector.
Firm behaviour in Christopoulos and Tsionas (2002), Burki and Khan (2004), and Khiabani and Hasani (2010) is erroneously modelled upon cost minimization principle, i.e. the production at minimum cost, which in reality is affected by the presence of inefficiency, and in turn, also impacts the elasticity of substitution estimates. Another key output of Christopoulos and Tsionas (2002), Burki and Khan (2004), and Khiabani and Hasani (2010) is that the presence of either allocative efficiency, technical efficiency or both impacts the elasticity of substitution result output. However, as I do not have the price information for input or output, thus I limit my focus to explore the link between the technical efficiency and factor substitution.

Finally, based on the earlier literature evidence, it is apparent that the Canadian food manufacturing industry is not keenly studied in the context of technical efficiency, factor substitutions and the link between those two. Thus, the critical literature gaps which my research intends to fill are listed below:

3.7 Gaps in the literature to be addressed
(1) The lack of analysis of the technical efficiency and factor substitution research for food manufacturing in Canada and USA.

(2) The link between technical efficiency levels and factor substitution of the food manufacturing industry.

Summary
Most of these studies which are cited above are very contextual, i.e. in the sense that they have been conducted in a different industry, country, time horizon, data inputs, theoretical or empirical methodologies. Most importantly, these studies have not investigated all the variables of interest (i.e. technical efficiency and the factor substitution) concerning the food
manufacturing industry together in one study, which means that the results from these studies cannot be assumed to hold for our case. Our study aims to bridge these gaps by using a more recent yet representative macro-data sample of the Canadian and U.S. food manufacturing industry.
Chapter 4- Theoretical model

This chapter presents the theoretical framework and the model that was estimated in order to provide answers to the research objectives. The purpose of this chapter is to describe the concept of technical efficiency and elasticity of substitution. This chapter presents the theoretical basis of this analysis. Firstly, the technical efficiency is presented, followed by the elasticity of substitution. Both concepts are ably supported with the diagrams for clarity in illustration.

4.1 Technical Efficiency

Following Koopmans (1951), a producer is deemed technically efficient if any increase in the level of output requires a reduction in another output or an increase in any input uptake, and similarly, the reduction in any input requires an increase in another input or a reduction in any output. Technical efficiency is illustrated in Figure 3.1, assuming two input and one output firm given by; single-output (Y) and two inputs (X1 and X2). Thus, the isoquant shows the combination of two inputs that produce a given level of output (Farrel, 1957).

In Figure 4.1, the points lying on and above the isoquant fall in the input requirement set, stating various feasible input combinations that can produce the given level of output production (Y). The points lying on the isoquant are termed as technically efficient as all produce the same level of output Y but use different combinations of inputs (X1 and X2). For example, firms lying at point V and Z are considered technically efficient as they are on the frontier of the isoquant. In contrast to firms V and Z, the firms lying at point U are considered technically inefficient because, at this point, the firm is using more of input combinations to yield a given level of output.
produced. It is also apparent that the firms at point U uses the same level of input X1 but uses more of input X2 to produce the same level of output (Y).

Figure 4.1: Graphical representation of technical efficiency (Farrell, 1957)

Following Figure 4.1, it has firms lying on the points U, V, and Z, respectively. For firm U, using input levels X1(U) and X2(U), the radial distance is the length of the line segment combining the origin to the inputs used with firm U. The radial distance from the origin to the boundary of production possibility set is OV. The radial distances of U and V can be used to measure the technical efficiency for U. The extent of technical inefficiency for firm U is OU/OV, i.e. the ratio of two radial distances. While the radial distance for U is OU, the distance function for firm U is the ratio of OU/OV, which is because it is greater than 1, as the value of OU>OV, and can be deemed relatively inefficient as it is using more of inputs for the given level of output production. Similarly, the radial distance for firm V is OV, and the distance function is unity, i.e. OV/OV, i.e. thus deemed fully technically efficient.
The technical efficiency is a purely technical concept with no prices considered, but efficiency can also involve the proper choice or allocation of the inputs to minimise the costs of producing the selected output, which suggests for allocative efficiency, which is another important factor determining the overall cost efficiency. However, as I do not have information on the prices, hence I limit discussion to the technical efficiency concept only.

4.2 Elasticity of factor substitution

The concept of elasticity of substitution between the factors of production is formally defined by Hicks (1932). Hicks (1932) states that the elasticity of substitution measures the percentage change in factor proportions due to a change in the marginal rate of technical substitution (MRTS). For illustration, assuming the production function as, \( Y = f(K, L) \) the elasticity of substitution between capital and labour is given by:

\[
\sigma = \frac{d \ln \left( \frac{L}{K} \right)}{d \ln \left( \frac{f_K}{f_L} \right)}
\]

where \( K \) is the quantity of capital

\( L \) is the quantity of labour

\( f_K \) is the marginal product of capital

\( f_L \) is the marginal product of labour

The notion of elasticity of substitution was designed to measure the ease with which the factor of productions can be substituted for each other. Lerner (1933) states that elasticity of substitution is effectively a measure of the curvature of an isoquant.
It can be illustrated better following the above-shown Figure 4.2, suppose we move from point M to point N on the isoquant. At point M, the MRTS is \( f_K/f_L \), represented by the slope of the line tangent to point M, while the labour-capital ratio is \( L/K \), as represented by the slope of the chord connecting M to the origin. When we move to N, the MRTS changes to \( f_K'/f_L' \) while the labour-capital ratio changes to \( L'/K' \). The elasticity of substitution, thus, compares the movement in the chord from \( L/K \) to \( L'/K' \) to the movement in the MRTS from \( f_K/f_L \) to \( f_K'/f_L' \).

**Summary**

This chapter introduced the theoretical foundations for the model in this paper. The initial section presented an overview of the technical efficiency, and the next section looked at the elasticity of substitution. These theory-based models form the basis for the mathematical description later in the empirical section. Taken together, these sections on the qualitative
discussion provide propositions about the potential outcomes of the empirical model, which will be developed in the next chapter.
Chapter 5- Empirical model

This chapter provides us with the econometric specification of the model, the stochastic production function for the estimation of the technical efficiency and the elasticity of substitution. It takes the primary motivation from the theoretical model chapter and translates into the actionable plan in terms of the model estimation.

5.1 Production Function

The production function deals with the maximum amount of output that can be generated from a given level of input usage. The core objective of our analysis is to generate a production function for Canadian food manufacturing industry. The analysis focuses on four primary inputs of production (i.e. capital (K), labour (L), energy (E), materials (M)) in the manufacturing parlance with one aggregate output level in the form of manufacturing value-added.

The production function will be: \( Y = Y(K, L, E, M) \)

where,

\( Y \) is the manufacturing value-added output (in CAN$ ‘000)

\( K \) is the capital input (in CAN$ ‘000)

\( L \) is labour input (in CAN$ ‘000)

\( E \) is energy input (in CAN$ ‘000)

\( M \) is the materials input (in CAN$ ‘000)
5.2 Assumptions of the Production Function Approach

Production functions adhere to certain assumptions to assure technical validity following Chambers (1988):

1. The production function is monotonic/strictly monotonic in the input, which means that an increase in input level can never diminish output levels.

2. The input requirement set (all input combinations capable of producing a particular output level) is assumed to be a convex set, and the inherent production function is deemed quasi-concave/ concave. This property follows the “law of diminishing marginal productivity”.

3. Production function must adhere to weak essentiality / strict essentiality. “Weak essentiality” implies that a strictly positive output is possible without the use of a particular input. ‘Strong essentiality’ implies that a positive output cannot be produced without a strictly positive utilisation of that particular input.

4. The input requirement set of the production function is closed and non-empty for any non-negative level of production.

5. The production function is finite, non-negative, real-valued, and single-valued for all non-negative and finite input levels.

6. The production function is continuous over its domain and is also twice continuously differentiable.
5.3 Stochastic Production Frontier

Stochastic production frontier (SPF) technique is used to estimate the technical efficiency of the food processing industry. The parametric SPF method reveals the nature of the technology, various hypotheses and statistical inferences can be tested, and the characteristics of firm-specific efficiency measures can be measured.

The general form of the model;

\[ y_i = f(x_i; \beta) + \varepsilon_i \]  

where \( \varepsilon_i = v_i - u_i \). Thus, the radial distances between the data points and the frontier could be due to either random error or noise \( (v_i) \), or technical efficiency \( (u_i) \), which is the standard SFA error structure.

The use of the appropriate functional form is an essential procedure in parametric efficiency analysis, as the production function depicts the technology under consideration. So, it is imperative to correctly identify the functional specification of the frontier. Regarding the functional form, mostly used are the Cobb-Douglas and translog functional forms. However as most traditional functional forms, like the Cobb-Douglas or the CES functional form, and their derived demand and supply systems suffer from limited flexibility, that is it does not have all the necessary parameters for the representation of all economically relevant effects.

As per Arrow et al. (1961) and Sato (1977), in the CES production function, the elasticity of substitution between the two inputs could be any number between zero and infinity. Further, for a given set of parameters, the elasticity of substitution is the same on any point along the isoquant, regardless of the ratio of input use at the point. Also, the CES production function
showed that only one elasticity of substitution value could be obtained from the production function, and this same value applies to all input pairs. For example, in the food manufacturing industry, one would expect that the elasticity of substitution between capital and labour would differ markedly from the elasticity of substitution between capital and energy. However, the CES would estimate the same elasticity of substitution between both input pairs. Therefore, the usefulness of the CES production function for serious research in applied economics in which more than two inputs are involved is limited.

Several studies have been conducted with Cobb Douglas production function due to its linearity in logarithms; however, its elasticity is constant, and the elasticity of substitution is unity. However, as I am looking to explore the elasticity of the substitution possibilities between the factors of production, hence it will not be appropriate to employ this functional form. The translog function is more flexible in the sense that it imposes few assumptions on the function and its elasticities. The translog production function was introduced by Christensen and Lau (1973) and has been used to assess factor substitution. The translog form does not impose any technological restriction and allow for economies of scale and size (Diewert & Wales, 1988).

As an appropriate functional form for the analysis will be followed using certain conditions, for example, it must obey certain restrictions such as concavity and nonnegativity of the input and output. Thus I follow the translog functional form for the stochastic production frontier in this study, because; translog is flexible; easy to calculate; as well as permits the imposition of homogeneity (e.g., Fare et al., 1994). The widespread application of the translog functional form in related studies (including, Goodwin & Brester, 1995; Huang, 1991), and its properties make this functional form a natural choice.
5.4 Elasticities of factor substitution

This analysis aims to arrive at the Hicks elasticity of complementarity (HEC), and the Morishima elasticity of complementarity (MEC). The Hicks elasticity of complementarity (HEC) is a measure of substitution defined in terms of quantities and measures the effect on the relative input price of change in the relative input quantity (Kim, 2000). As an illustration, HEC is used to show as to how an increase in the quantity of $j$ input affects the price for $i$ inputs. The Hicks elasticity of complementarity is useful in situations where there are constraints on the input prices, and the prices are not available or are not reliable (Kim, 2000). The Hicks elasticity of complementarity (HES) is a preferred choice in the primal (production function) technology approaches as opposed to Allen elasticities of substitution (AES) in the dual case of either cost or a profit function (Kim, 2000).

To explain the difference, the Allen elasticity of substitution assumes that the output is fixed whereas the Hicks elasticity of complementarity assumes that the output is variable (Kim, 2000). The Allen elasticity of substitution (AES) is expressed in terms of prices and registers the effect in quantity demanded of one factor to a change in the price of another factor, where the partial derivative is taken holding output, and other factor prices are held constant (Sato and Koizumi, 1973). Whereas, the Hicks elasticity of complementarity (HEC) is defined in terms of quantity and records the effect on the price of one factor to a change in the quantity of another factor, where the partial derivative is taken holding marginal cost and quantities of other factors constant (Sato and Koizumi, 1973).

Hicks elasticity of complementarity also assumes constant marginal cost as well as constant returns to scale, it also is limited for one output quantity and works well for simpler functional forms like Cobb-Douglas and Leontief only (Kim, 2000). If there is the scenario of
variable returns to scale or a multiple output case, then Antonelli elasticity of complementarity is the favoured choice (Kim, 2000). Antonelli elasticity of complementarity (AEC) is defined for distance function, whereas the Hicks elasticity of complementarity is defined for production function. Further, the Antonelli elasticity of complementarity does not require the marginal cost or the output price to be constant (Kim, 2000). The Antonelli elasticity of complementarity using the distance function gives the compensated inverse demand functions, whereas the Hicks elasticity of complementarity using the production function provides the uncompensated inverse demand functions (Kim, 2000). AEC defined by the distance function is symmetric to the Allen elasticity of substitution characterised by the cost function under variable returns to scale (Kim, 2000).

The Morishima elasticity of complementarity (MEC) is a more complete measure than Hicks elasticity of complementarity as it allows for implicit own as well cross-price effect. MEC measures the responsiveness of the price ratio of inputs (say $i$ and $j$) to change in the quantity of one input ($j$th input), holding constant all other input quantities as well as output.

