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Capacity utilization, factor substitution, and productivity growth in Canadian food processing sector

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Abstract

The food processing industry has been confronted with unprecedented challenges as the costs of raw materials have risen rapidly, owing in part to the increased use of grains for ethanol. It is critical to comprehend how these trends affect the industry and potential coping techniques. This study estimates capacity utilization, which is a measurement that is well-suited to identify how input prices affect productivity in the short-run. The results show that capacity utilization decreased significantly after the year 2005 when raw materials input prices skyrocketed. TFP growth has also slowed significantly because of this. According to the estimated elasticities, the industry has little potential to deal with the cost challenge through factor substitution. Another conclusion is that capacity utilization has a positive elasticity with respect to the cost of raw materials. Because it is related to induced capital stock adjustment, which is only achievable in the long run, this is an indicator of how the industry will be affected in the long-run.

Keywords: Food manufacturing, Trans-log cost, Capacity utilization, Productivity growth, The elasticity of substitution

Introduction

Addressing the harmful environmental repercussions of fossil fuel use are unquestionably a pressing policy problem of the day. Among the options being considered, the usage of renewable fuels, such as ethanol and biodiesel has recently gotten increased attention from policymakers. The world's economies have launched a near-simultaneous push to expand biofuel production and consumption, resulting in a huge increase in ethanol output for use as a gasoline additive.

In Canada, the Renewable Fuels Regulation, which went into effect in 2011 mandates fuel producers and importers to have an average renewable content of at least 5% of the gasoline they produce or import.[1] In the USA, the Renewable Fuel Standard (RFS) in the US Energy Independence and Security Act of 2007 requires renewable fuel to be blended into transportation fuel in increasing amounts each year (US EPA 2010). Similarly, in EU

[1] https://www.canada.ca/en/environment-climate-change/services/managing-pollution/energy-production/fuel-regulations/renewable.html.

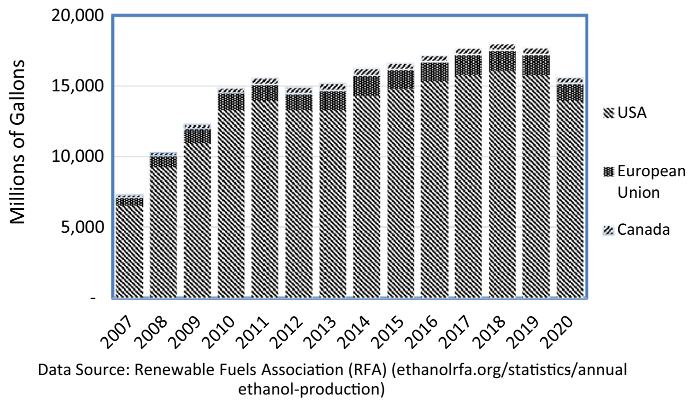

Fig. 1 Trends in ethanol production in Canada, USA, and the EU countries

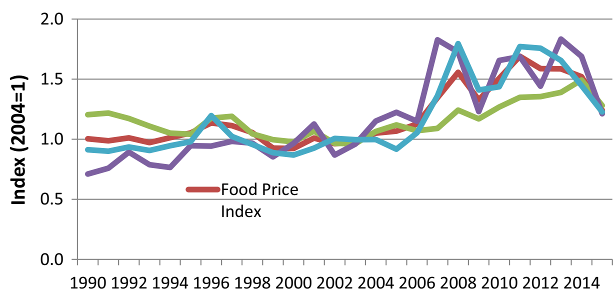

Fig. 2 Trends in World Food Price (Index, 2004 = 1). *Source*: Food and Agricultural Organization (FAO) statistics

countries, the 2009 Renewable Energy Directive requires the EU to meet at least 20% of its total energy needs with renewable by 2020 achieved through the attainment of individual national targets, with all EU countries ensuring that at least 10% of their transport fuels come from renewable sources by 2020.[2] As a result of these measures, ethanol production has been increasing significantly as shown in Fig. 1.