The production function model is specified as follows:

$$
\ln Y_t = \beta_0 + \beta_K \ln K + \beta_L \ln L + \beta_E \ln E + \beta_M \ln M + \frac{1}{2} \beta_{KK} \ln K^2 + \frac{1}{2} \beta_{LL} \ln L^2 + \frac{1}{2} \beta_{EE} \ln E^2 + \\
\frac{1}{2} \beta_{MM} \ln M^2 + \beta_{KL} \ln K \ln L + \beta_{KE} \ln K \ln E + \beta_{KM} \ln K \ln M + \beta_{LE} \ln L \ln E + \beta_{LM} \ln L \ln M + \\
\beta_{EM} \ln E \ln M + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \beta_{LL} \ln L t + \beta_{KL} \ln K t + \beta_{LE} \ln L t + \beta_{LM} \ln M t + \epsilon_t
$$

(2)

Where, $\beta_L, \beta_K, \beta_E, \beta_M, \beta_t, \beta_{tt}$ represent the first-order parameters
\(\beta_{LL}, \beta_{KK}, \beta_{EE}, \beta_{MM}, \beta_{KL}, \beta_{KE}, \beta_{KM}, \beta_{LE}, \beta_{LM}, \beta_{EM}, \beta_{LT}, \beta_{KL}, \beta_{EL}, \beta_{ML}\) represent second-order parameters. The variable \(t\) is a time trend perhaps capturing technical change and \(\varepsilon_{it}\) are errors which are assumed to be independently and identically distributed and have \(N(0, \sigma_v^2)\) distribution.

Young’s theorem imposes the following constraints:

\[
\beta_{LK} = \beta_{KL} , \quad \beta_{LE} = \beta_{EL} , \quad \beta_{LM} = \beta_{ML} , \quad \beta_{KE} = \beta_{EK} , \quad \beta_{KM} = \beta_{MK} , \quad \beta_{EM} = \beta_{ME}
\]

Using these conditions, the input elasticity of output will be:

\[
\frac{\partial \ln y}{\partial \ln K} = \theta_K = \beta_K + \beta_{KK} \ln K + \beta_{KE} \ln E + \beta_{KM} \ln M + \beta_{KL} \ln L + \beta_{KL} \times t
\]

\[
\frac{\partial \ln y}{\partial \ln L} = \theta_L = \beta_L + \beta_{LL} \ln L + \beta_{KL} \ln K + \beta_{LE} \ln E + \beta_{LM} \ln M + \beta_{LT} \times t \quad (3)
\]

\[
\frac{\partial \ln y}{\partial \ln E} = \theta_E = \beta_E + \beta_{EE} \ln E + \beta_{EM} \ln M + \beta_{LE} \ln L + \beta_{KE} \ln K + \beta_{EL} \times t
\]

\[
\frac{\partial \ln y}{\partial \ln M} = \theta_M = \beta_M + \beta_{MM} \ln M + \beta_{LM} \ln L + \beta_{KM} \ln K + \beta_{EM} \ln E + \beta_{MT} \times t
\]

The scale elasticity (\(\theta_T\)) is the sum of input elasticities of output, and given by;

\[
\theta_T = \theta_K + \theta_L + \theta_E + \theta_M
\]

If \(\theta_T = 1\), then it is CRTS (Constant returns to scale)

If \(\theta_T < 1\), then it is DRTS (Decreasing returns to scale)

If \(\theta_T > 1\), then it is IRTS (Increasing returns to scale)
Based on Kim (2000), assuming perfect competition, the first-order derivative of the production function is given by:

\[ f_i = \frac{\partial y}{\partial x_i} = \frac{\partial \ln y}{\partial \ln x_i} \cdot \frac{y}{x_i} \tag{4} \]

For the condition of monotonicity to adhere, \( f_i > 0 \)

Second-order derivatives of the translog production function are given by,

\[ f_{ii} = \frac{y}{x_i^2} \left[ \beta_{ii} + \theta_i^2 - \theta_i \right] \tag{5} \]

Similarly;

\[ f_{ij} = \frac{y}{x_i x_j} \left[ \beta_{ij} + \theta_i \theta_j \right], \text{ where } i \text{ is not equal to } j \tag{6} \]

In order to get the cost-share equations, I divide the input elasticities of output with scale elasticity;

\[ S_i = \frac{\theta_i}{\theta_T} \tag{7} \]

Equation (7) showing cost-share allows for variable returns to scale, but if I assume constant returns to scale then I get \( \theta_T = 1 \), then equation (7) collapses to input elasticity of output.

Equation (7) in the inverse demand form implies,

\[ w_i = \frac{\theta_i}{\theta_T x_i} \tag{8} \]

Partially differentiating equation (8) with respect to input quantities, I find the uncompensated quantity, or inverse price elasticities;
\[
\eta_{ii} = \frac{\beta_{ii}}{\theta_i} - \frac{\Sigma_j \beta_{ij}}{\theta_T} - 1
\]  
(9)

Similarly, I have,

\[
\eta_{ij} = \frac{\beta_{ij}}{\theta_i} - \frac{\Sigma_k \beta_{kj}}{\theta_T}, \text{ where } i \text{ is not equal to } j
\]  
(10)

The inverse output elasticities are obtained as,

\[
\eta_{iy} = \frac{\Sigma_j \beta_{ij}}{\theta_i + \theta_T} - \frac{\Sigma_k \Sigma_j \beta_{kj}}{\theta_T^2} - \frac{1}{\theta_T}
\]  
(11)

The Hicks elasticity of complementarity can also be calculated as follows,

\[
\rho^H_{ii} = \frac{\beta_{ii} + \theta_i^2 - \theta_i}{\theta_i^2}
\]  
(12)

Similarly, I have;

\[
\rho^H_{ij} = \frac{\beta_{ij} + \theta_i + \theta_j}{\theta_i \times \theta_j}
\]  
(13)

Finally, I derive the Morishima elasticity of complementarity (MEC);

\[
\rho^M_{ij} = S_J(\rho^H_{ij} - \rho^H_{jj})
\]  
(14)
Figure 5.1: Objective and Demand Functions for the calculation of elasticities

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</thead>
<tbody>
<tr>
<td></td>
<td>Maximization</td>
<td>Minimization</td>
</tr>
<tr>
<td><strong>Objective Function</strong></td>
<td>Production function / Output Distance function</td>
<td>Input Distance function</td>
</tr>
<tr>
<td><strong>Demand Function</strong></td>
<td>Inverse, gross</td>
<td>Inverse, net</td>
</tr>
<tr>
<td><strong>Variables Held Constant</strong></td>
<td>Output price and input quantity</td>
<td>Output quantity and input quantity</td>
</tr>
</tbody>
</table>

Source: Stern (2011)
5.5 Measuring Technical Efficiency (TE)

Technical efficiency is the ability to minimise input usage in order to produce a given output vector, or in the same vein, the ability to obtain maximum output from a given input vector (Kumbhakar and Lovell, 2003). In general, the value of TE lies between 0 and 1, where TE=1 suggests that the firms are operating on the frontier of production, and hence deemed fully efficient. In the same notion, TE<1 implies that firms are technically inefficient. In the studies where the technical efficiency was considered, it was necessary the estimation of two equations, the first one is to estimate the stochastic production frontier, and in the second one was to estimate technical inefficiency, using explanatory variables that could explain the technical inefficiency.

Secondly, if there is no explicit distribution for the efficiency component, then the production frontier could be estimated using the corrected ordinary least squares (COLS). However, if there is an assumption of the explicit distribution of the efficiency component, such as exponential, half-normal, truncated normal or gamma distribution, then the frontier is estimated by maximum likelihood estimates (Ndicu, 2015).

Battese and Coelli (1988) estimated technical inefficiency through an exponential equation, assuming time-invariant technical efficiency. I consider that the technical efficiency is time-invariant; thus, I am assuming that the efficiency of each firm is not varying over time, and further assuming that there is no learning and no change in technology over time. Constant inefficiency overtime is not a very sought-after assumption but is a very powerful one as it helps get consistent technical efficiency estimates (Ogundari and Brummer, 2010).
The distributional assumptions of the one-sided error term signifying the technical inefficiency is also an integral component of the analysis. Frontier fits a model in which the nonnegative distribution component \( u_i \) of the technical efficiency can have half normal, truncated normal, gamma, or exponential distribution (Murillo-Zamorano 2004). However, Chakraborty et al. (1999) and Baten and Hossain (2014) have suggested that various kinds of technical efficiency distributions do not lead to much difference in the technical efficiency estimates; thus I am assuming that \( u_i \)’s had exponential distribution. So, \( u_i \) is independent and identically distributed (i.i.d.) \( |N(\mu, \sigma_u^2)| \) and the \( v_i \) term is i.i.d as a random variable (i.e. \( v_i \sim N(0, \sigma_v^2) \)).

As proposed by Battese and Coelli (1988), the input-oriented technical efficiency (TE) scores can then be predicted using the conditional expectation predictor:

\[
TE_i = E[(\exp(-u_i)|\varepsilon_i)]
\]

(15)

where, \( \varepsilon_i = v_i - u_i \)

### 5.6 Technical Efficiency over provinces, subsectors and across time

Knowing the determinants of technical efficiency for a given firm or industry is essential. Since, if we know them, then we can implement policies that could reduce the factors inducing inefficiency and thus we could improve the efficiency levels. The technical efficiency (TE) levels rely on a host of factors, e.g. the physical and human capital, technical expertise, experience in the industry, market structure and the level of competition. In a similar vein, there are a bunch of external factors as well, such as changes in government and industrial policies. On top of that, there are firm-level characteristics also; ownership structure, the age of the firm
and firm size (Pitt and Lee, 1981). It is also a commonly accepted fact that the foreign firms tend to be more efficient than private domestic firms, as this higher efficiency level is based on the greater experience and organisational structure; however, sometimes the foreign firms could be less efficient since they are operating under unfamiliar circumstances.

It is also documented that, the older firms, in general, are more efficient because they had reached their learning curve earlier, but in hindsight, the older firms could be less flexible to use new technology because of the higher replacement cost of established capital. Firm size is also a significant factor which may affect the level of technical efficiency, as larger firms are better organised and have the more technical expertise and on the other hand, it can also be very tedious to manage larger firms. One another important determinant of technical efficiency could be the geographical location, as in general it is associated with the availability of inputs and technology, transportation cost and the proximity to markets. At last, the nature of the labour by skilled and unskilled labour also impacts the technical efficiency (Pavcnik, 2002; Aggrey, Eliab and Joseph, 2010). So, in order to further explore the possibility of TE heterogeneity and considering data limitations, I explored whether technical efficiencies vary with respect to sub-sector, provinces/states or across time.

5.7 Link between technical efficiency and the elasticity of substitution

Furthermore, the association between technical efficiency and the elasticity of substitution can be captured through an auxiliary regression equation. The direction of the relationship between technical efficiency (TE) and elasticity of substitution could go in either direction, (i.e. technical efficiency may depend on the elasticity of substitution or vice versa). However, as per Arrow, Chenery, Minhas and Solow (1961) and the Sato (1977) paper, where
they studied the Constant elasticity of substitution (CES) production function (using two inputs capital and labour). They stated that elasticity of substitution (As per Arrow et al. (1961) elasticity of substitution is less than unity, whereas Sato (1977) suggests it to be higher than unity, respectively). Both these studies suggest that elasticities of substitution have a bearing on the labour efficiency scores across countries.

In the recent past, Christopoulos and Tsionas (2002), Burki and Khan (2004), and Khiabani and Hasani (2010), using the translog cost function, studied the link between cost efficiency on the elasticity of factor substitution in Greek, Pakistani and Iranian manufacturing industry, respectively. Christopoulos and Tsionas (2002), Burki and Khan (2004), and Khiabani and Hasani (2010) primarily focused on allocative efficiency and its link to energy substitution. However, as I do not have information on the input and output prices, thus I have limited my discussion to the impact of technical efficiency on the factor substitution.

Based on Arrow, Chenery, Minhas and Solow (1961) and Sato (1977), I am assuming technical efficiency as the dependent variable, as the rising input costs might drive changes in the elasticity of substitution between the factors of production, which might, in turn, impact the technical efficiency. Hence the direction of the causation between the two and other associated factors can be shown through the following relationship:

\[ TE_i = \tau + \tau_1 EoS_i + \tau_2 f_i \]  

(16)

In equation (16), technical efficiency (TE) is a function of the factor substitution \((EoS_i)\), and \(\tau\) is the intercept, and the error term is given by \((f_i)\).
I need to recognise that an econometric issue in the estimation of the translog production function parameters and technical efficiency is the likelihood that some drivers of production are only observed by the firm and not by the econometrician. The firm’s (subsector’s in our case) input allocation is decided by its optimising behaviour where input choices may be correlated with these observed components. Thus, in the estimation of production functions, there could be a correlation between unobservable productivity shocks and input levels. For illustration, the profit-maximising firms respond to positive productivity shocks by increasing output, which requires additional inputs. Similarly, negative productivity shocks lead firms to cut output and thereby decreasing their input usage.

Usually, stochastic production frontier models presume that input choices are independent of the efficiency and productivity term. However, if a firm observes some part of its efficiency and productivity, its input choices may be influenced, thus resulting in an endogeneity problem in the estimation. The issues surrounding endogeneity in production function estimation are well documented in the literature, including Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2006). Olley and Pakes (1996) addressed endogeneity by taking investment to control for the unobserved productivity shocks. However, since most of the developing economies had issues with “zero investment” truncation problem as the firms did not have much investment in the manufacturing industries. Thus, Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2006) used intermediate input as proxies for the unobserved productivity shock instead of investment to avoid truncating all the zero investment firms, and these approaches responded more smoothly to the productivity shocks.

Shee and Stefanou (2014) argue that endogeneity corrected stochastic production frontier leads to a consistent estimate of the production parameters as well as a higher estimation of
technical efficiency in the Colombian food manufacturing industry. However, I have data limitations in my case, as for using this endogeneity corrected stochastic production frontier model one needs to have a firm/plant level and sufficiently long panel data. Since my data does not match these specifications, hence I need to acknowledge the endogeneity bias in my analysis.

**Summary**

This chapter has provided an overview of the empirical theory underpinning the measurement of technical efficiency and the elasticity of substitution. It began with the concept of a stochastic production frontier. Then I moved through and justified the use of a translog form of production function under the stochastic frontier analysis (SFA).

Further, I explored the use the translog production function to get to the elasticity of factor substitution in a multi-input setting and also justified using the measure of Hicks elasticity of complementary (HEC) and Morishima elasticity of complementary (MEC) for it. Then I showed as to how to estimate the technical efficiency (TE) and also suggested the various drivers of technical efficiency. Lastly, I suggested for the auxiliary regression relationship between the technical efficiency and the elasticity of factor substitution to draw the direction of causality. This chapter concludes the empirical framework.
Chapter 6- Data

I use annual data from Statistics Canada over the period 1990 and 2013 at the provincial level. The data are sourced from the Annual Survey of Manufactures and Logging (ASML) and the Fixed Capital Flows and Stocks program. The ASML is an annual survey program and covers detailed industrial statistics for the Canadian manufacturing and logging industries. The Fixed Capital Flows and Stocks program comprises information for all businesses and provides annual estimates of fixed capital stock information. For this study, one aggregate output (manufacturing value-added) and four aggregate inputs (capital, labour, energy, and materials) are defined for our empirical model for Canadian data.

The data for the US food manufacturing industry for the duration 2005-2011 is retrieved from the United States Census Bureau for one aggregate output (manufacturing value-added) and three aggregate inputs (capital, labour, and materials). The US data had all the variables similar to the Canadian data, but it did not have any values for the energy cost.

Thus, the US model is limited to $Y = K, L, M$, whereas the Canadian model is based on $Y= K, L, E, M$.

The objective of including the US data is solely for comparison purposes between the Canadian and US food manufacturing sectors, in order to draw a precise conclusion for better policy framing. Though I acknowledge the difference in both datasets as Canadian data has values for energy costs which the US data does not have. Also, the US data have the capital values at NAICS-4 level, whereas the Canadian data has capital values only for four major
provinces at NAICS-3 level. Thus, I cannot draw conclusions based on comparisons between these two-separate analyses.

6.1 Manufacturing Value-added

Manufacturing output can be classified into gross revenue and value-added. As per OECD (2001), productivity measurement at an industry level should be based on value-added. Manufacturing value-added is given at NAICS-4 level and is obtained from CANSIM table: 16-10-0054-01 (formerly CANSIM 301-0003) for years 1990-2003, CANSIM table: 16-10-0038-01 (formerly CANSIM 301-0006) for years 2004-2012, and CANSIM table: 16-10-0117-01 (formerly CANSIM 301-0008) for the year 2013. It is defined as the value of revenue from goods manufactured, taking into account the net change in goods-in-process and finished product inventories, minus the cost of materials and supplies, and the total cost of purchased energy, the water utility and vehicle fuel, and the amount paid for custom work.

6.2 Energy

In the similar vein, the nominal energy costs (in CAN$ ’000) were given at NAICS-4 level and obtained from CANSIM table: 16-10-0054-01 (formerly CANSIM 301-0003) for years 1990-2003, CANSIM table: 16-10-0038-01 (formerly CANSIM 301-0006) for years 2004-2012, and CANSIM table: 16-10-0117-01 (formerly CANSIM 301-0008) for the year 2013. Energy expenses include the cost of energy purchase (electricity, gasoline, fuel oil, and coal), water utilities expenses, and vehicle fuel.
6.3 Labour

I have used the sum of total salaries and wages for both direct and indirect labour to get the labour cost (in CAN$ '000). Again, the total salaries and wages were given at NAICS-4 level obtained from CANSIM table: 16-10-0054-01 (formerly CANSIM 301-0003) for years 1990-2003, CANSIM table: 16-10-0038-01 (formerly CANSIM 301-0006) for years 2004-2012, and CANSIM table: 16-10-0117-01 (formerly CANSIM 301-0008) for the year 2013. The OECD (2008) suggests using the labour price index to deflate nominal labour cost.

6.4 Materials

Similar to other inputs and output, the materials and supplies cost (in CAN$ '000) was stated at NAICS-4 level and obtained from CANSIM table: 16-10-0054-01 (formerly CANSIM 301-0003) for years 1990-2003, CANSIM table: 16-10-0038-01 (formerly CANSIM 301-0006) for years 2004-2012, and CANSIM table: 16-10-0117-01 (formerly CANSIM 301-0008) for the year 2013. It includes the cost of materials, and supplies used in manufacturing and related operations, the purchase of shipping and packaging material, and repair and maintenance.

6.5 Capital

Fixed Capital Flows and Stocks program provides information for the capital stock (in CAN$ 1000,000) by the North American Industry classification system (NAICS - 3 level). CANSIM table: 36-10-0236-01 (formerly CANSIM 031-0002) includes fixed non-residential capital stock in the food processing industry from 1990-2013. The non-residential capital stock comprises of information for four major asset groups, including; building construction,
engineering construction, machinery, and equipment and intellectual property products. The non-residential capital stock is only available at the national level and for just four major provinces (i.e. Ontario, British Columbia, Quebec, and Alberta) and at NAICS-3 level.

Thus, to generate capital stock for each province, I have followed Baldwin et al. (2013). Baldwin et al. (2013) suggest for the proportionality between the energy cost to capital stock. I allocate the national aggregate capital stock in the food manufacturing industry to each province basis their share of the total energy cost. Where each province’s share of total energy cost is calculated by using each province’s energy cost divide by national energy cost.

6.6 Deflator Index for the Canadian data

The deflator indexes (quantity index for gross output used for deflating manufacturing value-added, labour index for deflating labour input, the material index for deflating material input, energy index for deflating energy input, and capital index for deflating capital input) is used for converting the nominal data into the real value. These indexes are retrieved from Statistics Canada, and these indexes have a base value of 100 for the year 2012. The deflators were retrieved by personal communication with the staff of Statistics Canada.

6.7 US Data

The state-wise data for the food manufacturing industry in the USA was obtained from the United States Census Bureau. The data is available for the years between 2005 - 2011, and all the variables in the data were available at NAICS- 4 levels.
The variable annual payrolls (in USD$ ’000) is used for the labour costs. Total costs of materials (in USD$ ’000) is used for the material costs. Total capital expenditures (in USD$ ’000) used to retrieve capital costs. Lastly, value-added (in USD$ ’000) was used to retrieve the output in the form of manufacturing value-added.

6.8 Deflator index for the US data

The US data variables were converted from nominal to real terms with the use of the GDP deflator index, which was retrieved from the economic data of the Federal Reserve Bank of St. Louis.

Summary

As there are differences within the economic structures of food processing industries across provinces/states and heterogeneity in technology across food processing subsectors (NAICS-4 level). Given this, I estimate efficiency and elasticity of substitution at a subsector and provincial levels. To illustrate the point, Atlantic provinces lead the seafood production preparation and packaging industry, whereas the Prairie provinces dominate the meat processing and grain milling industry.
Chapter 7- Results Discussion (Canadian food manufacturing industry)

This chapter summarises the empirical results for the Canadian macro-level data for the years 1990-2013. The results discussed in this chapter are based on the data analysis conducted following the theoretical and empirical model illustrated in the earlier chapters. The structure of this chapter is as follows; first, summary statistics for the variables used in the analysis are explained. Second, the stochastic production frontier model is estimated for both the Cobb-Douglas and the translog forms. Third, based on the translog production frontier model, the first objective of the research “to explore the technical efficiency across the province, sub-sector and period” is served. Fourth, based on the same primal translog production frontier, the Hicks and Morishima elasticities of complementarities are calculated for the second research objective. In order to satiate the last objective, we explore the regression relationship between the technical efficiency and the elasticities of complementarities.

7.1. Descriptive statistics of the variables used for the analysis

Table 7.1: Descriptive statistics of variables used in the analysis

<table>
<thead>
<tr>
<th>Statistics</th>
<th>ln_mva</th>
<th>ln_labour</th>
<th>ln_material</th>
<th>ln_energy</th>
<th>ln_capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>12.1517</td>
<td>11.1254</td>
<td>12.8595</td>
<td>9.4853</td>
<td>13.8749</td>
</tr>
<tr>
<td>N</td>
<td>1122</td>
<td>1124</td>
<td>1114</td>
<td>1116</td>
<td>1116</td>
</tr>
<tr>
<td>Min</td>
<td>5.8005</td>
<td>4.7448</td>
<td>6.2039</td>
<td>3.2332</td>
<td>7.514</td>
</tr>
</tbody>
</table>
Table 7.1 shows the summary statistics for inputs and outputs used in the study. The Canadian data span from 1990-2013, and it comprises of four inputs (i.e., labour, capital, energy, and material). The only aggregate output is manufacturing value-added.

### 7.2 Production Function Estimation

Table 7.2 presents estimates of the coefficients of the Cobb-Douglas and translog production functions. The translog stochastic production frontier is estimated with symmetry imposed. For comparison purpose, I also estimated the Cobb-Douglas stochastic production frontier. *SFCROSS* command in STATA 15.1 software is used to run the stochastic production frontier. I check monotonicity and concavity of the production at each data point. Monotonicity in inputs is satisfied if the marginal products are positive. For the translog form using the marginal product (Pavelescu, 2011), I found that monotonicity is violated for 55.82% capital observations, 40.83% labour observations, 16.66% energy observations, and 32.67% material observations. For Cobb-Douglas, monotonicity is violated for capital input as the coefficient of capital is negative. I check the concavity of the production frontier at each data point using the bordered Hessian matrix, as for concavity to hold the bordered Hessian matrix of the first and second-order partial derivatives of the translog production function need to be negative definite. Concavity is violated for 86.81% of the observations.
Table 7.2: MLE estimates of the Cobb-Douglas and Translog production function

<table>
<thead>
<tr>
<th></th>
<th>Cobb-Douglas</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln_mva</td>
<td></td>
<td>ln_mva</td>
</tr>
<tr>
<td>log(m)</td>
<td>0.307***</td>
<td>0.301***</td>
</tr>
<tr>
<td></td>
<td>(7.7)</td>
<td>(7.28)</td>
</tr>
<tr>
<td>log(l)</td>
<td>0.434***</td>
<td>0.284***</td>
</tr>
<tr>
<td></td>
<td>(6.03)</td>
<td>(4.4)</td>
</tr>
<tr>
<td>log(e)</td>
<td>0.363***</td>
<td>0.525***</td>
</tr>
<tr>
<td></td>
<td>(6.29)</td>
<td>(6.79)</td>
</tr>
<tr>
<td>log(k)</td>
<td>-0.131 ***</td>
<td>-0.153 **</td>
</tr>
<tr>
<td></td>
<td>(-3.75)</td>
<td>(-2.15)</td>
</tr>
<tr>
<td>0.5 * lnk * lnl</td>
<td></td>
<td>0.704***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.07)</td>
</tr>
<tr>
<td>0.5 * lnk * lne</td>
<td></td>
<td>-0.0239</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.13)</td>
</tr>
<tr>
<td>0.5 * lnk * lnm</td>
<td></td>
<td>-0.418 ***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-2.61)</td>
</tr>
<tr>
<td>0.5 * lnl * lne</td>
<td></td>
<td>0.353</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.6)</td>
</tr>
<tr>
<td>0.5 * lnl * lnm</td>
<td></td>
<td>0.352***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.71)</td>
</tr>
<tr>
<td>0.5 * lne * lnm</td>
<td></td>
<td>-0.0371</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.20)</td>
</tr>
<tr>
<td>time trend</td>
<td>0.000642</td>
<td>-0.0000835</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(-0.02)</td>
</tr>
<tr>
<td>0.5 * _t * lnk</td>
<td></td>
<td>-0.0497***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-4.46)</td>
</tr>
<tr>
<td>0.5 * _t * lnl</td>
<td></td>
<td>0.0391***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.9)</td>
</tr>
<tr>
<td>0.5 * _t * lne</td>
<td></td>
<td>0.0287*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.77)</td>
</tr>
<tr>
<td>0.5 * _t * lnm</td>
<td></td>
<td>-0.0260 **</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-2.31)</td>
</tr>
<tr>
<td>0.5* _t_square</td>
<td>0.0173</td>
<td>0.0157***</td>
</tr>
<tr>
<td></td>
<td>(1.69)</td>
<td>(1.99)</td>
</tr>
<tr>
<td>0.5 * lnk_square</td>
<td></td>
<td>-0.123 *</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.90)</td>
</tr>
<tr>
<td>0.5 * lnl_square</td>
<td></td>
<td>-0.788 ***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-9.21)</td>
</tr>
<tr>
<td>0.5 * lne_square</td>
<td></td>
<td>-0.0692</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.40)</td>
</tr>
</tbody>
</table>
Table 7.2 presents the parameter estimates of the Cobb-Douglas and the translog stochastic production frontier. Most of the parameters are statistically significant at 99% confidence levels. The estimated Cobb-Douglas and translog parameters for the capital input are unexpected as it is negative, which fails common reasoning as one would think that a unit increase in the capital input usage ought to positively impact the output levels. Considerable violations to the concavity along with the fact that the capital input is just available for four provinces, it can explain this odd outcome. The coefficients of most other factors of production are statistically significant at 99% confidence levels and have positive coefficients for both the Cobb-Douglas and translog production function estimates. It means that most of the independent variables in both regression models positively affect the output.