As a result of this accelerated growth in ethanol production, the contribution of ethanol to the US gasoline fuel supply has reached approximately 10%, the result of which is that today, nearly 40% of the US national corn crop is used for ethanol production while approximately 30% of soy oil produced is used in biodiesel (The International Council on Clean Transportation 2021). Virtually all ethanol production in the US is based on corn (EIA 2020). This has significantly increased corn prices (Anderson and Coble 2010), but most importantly, those of meat, eggs, and dairy because animal feed makes up an estimated 50–69% of production costs for livestock farmers and primarily consists of corn, soybean meal, and dried distiller grains and soluble (EIA 2020). The increased use of corn acreage is displacing production of other crops and is also another important channel through which this affects consumer food prices.

The general impact on consumer food prices is obvious. According to Food and Agricultural Organization (FAO) data, the period 2008–2009 when ethanol production

[2] https://afdc.energy.gov/laws/RFS.html.

was leaked was also marked by significant food inflation globally. As shown in Fig. 2, the prices of many food items have increased significantly (Fig. 2).[3] Many studies have argued that the spike in ethanol production was the main culprit for the significant spike in food prices across the globe (Mueller et al. 2011; Hausman et al. 2012; Berry et al. 2013; Roberts and Schlenker 2013). The US Congressional Budget Office (2009) estimates that about 10–15% of the food price spikes were attributable to the use of corn for ethanol, while Hausman et al. (2012) estimate that increased corn ethanol production during the boom production year 2006/2007 explains approximately 27% of the experienced corn price rise, causing more acreage to be converted to corn production, which causes a rise in the overall food price. Berry et al. (2013) argue the fact that the US accounts for over 40% of the world's corn production justifies the link between ethanol and food inflation. Further, Robert and Schlenker (2013) predict that these "food-for-fuel" programs will increase food prices by about 30%, but the prediction could be as low as 20% if a third of the biofuel calories are recycled as feedstock for livestock.

The Canadian experience is not an exception. As Sparling and LeGrow (2015) noted, input costs for the Canadian food processing industry have skyrocketed, particularly from 2008 onward, leading to both plant closures and job losses. They reported that Canada's food manufacturing industry experienced the closure of 143 plants wand 23,807 jobs during the period 2006 to 2014, with both plant closures and job losses peaking during the 2007–2008 period. This is an important issue given the significance of the food processing industry in the Canadian economy in terms of manufacturing jobs and GDP contributions, and as an essential channel for Canadian agricultural products (Sparling and Cheney 2014).

This study is motivated by the descriptive studies of the Canadian food processing industry offered by Sparling and LeGrow (2015) and Sparling and Cheney (2014), specifically the observations related to how the industry is responding to the increased raw material costs and coping with consolidation and restructuring in the aftermath of the rise in raw material costs. The paper attempts to generalize these descriptions by employing econometric models and estimation methods that can characterize the cost economies of the food processing sector. In general, factor substitutions, capacity utilization, and technological changes are the main mechanisms by which input prices influence production costs and thus profitability. Accordingly, analyzing how these factors are influenced by raw materials prices in the context of the Canadian food industry is the objective of this study. It employs the econometric method of estimating capacity utilization and its elasticity with respect to input prices. It also explores the substitution possibilities among the inputs by estimating the elasticity of substitutions among the inputs.

The production cost of the Canadian food industry is studied using the restricted trans-log cost model to estimate the elasticity of substitutions, technological progress, and factor-bias of technical changes. Estimation of capacity utilization and its elasticity with respect to variable input prices are also offered. These are carried out using the Canadian KLEMS data set covering the period 1961–2014. The cutoff year is 2014 because of data availability. The KLEMS data reveals that there is a very close correlation

[3] https://www.fao.org/worldfoodsituation/FoodPricesIndex/en/.