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5 * ln_square</td>
<td></td>
<td>0.0295</td>
<td></td>
<td>(0.33)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.815***</td>
<td>(6.46)</td>
<td>11.97***</td>
<td>(24.11)</td>
</tr>
<tr>
<td>Usigma</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-3.024***</td>
<td>(-21.96)</td>
<td>-3.881 ***</td>
<td>(-9.17)</td>
</tr>
<tr>
<td>Vsigma</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.965***</td>
<td>(-14.65)</td>
<td>-2.857 ***</td>
<td>(-14.73)</td>
</tr>
<tr>
<td>Observations</td>
<td>1102</td>
<td>1102</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

t statistics in parentheses

*p < 0.10, **p < 0.05, ***p < 0.01

Source: Author’s calculations
7.3 Technical Efficiency Dispersion

Table 7.3 compares the technical efficiency measures for both the Cobb-Douglas form and the translog form. The value of technical efficiency is higher for the translog specification than for Cobb-Douglas form.

As per table 7.3 and figure 7.2, the translog model’s technical efficiency is 87.48%, whereas the technical efficiency from the Cobb-Douglas form is 82.19%. Thus, there a difference of about 5.5%. Therefore, I can interpret that there is still scope to increase the technical efficiency by 12.5% using the same level of resources for the translog model by removing inefficiencies.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>bc_cb</td>
<td>1,102</td>
<td>0.8219</td>
<td>0.1155</td>
<td>0.2153</td>
<td>0.979</td>
</tr>
<tr>
<td>bc_tl</td>
<td>1,102</td>
<td>0.8748</td>
<td>0.0653</td>
<td>0.3605</td>
<td>0.9762</td>
</tr>
</tbody>
</table>

Source: Author’s calculations

The correlation coefficient between the two technical efficiency measures, i.e., TE Cobb-Douglas and TE translog is 81.85%, which means that both TE results are strongly correlated in a positive manner. The strong positive correlation between the technical efficiency measures through Cobb-Douglas and translog production frontier model find favours with previous literature, which includes Ahmed and Bravo-Ureta (1996) and Shao and Lin (2001). I have shown the boxplot in figure 7.1 for better illustration of the comparison between technical efficiency estimates through Cobb-Douglas and translog estimates.
The difference between these two measures of technical efficiency is that the translog is a richer specification which includes more effects (double terms and cross terms) whereas a Cobb-Douglas is a much simpler specification. I can also see that there is a considerable range in the technical efficiency for both Cobb-Douglas and translog production frontiers. The range of the technical efficiency measure is a crucial statistic as it can help us gauge the extent to which, there is variation in the technical efficiency across the provinces, sub-sectors, and over time.

Figure 7.1: Boxplot for technical efficiency estimates of Cobb-Douglas and Translog form

Source: Author’s calculations
7.4 Technical Efficiency over provinces, subsectors and time

From figure 7.3, I can deduce that the mean technical efficiency level is 87.49%. There is only a slight variation in the technical efficiency between various Canadian provinces as all the provinces have TE levels in and around 85%, starting from the technical efficiency in Manitoba (84.51%) and finishing at the technical efficiency in Ontario (88.76%). Other significant provinces in the Canadian food manufacturing industry like Alberta and British Columbia have technical efficiency levels at 87.02% and 86.58%, respectively.
Thus, results indicate that the provincial effect is not much relevant to the technical efficiency of the food manufacturing industry. It should also be noted that Ontario, Quebec, Alberta and British Columbia are the only four provinces that constitute the data for the capital values, as the capital values are only available for these provinces. As I have distributed the capital stock (i.e., the capital values for these four provinces) based on the energy capital proportionality for the all the Canadian provinces (Baldwin et al. 2013), hence I must be cautious while interpreting these results as other provinces are not reflected adequately.

Based on the results, I think that major market concentration in these four provinces play an essential role as a determinant of technical efficiency as these four provinces are the focal point of most of the national economic activity. This region follows the “theory of industrial
clustering or agglomeration” (Krugman 1991) and offers better infrastructure, better local information, better services, labour pool, broader markets, and lower transport costs, which leads to higher levels of competition and therefore may lead to higher technical efficiency levels.

Figure 7.4 showcases the technical efficiency of the various food manufacturing sub-sectors in the form of NAICS-code for the Canadian industry. In order to throw more light on the NAICS classification system, the next table 7.4 discusses the NAICS nomenclature on which the NAICS code for various food processing sub-sectors is based upon. The objective of introducing table 7.4 is to give readers an insight as to which specific sub-sector, a particular NAICS-code denotes.

Source: Author’s calculations
Based on figure 7.4, the technical efficiency for various NAICS-4 level subsectors of the food manufacturing industry do not show much difference as these values are clustered around 86-87%, starting with subsectors 3112 (Grain and Oilseed milling) and 3114 (Fruit and Vegetable preserving and specialty food manufacturing) having mean technical efficiency levels of 85.61% and 85.91% respectively. The TE dispersion ends at sub-sectors 3117 (Seafood product preparation and packaging), 3118 (Bakeries and Tortilla manufacturing) as well as 3111
(Animal food manufacturing) having mean technical efficiency levels at 88.35%, 88.15%, and 88.10%, respectively.

Thus, based on the results, I can say that there are little differences in relative technical efficiency across food manufacturing subsectors. As different food processing sub-sectors have different production technologies from each other and hence explains for the slight heterogeneity between the technical efficiency estimates across subsectors.

![Technical efficiency across time](image)

**Figure 7.5: Technical efficiency over time**

**Source: Author’s calculations**

Figure 7.5 provides technical efficiency over time. I can deduce that the mean technical efficiency throughout the study period has been around 87.49% and having mean technical efficiency levels of 87.82% in the year 1990 to a minor decline in the mean technical efficiency to 86.54% in the year 2013. Though over these 23 years technical efficiency has been fluctuating but more or less stayed near the mean technical efficiency showing the little variation over time.
We must also recognise that provinces, sub-sector, and time-period across analysis do not have the same count of observations, as some of the provinces, sub-sectors and time-period have more observations than others; thus we should be cautious of this fact before drawing provincial, sub-sectoral, and temporal policy conclusion from these TE results.

7.5 Technical Efficiency comparison with prevailing literature

The TE findings in this thesis are different from earlier studies in terms of the dispersion of the technical efficiency in the Canadian context. Hamit-Haggar (2009) stated that there had been a decrease in the technical efficiency of the food, beverage and tobacco industry of the Canadian food manufacturing sector over the period 1990-2005. As in the year 2005, the average technical efficiency of the industry was 92.1% (Hamit-Haggar 2009). Zili (2015) and Piedrahita (2016), suggested that the Canadian food processing industry operates at full technical efficiency, but there was some variation in technical efficiency scores between various sub-sectors of the industry. However, as these earlier pieces of evidence followed a different methodology as well as estimation approach to mine, I cannot draw comparisons in exact terms to their findings.

Other notable pieces of evidence in the global food processing sector include; Coelli et al. (2003), who showed that the Indian dairy processing firms had average technical efficiency scores in the range of 76.90% to 89.70%. Aedo et al. (2011) found evidence of increasing average technical efficiency levels in the Chilean food processing firms from 83% to 86% over the study duration. Rodamanee and Huang (2013) showed that Thai food processing firms had average technical efficiency scores in the range of 31.38% to 93.15%. Ndicu (2015) findings showed that the Kenyan agro-processing industry had an overall technical efficiency score of
44%. Kapya (2016) suggested that the average technical efficiency of Zambia’s agro-processing sector was 42.5%. Rezitis and Kalantzi (2016) suggested the average technical efficiency for the Greek food manufacturing industry at 97.8%.

I must be cautious in drawing comparison of my results with the other studies in the global context as technical efficiency is a relative concept in which the best performing firms in the industry (of the given country) are benchmarks against other firms in that industry. Thus, these benchmarks are also different in each industry and country as well as across time. Nevertheless, we can compare the dispersion of the TE results, if the technical efficiency for the industry is closer to 100%, then we can say that there is less dispersion in the technical efficiency for that given industry as the firms are closer to each other in terms of their TE levels and are approaching full technical efficiency. Based on the results in this study, the mean technical efficiency for the Canadian food manufacturing industry has been around 87.50%; thus, for example, I can say that the relative dispersion of my TE results is much higher in comparison to Hamit-Haagar (2009), Zili (2015) and Piedrahita (2016).

7.6 Inverse Elasticities and Elasticities of Complementarity estimates

The next table 7.5 presents the mean estimates of inverse own and cross-price elasticities. The primary approach is to evaluate these elasticities at each observation and then to take the mean of the sample. The inverse elasticities and elasticities of complementarity are reported only at the mean of sample for better illustration and not at each province, subsector and across time.

In terms of inverse own-price elasticities, I find that the capital, labour, energy and material inputs are responsive to changes in their prices. As the inverse own-price elasticities
are expected to be negative. However, the inverse own-price elasticity for material input is an anomaly as it has a smaller magnitude and an unexpected sign. The considerable violations to the concavity condition can explain this peculiar phenomenon. As per the results, labour input is the most responsive to changes in its own prices with a value of -5.50, which means that if the quantity for labour increases by 1% then prices for labour decreases by 5.50%. Whereas as per the analysis, material input is the least responsive input with a value of 0.01, which means that if the material quantity increases by 1% then the price for material increases by 0.01%.

Table 7.5: Inverse own and cross-price elasticities

<table>
<thead>
<tr>
<th>Quantity changed across y-axis and resulting price change across the x-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Energy (e)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>-1.4432</td>
<td>-0.9284</td>
<td>-1.5528</td>
<td>-7.7076</td>
</tr>
<tr>
<td>Labour (l)</td>
<td>-8.6246</td>
<td>-5.5063</td>
<td>-7.7673</td>
<td>-2.9816</td>
</tr>
<tr>
<td>Energy (e)</td>
<td>-1.6857</td>
<td>-1.4013</td>
<td>-2.5485</td>
<td>-2.2498</td>
</tr>
<tr>
<td>Material (m)</td>
<td>0.8515</td>
<td>0.8949</td>
<td>0.5518</td>
<td>0.0128</td>
</tr>
</tbody>
</table>

Source: Author’s calculations

Table 7.5 also presents the cross-inverse price elasticities. A positive inverse cross-price elasticity means that the two inputs are substitutes and a negative inverse cross-price elasticity means that the two inputs are complementary. Based on the results in table 7.5, the strong complementarity is shown by the following pairs; capital and labour (-8.62), material and capital (-7.70), energy and labour (-7.76), and material and labour (-2.98). Substitutability is shown by
the following pairs; labour and material (0.89), capital and material (0.85), and energy and material (0.55). For a better illustration, the inverse cross-price elasticity of -8.62 for the capital and labour relationship means that a 1% increase in the quantity of labour leads to 8.62% decrease in price for capital. Similarly, the cross-price elasticity of 0.89 between labour and material suggests that the 1% increase in the quantity of material leads to 0.89% hike in price for labour input.

However, I need to take caution while interpreting these results, as inverse cross-price elasticities are limited to two factors of production. It measures as to how much change in one input quantity leads to an adjustment in another input’s price, but it does not consider the adjustment that can be done in other factors of production in a multi-input setting. For that scenario, I use the Hicks elasticity of complementarity as well as the Morishima elasticity of complementarity.

Table 7.6: Hicks elasticity of complementarity

<table>
<thead>
<tr>
<th>Quantity changed across the x-axis and resulting price change across the y-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Energy (e)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>-287.3018</td>
<td>-80.1379</td>
<td>2.2569</td>
<td>43.3604</td>
</tr>
<tr>
<td>Labour (l)</td>
<td>-1970.3367</td>
<td>2.3121</td>
<td>50.4884</td>
<td></td>
</tr>
<tr>
<td>Energy (e)</td>
<td></td>
<td>-374.7024</td>
<td>9.2944</td>
<td></td>
</tr>
<tr>
<td>Material (m)</td>
<td></td>
<td></td>
<td></td>
<td>18857.5130</td>
</tr>
</tbody>
</table>

Source: Author’s calculations
The Hicks elasticities of complementarity are calculated directly from the parameter estimation of the translog production function. Table 7.6 presents the Hicks elasticity of complementarity (HEC). Hicks elasticity of complementarity (HEC) and Morishima elasticity of complementarity (MEC) follow the q nomenclature (q for quantity) for the elasticity of complementarity as we do not have the information on prices in this primal model using the production function. Thus inputs are deemed as q-substitutes if the value is less than 0 or otherwise deemed as q-complements if the value is more than 0 (Stern, 2008).