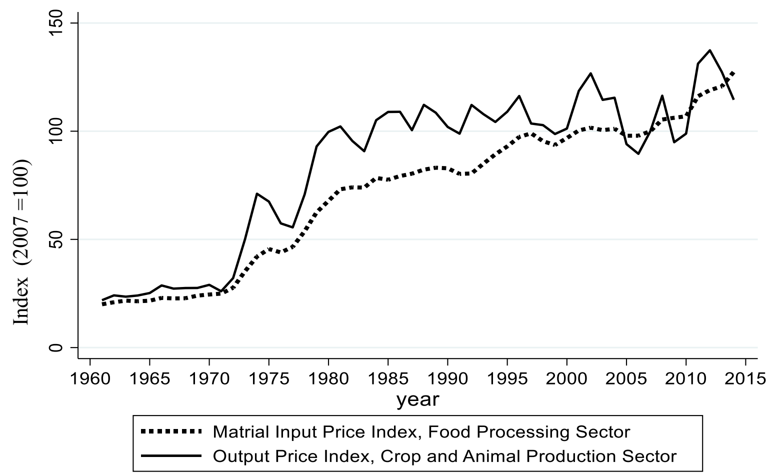

Fig. 3 Raw material price and output price of crop and animal production. Data source: Statistics Canada, Productivity Data (KLEMS)

between the raw material input price index of the food processing sector and the output price index of the crop and animal production sectors (Fig. 3). This reveals that the raw materials used in the Canadian food processing industry come primarily from crop and animal production. Accordingly, a rise in crop prices driven by ethanol production has an impact on the food industry through its impact on the cost of raw materials, as hypothesized earlier.

The findings reveal that the industry has experienced a negative productivity shock, mainly through a significant drop in capacity utilization. Given the finding that raw material inputs are substituted with other variable inputs, factor substitution possibilities and harnessing excess capacities provide potential coping mechanisms, implying that firms in the industry could mitigate production costs by substituting other inputs for raw materials to the extent possible. Capacity utilization is also found to respond positively to a rise in variable input prices, more so to that of raw materials. We further find evidence of the existence of raw material-saving technical changes. These findings suggest the existence of various cost-saving responses to the rise in raw material input prices.

The rest of the paper is organized as follows. In Section two, we offer a brief discussion of the theoretical framework and present the restricted trans-log cost specification along with the derivation of the measurements of our interest. The data and estimation method are discussed in Section three, followed by a presentation and discussion of the results in Section four. Section five concludes.

Theoretical framework and the restricted trans-log cost function

Theoretical framework

The cost-based estimate for capacity output and capacity utilization was revolutionized in scholars aiming to unravel the productivity shocks in the aftermath of the 1970s oil price shock (Berndt and Hess 1986; Morrison 1985, 1988, 1999). Conceptually, capacity utilization is measured by the ratio of actual to optimal steady state output or the desired level of output (Y/Y^*). This measurement is a short-run concept. Accordingly,

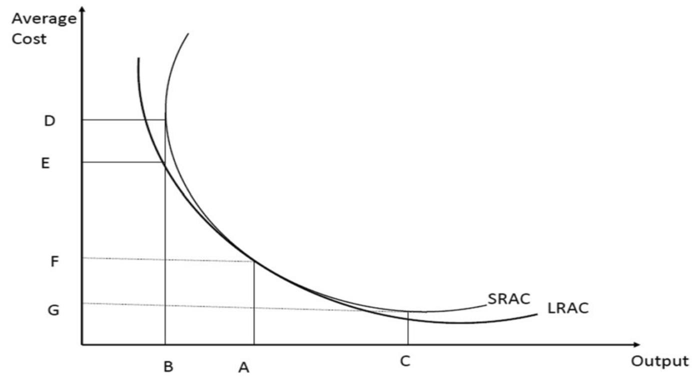

Fig. 4 Cost-based theory of capacity utilization and productivity

the desired level of output is the one that corresponds with the tangency of the short-run average cost (SRATC) curve with the long-run average cost (LRATC). This tangency occurs at the minimum of the SRATC if we assume a constant returns to scale technology. Accordingly, the capacity utilization rate estimated in this manner can be both above and below one.

Figure 4, adapted from Morrison (1988), illustrates the cost-based theory that underpins conceptualization and calculation of capacity utilization based on cost functions. Figure 4 summarizes this framework. If the output level is at *A*, it is the desired level since there is no cost-reduction potential by changing capacity utilization, given the production technology and fixed capacity (scale), which implies that the capacity utilization rate is equal to one. On the other hand, if realized output is equal to *C*, there is capacity overutilization so that the cost-based capacity utilization is above one. The opposite occurs if output is at B. Since the position and shape of the short-run average cost curve depend on the level of factor prices and the amount of capital, it is straightforward to imply that the capacity utilization rate depends on factor prices. The information that indicates how a factor price affects capacity utilization is the elasticity of capacity utilization rate with respect to factor prices (Berndt and Hess 1986).

Figure 4 also illustrates the relationship between capacity utilization and the cost-based measure of productivity, which measures the decline in the average cost of producing a given level of output. If, for example, we consider the case of capacity underutilization (output level B), producers could either change their production technology or adjust their capacity, which changes capacity output. Both of these could improve the capacity utilization rate. This is the theoretical linkage between input prices and capacity utilization (Morrison 1985, 1988), a relationship that can be measured using the elasticity of capacity utilization with respect to variable input prices. In addition, the Hicksian theory of induced innovation implies that an increase in the price of one production factor relative to other factor prices induces a sequence of technical changes that can reduce the use of the factor whose cost has risen (Kennedy 1964). This is known as "biased technological progress" in the sense that it saves the use of the relatively expensive inputs. Accordingly, estimation of the factor-bias of technological progress allows us to establish the long-run relationship between input prices and technological progress. That is, if a disembodied technical progress is factor-i-using (saving), then a rise in the price of factor i, all else remaining the same, reduces (increases) the rate of multi-factor productivity growth (Jorgenson and Wilcoxen 1993).[4]

The restricted trans-log cost function

Specification of the restricted (short-run) cost function allows us to analytically derive a measurement for cost-based capacity utilization and its elasticity with respect to input prices. It also allows us to derive an expression for the growth rate in total factor productivity. Following Berndt and Hess (1986), the trans-log restricted cost specification is given as follows:

$$\begin{aligned} \ln VC = {} & \alpha_0 + \alpha_Y \ln Y + \frac{1}{2}\gamma_{YY}(\ln Y)^2 + \beta_K \ln K + \frac{1}{2}\gamma_{KK}(\ln K)^2 + \alpha_t t \\ & + \frac{1}{2}\alpha_{tt}t^2 + \sum_i \alpha_i \ln P_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln P_i \ln P_j + \sum_i \rho_{Yi} \ln P_i \ln Y \\ & + \sum_i \rho_{Ki} \ln P_i \ln K + \sum_i \rho_{ti} t \ln P_i + \rho_{tY} t \ln Y + \rho_{tK} t \ln K, \end{aligned} \tag{1}$$

where $\ln VC$ is log of variable costs, $\ln P_i$s are the variable input prices, t is the time trend, i and j are labor (L), energy (E), raw materials (M), and Services (S); and $\ln K$ and $\ln Y$ are logs of capital input and output, respectively. Restrictions regarding symmetry ($\gamma_{ij} = \gamma_{ji}$) and linear homogeneity of degree one in prices are still applicable but, restrictions guaranteeing homogeneity of a constant degree in K and Y are also imposed in addition. These are given as:

$$\begin{aligned} & \sum_i \alpha_i = 1; \sum_i \gamma_{ij} = 0 \forall i \& j; \sum_i \rho_{ti} = \sum_i \rho_{Ki} = \sum_i \rho_{Yi} = 0 \\ & \quad \gamma_{YY} + \gamma_{KK} = \rho_{Yi} + \rho_{Ki} = \rho_{tY} + \rho_{tK} = 0 \end{aligned} \tag{2}$$

so that $\alpha_Y + \beta_K = \eta$, a measure of long-run returns to scale. After imposing the restriction of homogeneity of a constant degree in K and Y, we can write Eq. 1 as

$$\begin{aligned} \ln VC = {} & \alpha_0 + \alpha_Y \ln Y + \beta_K \ln K + \frac{1}{2}\gamma_{YY}\left(\ln\left(\frac{Y}{K}\right)\right)^2 \\ & + \alpha_t t + \frac{1}{2}\alpha_{tt}t^2 + \sum_i \alpha_i \ln P_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln P_i \ln P_j \\ & + \sum_i \rho_{Yi} \ln P_i \ln\left(\frac{Y}{K}\right) + \sum_i \rho_{ti} t \ln P_i + \rho_{tY} t \ln\left(\frac{Y}{K}\right) \end{aligned} \tag{3}$$