Kim (2000) defines that two inputs are HEC q-complements “if an increase in quantity of one input increases the marginal product of other input”, the highest level of substitutability is shown by the input pair of labour and labour, which have a mean value of -1970, which means that the unit per cent rise in the demand of the labour input leads to decrease in the price of the labour input by 1970 per cent. Whereas the relationship showing the largest complementary is between the material and material input as they have a value of 18857. It shows that the unit per cent increase in the demand for material leads to an increase in the material input price by 18857 per cent. Following the similar analogy, from table 7.6, it is clear that the HEC relationships document both the substitution as well as the complementary relationship between factors of production in a multi-input setting. However, the Morishima elasticities of complementarity (MEC) is a better measure than the Hicks elasticity of complementarity (HEC) as it allows for both the implicit own price as well as the cross-price effect (Kim, 2000).

Table 7.7 presents the Morishima elasticity of complementarity (MEC). Following Kim (2000) interpretation of Morishima elasticity of complementarity that “it measures the responsiveness of the prices of inputs $i$ and $j$ to a change in the quantity of the $j$th input”. The MEC relationship between the capital and labour is -129, which means that if there is a unit per
cent rise in the input demand of labour then the price of capital to labour ratio decreases by 129 per cent. It suggests a very strong substitution. MEC relationship between capital and material is 90, which means that if there is unit per cent rise in the input demand of material, then the price of capital to material ratio increases by 90 per cent. It suggests a strong complementarity. I can follow this analogy and interpret all other MEC coefficients.

### Table 7.7: Morishima elasticity of complementarity

<table>
<thead>
<tr>
<th>Quantity changed across the x-axis and resulting change in ratio price across the y-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Energy (e)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>-129.2837</td>
<td>11.8108</td>
<td>90.2739</td>
<td></td>
</tr>
<tr>
<td>Labour (l)</td>
<td></td>
<td>-2.8123</td>
<td></td>
<td>13.6227</td>
</tr>
<tr>
<td>Energy (e)</td>
<td></td>
<td></td>
<td></td>
<td>23.2521</td>
</tr>
<tr>
<td>Material (m)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s calculations

#### 7.7 Elasticities of Complementarity comparison with prevailing literature

To draw comparisons, I have focused only on the food manufacturing industry. Thus, I have a narrow body of literature to compare our results from, which comprises of Ball and Chambers (1982), who stated that most of the factors of production (capital, labour, energy, materials and structures) are substitute with each other in the US meat products industry. Lopez (1984) studied the Canadian food processing industry and found a mixed result for the factor
substitution suggesting both complementarity and substitutability between the factors of production (labour, energy, intermediate goods, and capital goods). Huang (1991) focusing on US food manufacturing industry, found that the production factors (capital, labour, and energy) are substitutable, especially capital and labour.

Goodwin and Brester (1995) studying the US food manufacturing sector, state that nearly all the factors (labour, capital, food materials, energy and other inputs) are substitutes for one another. Nguyen and Streitweiser (1999) studied the factor substitution for the US manufacturing industry and suggested that all the factors of production (capital, labour, energy and material) are a substitute for each other. Alarcon (2005) studied the input substitution in the Spanish food industry and found that there is substitutability between labour and capital and complementarity between labour and material. Hailu et al. (2010) studied the substitutability between sweeteners in the U.S. food processing sector and suggests that material input is substitutable with capital, labour, and energy, while capital and energy are substitutes.

Thus, in short, the results from Ball and Chambers (1982), Huang (1991), Goodwin and Brester (1995), Nguyen and Streitweiser (1999), Alarcon (2005) and Hailu et al. (2010) suggest that capital, labour and energy are substitutes. All these previous studies have stated the elasticities of substitution using the dual approach as opposed to the elasticities of complementarity in our case using the primal approach. So, I must be cautious of comparing these results to ours as these studies follow different estimation approaches, non-similar data variables, varying temporal, as well as geopolitical contexts.

To summarize results of the elasticities of complementarities (HEC as well as MEC), we can say that; as per the technical relationship between the capital and labour inputs are substitute,
which is also evident from Ball and Chambers (1982), Andrikopoulous et al. (1989), Huang (1991), Goodwin and Brester (1995), Nguyen and Streitweiser (1999), Alarcon (2005) and Hailu et al. (2010). The rest of the technical relationships between the factors of production have shown complementarity, with the prominent relationship between capital and energy also being complementarity as also evidenced in Hudson and Jorgenson (1974), Berndt and Wood (1975), Fuss (1975) and Andrikopoulous et al. (1989). Regarding capital formation, a widespread belief is that rising energy prices are an essential factor which might lead to the deceleration of the growth of net investment (Garofalo and Malhotra, 1985). This premise assumes that capital and energy are complementary inputs. Thus, based on this rationale, the rising energy prices in Canada might dis-incentivise capital formation in the food manufacturing industry. All the key relationships also have a similar sign in the HEC as well as MEC relationships, but except for labour and energy relationship which has a similar magnitude but the opposite sign for both HEC and MEC values.

7.8 Relationship between the Technical Efficiency and the Elasticity of Complementarity (HEC and MEC)

The regression relationship between technical efficiency and the elasticity of substitution is formulated. Based on Arrow, Chenery, Minhas and Solow (1961) and Sato (1977), I assume that technical efficiency is the dependent variable and elasticities of complementarity (HEC and MEC) are the independent variables, respectively.
Table 7.8: Relationship between TE and HEC

| Name of the independent variable | Dependent variable-Technical efficiency via E[exp(-u)|e] | t-values | R-squared |
|----------------------------------|----------------------------------------------------------|----------|-----------|
| s_kk                             | -0.0000000146                                           | (-0.61)  | 0.0626    |
| s_ll                             | 3.79e-08                                                 | (1.99)   | 0.0630    |
| s_ee                             | 0.000000201                                              | (0.49)   | 0.0629    |
| s_mm                             | 1.59e-09*                                                | (1.74)   | 0.0627    |
| s_kl                             | 0.000000760***                                           | (5.22)   | 0.0636    |
| s_ke                             | 0.0000511                                                | (0.89)   | 0.0631    |
| s_km                             | 0.00000053                                               | (1.41)   | 0.0627    |
| s_le                             | 0.0000192                                                | (1.19)   | 0.063     |
| s_lm                             | 0.000000499*                                             | (1.7)    | 0.0627    |
| s_em                             | 0.00000356                                               | (1.55)   | 0.0627    |

* p < 0.10, ** p < 0.05, *** p < 0.01

Source: Author’s calculations

Table 7.8 presents the regression relationship between the technical efficiency and the Hicks elasticity of complementarity (HEC). The relationship is very weak, as most of the
independent variables have infinitesimal values approaching 0. To illustrate the independent coefficients, the parameter the HEC capital and energy having a value of 0.00005, suggests that if there is a unit per cent rise in the value of HEC capital and energy, then technical efficiency increases by 0.00005 per cent. Similarly, I can interpret the other independent variable coefficients of the regression equation.

**Table 7.9: Relationship between TE and MEC**

| Name of the independent variable | Dependent variable - Technical efficiency via $E[\exp(-u)|e]$ | t-values | R-squared |
|----------------------------------|-------------------------------------------------------------|----------|-----------|
| MEC_kl                           | -0.000000359***                                            | (-3.53)  | 0.0631    |
| MEC_ke                           | 0.00000362***                                              | (3.43)   | 0.0632    |
| MEC_km                           | 0.00000566***                                              | (4.23)   | 0.0632    |
| MEC_le                           | -0.000000534                                               | (-0.12)  | 0.0625    |
| MEC_lm                           | 0.000000394                                                | (1.62)   | 0.0626    |
| MEC_em                           | 0.000000601**                                               | (2.54)   | 0.0628    |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Source: Author’s calculations**

Table 7.9 presents the regression relationship between technical efficiency and the Morishima elasticity of complementarity (MEC). The relationship is very weak, as the...
independent variables again have very small values approaching 0. To illustrate the independent coefficients in the equation, the parameter MEC capital and energy having a value of about 0.000003, suggests that if there is a unit per cent rise in the value of MEC capital and energy then the technical efficiency increases by 0.000003 per cent. Similarly, I can interpret all the other independent variable coefficient of the regression equation.

In general, this suggests that Hicks or Morishima elasticity of complementarity does not affect technical efficiency very much, which in turn means that ease to substitute between the factors of production does not lead to higher technical efficiency. It is worth noting that in both the above tables there are also positive as well as negative coefficients of the independent variables, but as I can see that the values of the coefficient approaches zero, that is why I am not paying much attention to the direction of these magnitudes.

The endogeneity might explain for this peculiar outcome, as suggested by Shee and Stefanou (2014) that endogeneity corrected stochastic frontier analysis yield consistent estimates of the parameters of the production function as well as higher estimates of the technical efficiency. However, as I do not have firm/plant level longer panel data, thus due to data limitations, I am unable to adopt this methodology. Therefore, I acknowledge the endogeneity bias in my analysis.

**Summary**

This chapter gives us the results of the data analysis focusing on the Canadian food manufacturing industry. The key takeaways of the analysis can be summarised as follows; the technical efficiency of the food manufacturing sector has been robust over the 23 years of the study as the mean technical efficiency of 87.50% have been achieved. There are some variations
in terms of the technical efficiency over provinces, subsectors and period. Secondly, the key outputs from the elasticity of complementarity analysis based on the translog production function indicate that the capital and labour technical relationship is a substitute in nature, whereas the other meaningful relationship between capital and energy suggests that both inputs are complements. These findings are robust as they have a similar direction (but not similar magnitude) in both Hicks elasticity of complementarity and the Morishima elasticity of complementarity.

Finally, the relationship between the technical efficiency (dependent variable) and elasticity of complementarity (independent variables) is also explored through a regression formulation, but the coefficient of the independent variable approaches zero, suggesting a weak relationship. Which, in turn, means that increasing the ease to substitute between the factors of production does not lead to higher technical efficiency.
Chapter 8- Results Discussion (US food manufacturing industry)

This chapter summarises empirical results for the US macro-level data for years 2005-2011. The results discussed are based on conducting data analysis similar to the Canadian results but for the US data. The structure of this chapter follows the previous chapter, and resultanty the three main research objectives are served. First, based on the translog production frontier model, the measure of technical efficiency across the province, sub-sector and period are calculated. Then, the Hicks and Morishima elasticities of complementarities are calculated. Lastly, the regression relationship between technical efficiency and the elasticities of complementarities is explored.

8.1 Descriptive statistics of the variables used for the analysis

Table 8.1 shows the summary of the data used for the analysis. The US data span from 2005-2011, and it comprises of three inputs (i.e., labour, capital, and material). The only aggregate output is manufacturing value-added.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>ln_mva</th>
<th>ln_labour</th>
<th>ln_material</th>
<th>ln_capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>13.73918</td>
<td>12.17551</td>
<td>14.01731</td>
<td>10.78176</td>
</tr>
<tr>
<td>N</td>
<td>2639</td>
<td>2639</td>
<td>2637</td>
<td>2639</td>
</tr>
<tr>
<td>Min</td>
<td>10.47892</td>
<td>9.837134</td>
<td>10.27577</td>
<td>7.027315</td>
</tr>
<tr>
<td>Max</td>
<td>17.16055</td>
<td>15.62975</td>
<td>17.58657</td>
<td>14.49421</td>
</tr>
</tbody>
</table>

Source: Author’s calculations
8.2 Production Function Estimation

Table 8.2 presents the estimate of the coefficients of the Cobb-Douglas and translog production functions. The translog stochastic production frontier is estimated with symmetry imposed. For comparison purpose, I also estimated the Cobb-Douglas stochastic production frontier. The Stata **SFCROSS** command in Stata 15.1 software is used to run the stochastic production frontier. I check monotonicity and concavity of the production at each data point. I found that monotonicity is violated for 11.82% capital observations, 0% labour observations, and 31.32% material observations. I check the concavity of the production frontier at each data point using the bordered Hessian matrix. Concavity is violated for 64.23% of the observations.

<table>
<thead>
<tr>
<th></th>
<th>Cobb-Douglas</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln_mva</td>
<td>ln_mva</td>
<td></td>
</tr>
<tr>
<td>ln_material</td>
<td>0.185***</td>
<td>0.196***</td>
</tr>
<tr>
<td></td>
<td>(9.01)</td>
<td>(9.11)</td>
</tr>
<tr>
<td>ln_labour</td>
<td>0.783***</td>
<td>0.728***</td>
</tr>
<tr>
<td></td>
<td>(30.65)</td>
<td>(24.82)</td>
</tr>
<tr>
<td>ln_capital</td>
<td>0.0654***</td>
<td>0.110***</td>
</tr>
<tr>
<td></td>
<td>(4.5)</td>
<td>(6.12)</td>
</tr>
<tr>
<td>0.5 * lnk * lnl</td>
<td></td>
<td>-0.116**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-2.13)</td>
</tr>
<tr>
<td>0.5 * lnk * lnm</td>
<td></td>
<td>0.0815**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.07)</td>
</tr>
<tr>
<td>0.5 * lnl * lnm</td>
<td></td>
<td>0.246***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.89)</td>
</tr>
<tr>
<td>0.5 * _t * lnk</td>
<td></td>
<td>-0.00398</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.32)</td>
</tr>
<tr>
<td>0.5 * _t * lnl</td>
<td></td>
<td>-0.0475***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.60)</td>
</tr>
</tbody>
</table>
Based on table 8.2, most of the estimated translog and Cobb-Douglas coefficients have the desired positive magnitudes and are significant at the 99 per cent confidence levels. In the Cobb-Douglas estimates, the most important input is the labour input as the coefficient 0.728 suggests that a unit increase in the labour input leads to 0.728 increase in the output (manufacturing value-added). Similarly, the least important input is the capital input having a
coefficient of 0.110, which suggest that a unit rise in the capital input leads to 0.110 increase in the output (manufacturing value-added).

8.3 Technical Efficiency Dispersion

Table 8.3 compares the technical efficiency measures for both the Cobb-Douglas form and the translog form.

As per Table 8.3 and figure 8.2, the translog model technical efficiency is 86.41%, whereas the technical efficiency of the Cobb-Douglas form is 86.66%. Thus, basis results, there is still scope to increase the technical efficiency to the extent of about 13.5% by using the same level of resources by removing inefficiencies for the translog model. The correlation coefficient between the two technical efficiency measures, i.e. TE Cobb-Douglas and TE translog is 99.11%, which means that both TE results are very strongly correlated positively, thus the results taken from any of the Cobb-Douglas or translog production frontier yield approximately similar technical efficiency readings. The strong positive correlation between the technical efficiency measures through Cobb-Douglas and translog production frontier model find favours with previous literature, which includes Ahmed and Bravo-Ureta (1996) and Shao and Lin (2001). I have shown the boxplot in figure 8.1 for better illustration of the comparison between technical efficiency estimates through Cobb-Douglas and translog estimates.

Table 8.3: Technical efficiency measures for Cobb-Douglas and Translog form

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>bc_cb</td>
<td>2,637</td>
<td>0.866672</td>
<td>0.070055</td>
<td>0.188845</td>
<td>0.966486</td>
</tr>
<tr>
<td>bc_tl</td>
<td>2,637</td>
<td>0.864195</td>
<td>0.07304</td>
<td>0.182423</td>
<td>0.966724</td>
</tr>
</tbody>
</table>

Source: Author's calculations
I can see that there is a considerable range in the technical efficiency for both Cobb-Douglas model (TE ranges from 18.88% to 96.64%) and for the translog model (TE ranges from 18.24% to 96.67%). The range of the technical efficiency is important as this statistic can help explain, if there is variation in the technical efficiency parameter across the states, sub-sectors, and over time.

Figure 8.1: Boxplot for technical efficiency estimates of Cobb-Douglas and Translog form

Source: Author’s calculations
8.4 Technical Efficiency over sub-sectors, states, and time

From figure 8.3, I can deduce that the mean technical efficiency level is 86.42%, and the technical efficiency range spans from 82.28% to 88.56%. The technical efficiency in terms of the various states is very close by; thus, there is a slight variance across states. The dispersion of the technical efficiency starts from Nebraska and Kansas having relative mean technical efficiency of 82.28% and 83.65%, respectively. Technical efficiency dispersion finishes off at the other end of the spectrum with Montana and Idaho having relative mean technical efficiency of 88.56% and 88.50%, respectively. Thus, results indicate that the state effect is not of much relevance to technical efficiency.

Figure 8.2: TE Kernel density for the Translog form

Source: Author’s calculations
Figure 8.3: Technical efficiency scores for states

Source: Author's calculations
Figure 8.4 shows the technical efficiency of the various food manufacturing sub-sectors in terms of NAICS code. The next table 8.4 discusses the NAICS nomenclature on which the NAICS code for various food processing sub-sectors is based upon.

**Table 8.4: NAICS Classification**

<table>
<thead>
<tr>
<th>NAICS-code</th>
<th>Name of the sub-sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>3111</td>
<td>Animal food manufacturing</td>
</tr>
<tr>
<td>3112</td>
<td>Grain and oilseed milling</td>
</tr>
<tr>
<td>3113</td>
<td>Sugar and confectionary product manufacturing</td>
</tr>
<tr>
<td>NAICS Code</td>
<td>Description</td>
</tr>
<tr>
<td>------------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td>3114</td>
<td>Fruit and vegetable preserving and specialty food manufacturing</td>
</tr>
<tr>
<td>3115</td>
<td>Dairy product manufacturing</td>
</tr>
<tr>
<td>3116</td>
<td>Animal slaughtering and processing</td>
</tr>
<tr>
<td>3117</td>
<td>Seafood product preparation and packaging</td>
</tr>
<tr>
<td>3118</td>
<td>Bakeries and tortilla manufacturing</td>
</tr>
<tr>
<td>3119</td>
<td>Other food manufacturing</td>
</tr>
</tbody>
</table>

Source: United States Census Bureau

As per figure 8.4, the technical efficiency for various NAICS-4 level subsectors shows little deviation, and the range starts with TE of 85% for sub-sector 3112 (Grain and Oilseed milling) and finishes at TE of 87.29% for sub-sector 3118 (Bakeries and Tortilla manufacturing). Thus, based on the results, there are slight differences in technical efficiency across food manufacturing subsectors. The main reason for these slight deviations is different production technologies used in different sub-sectors.

Figure 8.5 provides average technical efficiency over time. I can deduce that the mean technical efficiency throughout the study period has been 86.42% and having mean technical efficiency levels of 86.58% in the year 2005 to a minor decline in the mean technical efficiency to 86.46% in the year 2011. Thus, over these six years, technical efficiency has stayed near the mean technical efficiency showing the little variation over time. I need to acknowledge that the various states, sub-sectors and time-periods studied in the analysis are not having a similar count.
of observations, so we ought to exercise restraint before making policy claims from these TE results.

![Technical efficiency across time period](image)

**Figure 8.5: Technical efficiency scores across time**

*Source: Author’s calculations*

### 8.5 Technical Efficiency comparisons with prevailing literature

Results of the technical efficiency for U.S. data is different from earlier studies in terms of the dispersion of the technical efficiency. Hamit-Haggar (2009) studied the Canadian food manufacturing sector over the period 1990-2005 and stated that the average technical efficiency of the sector was 92.1% (Hamit-Haggar 2009). Zili (2015) and Piedrahita (2016), suggested that the Canadian food processing industry operates at full technical efficiency. However, as these shreds of evidence are limited to Canada in scope and followed a different methodology and estimation approach to mine, I cannot draw comparisons in exact terms to their findings.

Other notable pieces of evidence in the global food processing sector include Coelli et al. (2003), who studied the technical efficiency of Indian dairy processing firms and projected
the technical efficiency range of 76.90% to 89.70%. Aedo et al. (2011) projected the technical efficiency dispersion of 83% to 86% in the Chilean food processing firms. Rodamanee and Huang (2013) showed the technical efficiency range of 31.38% to 93.15% for the Thai food processing firms. Ndicu (2015) showed the TE score of 44% of Kenyan agro-processing industry. Kapya (2016) suggested the TE of 42.5% for Zambia’s agro-processing sector. Rezitis and Kalantzi (2016) showed TE at 97.8% for Greek food manufacturing.

I must be careful in drawing comparison of my results with the other studies as technical efficiency is a relative concept so the best possible comparisons can only be with the TE studies based on the same industry as well as in the same country during the identical period. Technical efficiency is the concept in which the best performing firm in each industry benchmarks against other firms in that industry and act as an industry leader. Thus, as these benchmarks are different in each industry and country as well as across time so we can not make worthwhile comparison with other studies in the global context. However, we can compare the dispersion of the TE results, which means if the industry TE is closer to 100%, then we can say that the industry is approaching full TE and there is less dispersion in the TE for that given industry as the firms are closer to each other in terms of their TE levels.

8.6 Inverse Elasticities and Elasticities of Complementarity estimates

The next table 8.5 present estimates of inverse own price elasticities. The approach to evaluating these elasticities is at each observation and then taking the mean of the sample. Thus, the elasticities are reported only at the mean of a sample and not at each province, subsector and across time.
In terms of inverse own-price elasticities, I find that capital, labour and material inputs are relatively inelastic to changes in their prices. The inverse own-price elasticities have the expected negative sign but a smaller magnitude. As per the results, capital is the most responsive to changes in its own prices with a value of -1. It means that if the quantity for capital increases by 1%, then the price for capital decreases by 1%. Whereas labour is the least responsive input with a value of – 0.7, which means that if the labour quantity increases by 1%, then the price for labour decreases by 0.7%. The inverse own-price elasticity of the material is also negative (-0.89), suggesting the similar direction of the relationship.

Table 8.5 also presents the cross-inverse price between the inputs. The most complementarity is shown by the following pairs; material and labour (-1.19), labour and material (-0.40), and capital and material (-0.25). Substitutability is shown by the only pair; material and capital (0.47). For a better illustration, the inverse cross-price elasticity of -1.19 for the material and labour relationship means that a 1% increase in the quantity of labour leads

### Table 8.5: Inverse own and cross-price elasticities

<table>
<thead>
<tr>
<th>Quantity changed across y-axis and resulting price change across the x-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>-1.01587</td>
<td>-0.07014</td>
<td>0.471464</td>
</tr>
<tr>
<td>Labour (l)</td>
<td>-0.12468</td>
<td>-0.74557</td>
<td>-1.19422</td>
</tr>
<tr>
<td>Material (m)</td>
<td>-0.24749</td>
<td>-0.40088</td>
<td>-0.8982</td>
</tr>
</tbody>
</table>

Source: Author’s calculations
to 1.19% decrease in price for the material. Similarly, the inverse cross-price elasticity of 0.47 between material and capital suggests that the 1% increase in the quantity of capital leads to a 0.47% hike in price for material input.

As inverse cross-price elasticities are limited to two factors of production, it measures as to how much change in one input quantity leads to an adjustment in another input’s price, but it does not consider the adjustment that can be done in other factors of production in a multi-input setting. For that scenario, I use the Hicks elasticity of complementarity as well as the Morishima elasticity of complementarity.

<table>
<thead>
<tr>
<th>Quantity changed across the x-axis and resulting price change across the y-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>-4038.24</td>
<td>0.683951</td>
<td>-1.21241</td>
</tr>
<tr>
<td>Labour (l)</td>
<td></td>
<td>-0.28036</td>
<td>-1.90626</td>
</tr>
<tr>
<td>Material (m)</td>
<td></td>
<td></td>
<td>18.52175</td>
</tr>
</tbody>
</table>

Source: Author’s calculations

Table 8.6 presents the Hicks elasticity of complementarity (HEC) calculated directly from the parameter estimation of the translog production function. Hicks elasticity of complementarity (HEC) and Morishima elasticity of complementarity (MEC) between the factors of production are substitute if the value is less than 0 or is termed complement if the value is more than 0 (Stern, 2008).
Kim (2000) defines that two inputs are HEC complements “if an increase in quantity of one input increases the marginal product of other input”, the largest substitution relationship is shown by HEC capital and capital, which has a mean value of -4038, meaning that the unit per cent rise in the demand of the capital input leads to decrease in the price of the capital input by 4038 per cent. Whereas the HEC relationship showing the largest complement is between the material and material input as it has a value of 18.52. It shows that the unit per cent increase in the demand for material leads to an increase in the material input price by 18.52 per cent. Following a similar analogy, it is clear that the HEC relationships document both the substitution as well as complementary relationships between the factors of production in a multi-input setting. However, the Morishima elasticities of complementarity (MEC) is a better measure than the Hicks elasticity as it allows for both the implicit own price as well as the cross-price effect (Kim, 2000).

Table 8.7: Morishima elasticity of complementarity

<table>
<thead>
<tr>
<th>Quantity changed across the x-axis and resulting price ratio change across the y-axis</th>
<th>Capital (k)</th>
<th>Labour (l)</th>
<th>Material (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital (k)</td>
<td>0.6509</td>
<td>0.6738</td>
<td></td>
</tr>
<tr>
<td>Labour (l)</td>
<td></td>
<td>0.4549</td>
<td></td>
</tr>
<tr>
<td>Material (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s calculations
Table 8.7 presents the Morishima elasticity of complementarity (MEC) relationship. The results suggest that all the factors of production are a complement to each other as the mean values are positive in each of the technical relationships. Kim (2000) defined the Morishima elasticity of complementarity as “MEC measures the responsiveness of the prices of inputs $i$ and $j$ to a change in the quantity of the $j$th input”. Thus, the largest complementarity is reflected by MEC capital and material, having value 0.67 meaning that if there is a unit per cent rise in the input demand of material then the price of capital/material increases by 0.67 per cent. Following this analogy, other MEC relationships also suggest for complementarity.

8.7 Elasticities of Complementarity comparisons with prevailing literature

I have focused only on the narrow body of literature pertaining to the food manufacturing industry for drawing comparisons. It includes Ball and Chambers (1982), who stated that inputs are substitute with each other in the US meat products industry. Lopez (1984) studied the Canadian food processing industry and found a mixed result (both complementarity and substitutability) for the factor substitution between the factors of production. Huang (1991) focusing on US food manufacturing industry, found that all the factors of production are substitutable.

Goodwin and Brester (1995) studied the US food manufacturing sector, and state that all the inputs of production are substitutes for one another. Nguyen and Streitweiser (1999) studied the factor substitution for the US manufacturing industry and suggested that all the factors of production are a substitute for each other. Alarcon (2005) studied the input substitution in the Spanish food industry and found substitutability between labour and capital. Hailu et al. (2010)
studied the substitutability between sweeteners in the U.S. food processing sector and suggested that capital and energy are substitutes.

The results from Ball and Chambers (1982), Huang (1991), Goodwin and Brester (1995), Nguyen and Streitweiser (1999), Alarcon (2005) and Hailu et al. (2010) suggest that capital, labour and energy are substitutes to each other. These previous studies have used the dual approach and stated the elasticities of substitution. Whereas due to data limitations, I am using the primal approach. Thus, I must be careful while comparing these results to mine as these studies follow different estimation approaches, differing data variables, and varying time contexts.

My result for the US data states that the capital and labour are complements in nature for both the Hicks elasticity of complementarity (HEC) and the Morishima elasticity of complementarity (MEC) which is not in favour of these earlier pieces of evidence. The rest of the technical relationships (capital and material, and labour and material) have opposing signs for both MEC and HEC; both relationships are complements for MEC and substitutes for HEC; thus, we can not clearly state the nature of the relationships.

8.8 Relationship between the technical efficiency and the elasticity of complementarity (HEC and MEC)

The regression relationship between technical efficiency and the elasticity of substitution is formulated based on Arrow, Chenery, Minhas and Solow (1961) and Sato (1977). I assume that technical efficiency is the dependent variable and elasticities of complementarity (HEC and MEC) are the independent variables, respectively.
### Table 8.8: Relationship between TE and HEC

| Name of the independent variable | Dependent variable- Technical efficiency via $\exp(-u)|e$ | t-values | R-squared |
|----------------------------------|---------------------------------------------------------|----------|-----------|
| s_kk                             | -5.48E-11                                               | (-1.39)  | 0.0614    |
| s_ll                             | -0.00140***                                             | (-3.05)  | 0.0620    |
| s_mm                             | -8.90e-09*                                              | (-1.81)  | 0.0616    |
| s_kl                             | -0.00000192                                             | (-1.40)  | 0.0614    |
| s_km                             | -4.99E-10                                               | (-1.30)  | 0.0614    |
| s_lm                             | 0.0000309*                                              | (1.94)   | 0.0620    |

*p < 0.10, **p < 0.05, ***p < 0.01

**Source:** Author’s calculations

Table 8.8 presents the regression relationship between the technical efficiency and the Hicks elasticity of complementarity (HEC). The relationship is very weak as most of the coefficient of independent variables have values approaching 0. To illustrate the independent variable coefficients, HEC labour and the material having a value of 0.00003, suggests that if there is a unit per cent rise in the value of HEC labour and material then technical efficiency increases by 0.00003 per cent. Similarly, I can interpret the other independent variable coefficient of the regression equation.
Table 8.9: Relationship between TE and MEC

| Name of the independent variable | Dependent variable- Technical efficiency via $E[\exp(-u)|e]$ | t-values | R-squared |
|----------------------------------|-------------------------------------------------------------|----------|-----------|
| MEC_kl                           | -0.00000207                                                | (-1.35)  | 0.0614    |
| MEC_km                           | 0.00000348                                                  | (1.35)   | 0.0615    |
| MEC_lm                           | .0000465                                                    | (1.7)    | 0.0619    |

Source: Author’s calculations

Table 8.9 presents the regression relationship between technical efficiency and the Morishima elasticity of complementarity (MEC). The relationship is very weak, as the independent variables again have very small values approaching 0 and none of the coefficients of the independent variable is significant. In order to illustrate the independent coefficients in the equation, the MEC labour and material having a value of about 0.00004, suggests that if there is unit per cent rise in the value of MEC labour and material then technical efficiency increases by 0.00004 per cent. In a similar manner, I can interpret all the other independent variable coefficient of the regression equation.

These tables suggest that Hicks or Morishima elasticity of complementarity do not affect technical efficiency much, which in turn means that ease to substitute between the factors of production does not lead to higher technical efficiency. The endogeneity corrected model by Shee and Stefanou (2014) can overcome this issue and may lead to robust estimates of the parameters of the production function and technical efficiency. However, the adoption of this
methodology requires a longer firm/plant-level panel data. Thus I am unable to use this approach. Therefore, I acknowledge the endogeneity bias in my analysis.

**Summary**

This chapter gives us the results of the data analysis focusing on the U.S. food manufacturing industry. The results can be summarised as follows; the technical efficiency of the food manufacturing sector has been robust over the six years of the study as the mean technical efficiency of 86.42% have been achieved. Secondly, the key outputs from the elasticity of complementarity analysis based on the translog production function indicate that the capital and labour technical relationship is complementary in nature. This finding is robust as both the magnitude as well as sign are similar in both Hicks elasticity of complementarity and the Morishima elasticity of complementarity. Finally, the relationship between the technical efficiency (dependent variable) and elasticity of complementarity (independent variables) is also explored through a regression formulation, but the coefficient of the independent variables approaches zero, suggesting a weak relationship.
Chapter 9- Summary, Future Extensions, and Conclusion

This chapter provides the key takeaways from this research. Based on the econometric analysis using the theoretical and empirical framework, the desired objectives of the study are fulfilled for both the Canadian as well as US food manufacturing sectors. The resulting output is summarised in the below sections, along with the vital policy implications emanating from the study. Later, the data limitations are explored with an eye for future extension possibilities. Lastly, the conclusion is presented to provide the crux of the study in a nutshell.

9.1 Summary

The ongoing changes in the structure and technology present a crucial challenge for the efficiency of the Canadian food processing industry. The macroeconomic changes, including the foreign exchange rate and the recent rise in the cost stress due to the increase in prices of the factor of production, is also a vital driver of this ongoing change in the business environment. The free trade bloc NAFTA signed in 1994 increased the demand for Canadian processed food. The value of the Canadian dollar showed different trends before and after the year 2000. These changes suggest that there has been high volatility in the macro-economic changes in the Canadian business environment. Given the fact that Canada’s primary trade partner is the U.S., diversifying into other markets may help increase the demand for Canadian processed food, as it is among the chief contributor to the foreign currency as well as a tax revenue generator for the government. Thus, the present study contributes empirical information to the existing literature.
The main gaps in the present literature this study intends to cater were: (1) The lack of research on technical efficiency in the Canadian and US food manufacturing industry. (2) The lack of research on the factor substitution in the Canadian and US food manufacturing industry. (3) The relationship between technical efficiency and factor substitution in the food manufacturing industry.

The results provide evidence on the technical efficiency and factor substitution for the food manufacturing industry. I have also shown the relationship between technical efficiency and the elasticity of substitution. As per results, the mean technical efficiency of the Canadian food manufacturing sector is 87.5%, whereas the US counterparts are estimated at 86.5%. Since I am using a different frontier, non-similar data structure; thus, I cannot make comparisons between these two separate results.

Based on the factor substitution results, the capital and labour technical relationship is deemed as a substitute, whereas the capital and energy technical relationship is deemed as a complement through both the Hicks elasticity of complementarity (HEC) as well as Morishima elasticity of complementarity (MEC) estimates for Canadian industry. Whereas in the US industry, the capital and labour technical relationship is deemed as complement through both HEC and MEC estimates. Lastly, the regression equation states that the influence of the elasticity of complementarity (independent variables) on the technical efficiency (dependent variable) is minuscule as most of the coefficients of the independent variable are approaching zero and have low R-squared.
9.2 Policy Implications

The key policy implications emanating for the Canadian food manufacturing industry include reducing the 12.5% technical inefficiencies in the industry to improve its competitiveness. As the technical efficiency estimates vary with respect to various subsectors, provinces and across time, thus, we cannot follow a blanket policy and entities should be treated individually. Secondly, as I could not explore the drivers of technical inefficiencies because of data constraints, thus knowing those determinants and improving upon them is imperative for improving the industry standing.

Secondly, as it is evident from the study, that capital and labour are substitutes to each other, thus rise in minimum wages might incentivise the industry to take up capital-intensive measures with the aim of saving labour. On similar lines, capital and energy complementary suggests that the hike in the energy prices would disincentivize the industry to take up energy-efficient capital-intensive measures.

9.3 Limitations of this study and Future Extensions

This study uses the stochastic frontier approach to estimate the Canadian food processing industry’s technical efficiency and the elasticity of substitution. The study uses the production function led primal approach due to lack of input and output price information. Thus, future studies could improve on the current study by estimating a cost function or a profit function using a dual approach, conditional on data availability.
The Canadian data spanned 1990-2013, but it did not have capital values for all the provinces as I had capital values (assuming it as aggregate capital stock) for just four major provinces (Alberta, Quebec, British Columbia, and Ontario). It would have been better if I could have had the capital values for each province/subsector in order to conduct a much smoother analysis.

The US data also had its share of issues. Mainly, the data available was not of the same duration as was the Canadian data. US data was just for the six years between 2005-2011. Secondly, US data did not have values for energy input. So, it just had three inputs (capital, labour and materials) and unlike the Canadian data, which is for four inputs (capital, labour, material and capital (aggregated capital)). Thus, both analyses were based on different frontier following distinct data structure and hence cannot be compared to each other.

Both the Canadian and US data sets were unbalanced in terms of observations for each province/state, subsector and across time. It would have been a much easier and explorative analysis if there were an equal count of observations in this macro-level data. There were numerous counts of missing variables in manufacturing value-added, capital, labour, energy, and material.

Likewise, the use of the stochastic frontier analysis (SFA) approach in order to estimate the technical efficiency and factor substitution provides more robustness to the results, since this method allows inference regarding returns to scales, choice of inputs, the structure of technology and the significance of technical efficiency. However, it is also recommended that further research using a more advanced technique to improve the results of this study, e.g. the
Meta frontier method, since this method allows to estimate and to compare technical efficiency levels from sub-sectors operating under different technologies.

Since the Canadian and US dataset used for the analysis were not collected to conduct technical efficiency and factor substitution analysis, so, there are not enough suitable variables to study the drivers of both. It would have been interesting to investigate the effect of age of the firm; the size of the firm; the ownership of the firm; export orientation; government policies such as supply management; and interprovincial trade on the technical efficiency and factor substitution.

Conditional on data availability, the intra-factor substitution relationships can also be explored, for example within multiple kinds of energy (ex. oil, coal, renewable, and nuclear) measures, and within different kinds of labour (ex. production and nonproduction labour).

Further, the study uses a macro-level database, so the future studies may improve on the current study by using a firm/plant-level (micro-level) data as it would be more explorative. Thus, the results from our study can be more effective if it explores the plant-level data because if there is no appropriate improvement at the microeconomic level, then macroeconomic, political, legal and social reforms will not yield much (Porter, 2004).

I also recommend future researchers to go with endogeneity corrected stochastic production frontier to analyse technical efficiency and factor substitution. Conditional on the availability of plant/firm-level sufficiently long panel data, this approach can be used to get much more robust estimates.
Lastly, I suggest future researchers address that how do the technical efficiency and the elasticity of substitution affect broader productivity growth of food processing and the extent of the impact of these factors on total factor productivity.

9.4 Conclusion

In short, this study provides with a technical glimpse of the Canadian food manufacturing industry. The analysis focusses on two key drivers of productivity growth of the food manufacturing industry, i.e. technical efficiency, factor substitution, and the link between the two. The similar analysis is also conducted for the U.S. food manufacturing industry, but in this case, we estimate using a different frontier as I use non-similar data points. Lastly, as technical efficiency and factor substitution are microeconomic phenomena; thus, the results of the analysis using the micro-level data would have been more explorative as well as insightful.
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Appendix A

Expanded formulas for getting the factor substitutions:

The trans log production function model is specified as follows:

\[ \ln Y_i = \beta_0 + \beta_K \ln K + \beta_L \ln L + \beta_E \ln E + \beta_M \ln M + \frac{1}{2} \beta_{KK} \ln K^2 + \frac{1}{2} \beta_{LL} \ln L^2 + \frac{1}{2} \beta_{EE} \ln E^2 + \frac{1}{2} \beta_{MM} \ln M^2 + \beta_{KL} \ln K \ln L + \beta_{KE} \ln K \ln E + \beta_{KM} \ln K \ln M + \beta_{LE} \ln L \ln E + \beta_{LM} \ln L \ln M + \beta_{EM} \ln E \ln M + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \beta_{KL} \ln K t + \beta_{EL} \ln E t + \beta_{LM} \ln L t + \epsilon_i \]

(A.1)

Where, \( \beta_L, \beta_K, \beta_E, \beta_M, \beta_t, \beta_{tt} \) represent the first-order parameters \( \beta_{LL}, \beta_{KK}, \beta_{EE}, \beta_{MM}, \beta_{KL}, \beta_{KE}, \beta_{KM}, \beta_{LE}, \beta_{LM}, \beta_{EM}, \beta_{LL}, \beta_{KL}, \beta_{EL}, \beta_{LM} \) represent second-order parameters. The variable \( t \) is a time trend perhaps capturing technical change and \( \epsilon_i \) are errors which are assumed to be independently and identically distributed and have \( N (0, \sigma^2) \) distribution.

Young’s theorem imposes the following constraints:

\[ \beta_{LK} = \beta_{KL}, \beta_{LE} = \beta_{EL}, \beta_{LM} = \beta_{ML}, \beta_{KE} = \beta_{EK}, \beta_{KM} = \beta_{MK}, \beta_{EM} = \beta_{ME} \]

Using these conditions, the input elasticity of output will be:

\[ \frac{\partial \ln Y}{\partial \ln K} = \theta_K = \beta_K + \beta_{KK} \ln K + \beta_{KE} \ln E + \beta_{KM} \ln M + \beta_{KL} \ln L + \beta_{KL} t \]

\[ \frac{\partial \ln Y}{\partial \ln L} = \theta_L = \beta_L + \beta_{LL} \ln L + \beta_{KL} \ln K + \beta_{LE} \ln E + \beta_{LM} \ln M + \beta_{KL} t \]

\[ \frac{\partial \ln Y}{\partial \ln E} = \theta_E = \beta_E + \beta_{EE} \ln E + \beta_{EM} \ln M + \beta_{LE} \ln L + \beta_{KE} \ln K + \beta_{EL} t \]

\[ \frac{\partial \ln Y}{\partial \ln M} = \theta_M = \beta_M + \beta_{MM} \ln M + \beta_{LM} \ln L + \beta_{KM} \ln K + \beta_{EM} \ln E + \beta_{ML} t \]

(A.2)
The scale elasticity ($\theta_T$) is the sum of input elasticities of output, and given by;

$$\theta_T = \theta_K + \theta_L + \theta_E + \theta_M$$

If $\theta_T = 1$, then it is CRTS (Constant returns to scale)

If $\theta_T < 1$, then it is DRTS (Decreasing returns to scale)

If $\theta_T > 1$, then it is IRTS (Increasing returns to scale)

Assuming perfect competition, the first-order derivative of the production function is given by;

$$f_i = \frac{\partial Y}{\partial x_i} = \frac{\partial \ln Y}{\partial \ln x_i} \times \frac{Y}{x_i} \quad (A.3)$$

Expanding this expression for each input I get,

$$f_K = \theta_K \times \frac{Y}{x_K}$$

$$f_L = \theta_L \times \frac{Y}{x_L}$$

$$f_E = \theta_E \times \frac{Y}{x_E}$$

$$f_M = \theta_M \times \frac{Y}{x_M}$$

For the condition of monotonicity to adhere, $f_i > 0$

Second-order derivatives of the translog production function are given by,

$$f_{ii} = \frac{Y}{x_i^2} [\beta_{ii} + \theta_i^2 - \theta_i] \quad (A.4)$$

Expanding this expression for each input I get,

$$f_{KK} = \frac{Y}{x_K^2} [\beta_{KK} + \theta_K^2 - \theta_K]$$

$$f_{LL} = \frac{Y}{x_L^2} [\beta_{LL} + \theta_L^2 - \theta_L]$$

$$f_{EE} = \frac{Y}{x_E^2} [\beta_{EE} + \theta_E^2 - \theta_E]$$
\[ f_{MM} = \frac{Y}{X_M} \left[ \beta_{MM} + \theta_M^2 - \theta_M \right] \]

Similarly,

\[ f_{ij} = \frac{Y}{X_iX_j} \left[ \beta_{ij} + \theta_i \theta_j \right] \], where \( i \) is not equal to \( j \) \hspace{1cm} (A.5)

Expanding this for each input I get,

\[ f_{KL} = \frac{Y}{X_KX_L} \left[ \beta_{KL} + \theta_K \theta_L \right] \]
\[ f_{KE} = \frac{Y}{X_KX_E} \left[ \beta_{KE} + \theta_K \theta_E \right] \]
\[ f_{KM} = \frac{Y}{X_KX_M} \left[ \beta_{KM} + \theta_K \theta_M \right] \]
\[ f_{LE} = \frac{Y}{X_LX_E} \left[ \beta_{LE} + \theta_L \theta_E \right] \]
\[ f_{LM} = \frac{Y}{X_LX_M} \left[ \beta_{LM} + \theta_L \theta_M \right] \]
\[ f_{EM} = \frac{Y}{X_EX_M} \left[ \beta_{EM} + \theta_E \theta_M \right] \]

In order to get the cost-share equations, I divide the input elasticities of output with scale elasticity;

\[ S_i = \frac{\theta_i}{\theta_T} \] \hspace{1cm} (A.6)

Expanding this equation for all inputs, I get

\[ S_K = \frac{\theta_K}{\theta_T} \]
\[ S_L = \frac{\theta_L}{\theta_T} \]
\[ S_E = \frac{\theta_E}{\theta_T} \]
\[ S_M = \frac{\theta_M}{\theta_T} \]
Equation (6) showing cost-share allows for variable returns to scale, but if I assume constant returns to scale then we get \( \theta_T = 1 \), then equation (6) collapses to input elasticity of output.

Equation (6) in the inverse demand form implies,

\[
\omega_i = \frac{\theta_i}{\theta_T \times x_i} \tag{A.7}
\]

Partially differentiating equation (7) with respect to input quantities, I can find the uncompensated quantity, or inverse price elasticities;

\[
\eta_{ii} = \frac{\beta_{ii}}{\theta_i} - \frac{\sum_j \beta_{ij}}{\theta_T} - 1 \tag{A.8}
\]

Expanding this equation for all the inputs

\[
\eta_{KK} = \frac{\beta_{KK}}{\theta_K} - \frac{\beta_{KK} + \beta_{KL} + \beta_{KE} + \beta_{KM} + \beta_{KL}}{\theta_T} - 1
\]

\[
\eta_{LL} = \frac{\beta_{LL}}{\theta_L} - \frac{\beta_{LL} + \beta_{KL} + \beta_{LE} + \beta_{LM} + \beta_{LL}}{\theta_T} - 1
\]

\[
\eta_{EE} = \frac{\beta_{EE}}{\theta_E} - \frac{\beta_{EE} + \beta_{KE} + \beta_{LE} + \beta_{EM} + \beta_{EE}}{\theta_T} - 1
\]

\[
\eta_{MM} = \frac{\beta_{MM}}{\theta_M} - \frac{\beta_{MM} + \beta_{KM} + \beta_{LM} + \beta_{EM} + \beta_{MT}}{\theta_T} - 1
\]

Similarly, I have,

\[
\eta_{ij} = \frac{\beta_{ij}}{\theta_i} - \frac{\sum_k \beta_{kj}}{\theta_T} \quad \text{, where } i \text{ is not equal to } j \tag{A.9}
\]

Expanding I get,

\[
\eta_{LK} = \frac{\beta_{KL}}{\theta_L} - \frac{\beta_{KL} + \beta_{KE} + \beta_{KM}}{\theta_T}
\]

\[
\eta_{EK} = \frac{\beta_{KE}}{\theta_E} - \frac{\beta_{KL} + \beta_{KE} + \beta_{KM}}{\theta_T}
\]
\[ \eta_{MK} = \frac{\beta_{KM}}{\theta_M} - \frac{\beta_{KL} + \beta_{KE} + \beta_{KM}}{\theta_T} \]

\[ \eta_{KL} = \frac{\beta_{KL}}{\theta_K} - \frac{\beta_{KL} + \beta_{LE} + \beta_{LM}}{\theta_T} \]

\[ \eta_{EL} = \frac{\beta_{LE}}{\theta_E} - \frac{\beta_{KL} + \beta_{LE} + \beta_{LM}}{\theta_T} \]

\[ \eta_{ML} = \frac{\beta_{LM}}{\theta_M} - \frac{\beta_{KL} + \beta_{LE} + \beta_{LM}}{\theta_T} \]

\[ \eta_{KE} = \frac{\beta_{KE}}{\theta_K} - \frac{\beta_{KE} + \beta_{LE} + \beta_{EM}}{\theta_T} \]

\[ \eta_{LE} = \frac{\beta_{LE}}{\theta_L} - \frac{\beta_{KE} + \beta_{LE} + \beta_{LM}}{\theta_T} \]

\[ \eta_{ME} = \frac{\beta_{EM}}{\theta_M} - \frac{\beta_{KE} + \beta_{LE} + \beta_{LM}}{\theta_T} \]

\[ \eta_{KM} = \frac{\beta_{KM}}{\theta_K} - \frac{\beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T} \]

\[ \eta_{LM} = \frac{\beta_{LM}}{\theta_L} - \frac{\beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T} \]
\[ \eta_{EM} = \frac{\beta_{EM}}{\theta_E} - \frac{\beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T} \]

The inverse output elasticities are obtained as,

\[ \eta_{iy} = \frac{\sum_i \beta_{ij}}{\theta_i \theta_T} - \frac{\sum_k \sum_j \beta_{kj}}{\theta_i^2 \theta_T} \]  

\[ \eta_{ky} = \frac{\beta_{KL} + \beta_{KE} + \beta_{KM}}{\theta_K \theta_T} - \frac{\beta_{LM} + \beta_{LE} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{ly} = \frac{\beta_{KL} + \beta_{LE} + \beta_{LM}}{\theta_L \theta_T} - \frac{\beta_{MM} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{ey} = \frac{\beta_{KL} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_E \theta_T} - \frac{\beta_{LM} + \beta_{LE} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{my} = \frac{\beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_M \theta_T} - \frac{\beta_{MM} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T^2} \]

Expanding for each input I get;

\[ \eta_{iy} = \frac{\sum_i \beta_{ij}}{\theta_i \theta_T} - \frac{\sum_k \sum_j \beta_{kj}}{\theta_i^2 \theta_T} \]  

\[ \eta_{ky} = \frac{\beta_{KL} + \beta_{KE} + \beta_{KM}}{\theta_K \theta_T} - \frac{\beta_{LM} + \beta_{LE} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{ly} = \frac{\beta_{KL} + \beta_{LE} + \beta_{LM}}{\theta_L \theta_T} - \frac{\beta_{MM} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{ey} = \frac{\beta_{KL} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_E \theta_T} - \frac{\beta_{LM} + \beta_{LE} + \beta_{EM}}{\theta_T^2} \]

\[ \eta_{my} = \frac{\beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_M \theta_T} - \frac{\beta_{MM} + \beta_{KM} + \beta_{LM} + \beta_{EM}}{\theta_T^2} \]
The Hicks elasticity of complementarity can also be calculated as follows,

\[ \rho_{u}^{H} = \frac{\beta_{i} + \theta_{i}^{2} - \theta_{i}}{\theta_{i}^{2}} \]  

(A.11)

Expanding for each input;

\[ \rho_{KK}^{H} = \frac{\beta_{K} + \theta_{K}^{2} - \theta_{K}}{\theta_{K}^{2}} \]

\[ \rho_{LL}^{H} = \frac{\beta_{L} + \theta_{L}^{2} - \theta_{L}}{\theta_{L}^{2}} \]

\[ \rho_{EE}^{H} = \frac{\beta_{E} + \theta_{E}^{2} - \theta_{E}}{\theta_{E}^{2}} \]

\[ \rho_{MM}^{H} = \frac{\beta_{M} + \theta_{M}^{2} - \theta_{M}}{\theta_{M}^{2}} \]

Similarly, I have;

\[ \rho_{ij}^{H} = \frac{\beta_{ij} + \theta_{i} + \theta_{j}}{\theta_{i} + \theta_{j}} \]  

(A.12)

Expanding for each input, I get;

\[ \rho_{KL}^{H} = \frac{\beta_{KL} + \theta_{K} + \theta_{L}}{\theta_{K} + \theta_{L}} \]

\[ \rho_{KE}^{H} = \frac{\beta_{KE} + \theta_{K} + \theta_{E}}{\theta_{K} + \theta_{E}} \]

\[ \rho_{KM}^{H} = \frac{\beta_{KM} + \theta_{K} + \theta_{M}}{\theta_{K} + \theta_{M}} \]

\[ \rho_{LE}^{H} = \frac{\beta_{LE} + \theta_{L} + \theta_{E}}{\theta_{L} + \theta_{E}} \]

\[ \rho_{LM}^{H} = \frac{\beta_{LM} + \theta_{L} + \theta_{M}}{\theta_{L} + \theta_{M}} \]

\[ \rho_{EM}^{H} = \frac{\beta_{EM} + \theta_{E} + \theta_{M}}{\theta_{E} + \theta_{M}} \]

Finally, I can derive the Morishima elasticity of complementarity (MEC);
\[
\rho^M_{ij} = S_j (\rho^H_{ij} - \rho^H_{jj}) \tag{A.13}
\]

Thus, expanding this equation, I get

\[
\rho^M_{KL} = S_L (\rho^H_{KL} - \rho^H_{LL})
\]

\[
\rho^M_{KE} = S_E (\rho^H_{KE} - \rho^H_{EE})
\]

\[
\rho^M_{KM} = S_M (\rho^H_{KM} - \rho^H_{MM})
\]

\[
\rho^M_{LE} = S_E (\rho^H_{LE} - \rho^H_{EE})
\]

\[
\rho^M_{LM} = S_M (\rho^H_{LM} - \rho^H_{MM})
\]

\[
\rho^M_{EM} = S_M (\rho^H_{EM} - \rho^H_{MM})
\]