Optimal variable cost share equations are obtained by logarithmically differentiating Eq. 3 with respect to the input prices and is given as

$$s_i = \alpha_i + \sum_i \gamma_{ij} \ln P_j + \rho_{Yi} \ln (Y/K) + \rho_{ti} t \tag{4}$$

[4] Technological progress is input saving if the coefficient of the time trend in the respective cost share equation is negative and statistically significant, whereas a positive and statistically significant coefficient indicates that technological progress increases the use of the input.

Equations 3 and 4 are estimated by pre-imposing the restrictions pertaining to the adding-up, symmetry, and homogeneity of degree one in prices. Estimating the cost function along with the share equations permits efficiency gains without loss of a degree of freedom since doing so does not imply estimating more parameters than those of the cost function. What this requires is estimation of the system of equations by pre-imposing the relevant restrictions. The adding up restriction ($\sum \alpha_i = 1$) requires the exclusion of one of the share equations. This can be done by excluding any of the share equations since the results are not sensitive to the share equation chosen to be excluded. We estimate by excluding the service input share equation. Thus, the elasticities for this variable will be estimated using the identity that the service share equation is equal to $1 - s_s = 1 - \sum_i s_i$ where i in s_i stands for labor, energy, and raw materials. Homogeneity of degree one in prices requires restrictions $\sum_i \gamma_{ij} = 0 \forall i\&j$; $\sum_i \rho_{ti} = \sum_i \rho_{Yi}$. In addition to these, estimating the cost function along with the share equations also requires cross-equation restrictions that guarantee the estimated coefficients are identical in cost and share equations. For example, the coefficient of the unit price of labor in the labor share equation must be equal to the coefficient of the square of the unit labor price in the cost equation. All together, the estimation using Eq. 3 and its corresponding share equation involves 22 restrictions. Then, the elasticities with respect to Y and K are computed as follows:

$$\frac{\partial \ln VC}{\ln Y} = \alpha_Y + \gamma_{YY} \ln\left(\frac{Y}{K}\right) + \sum_i \rho_{Yi} \ln P_i + \rho_{tY} t \tag{5}$$

$$\frac{\partial \ln VC}{\ln K} = \alpha_K - \left(\gamma_{YY} \ln\left(\frac{Y}{K}\right) + \sum_i \rho_{Yi} \ln P_i + \rho_{tY} t\right) \tag{6}$$

After estimating the parameter values, we follow the following definitions to obtain the summary measurements needed for our interpretations and generalizations:

i. The bias of technological progress is determined by the coefficient ρ_{it}. If $\rho_{it} < 0 (> 0)$, technological progress is input-i-saving (using), and therefore, an increase in the price of that input contributes to improvements in (worsening of) total factor productivity growth.
ii. The Allen-Uzawa partial elasticity of substitution is computed as

$$\delta_{ij} = \frac{\gamma_{ij} + \widehat{s_i}\widehat{s_j}}{\widehat{s_i}\widehat{s_j}}, i \neq j \text{ and } \delta_{ii} = \frac{\gamma_{ii} + \widehat{s_i}^2 - \widehat{s_j}}{\widehat{s_i}^2}, \tag{7}$$

and the price elasticities are computed from the Allen-Uzawa partial elasticity as

$$\varepsilon_{ij} = \widehat{s_j}\delta_{ij} = \frac{\gamma_{ij}}{\widehat{s_i}} + \widehat{s_j} \text{ and } \varepsilon_{ii} = \widehat{s_i}\delta_{ii} = \frac{\gamma_{ii}}{\widehat{s_i}} + \widehat{s_1} - 1 \tag{8}$$

where $\widehat{s_i}$and$\widehat{s_j}$ denote the fitted shares, that must be positive according to the monotonicity restrictions. Since the shares for service inputs is not estimated, their values are generated using $\widehat{s}_s = 1 - \widehat{s}_L - \widehat{s}_E - \widehat{s}_M$.

Positive values of cross-elasticity suggest that the inputs are substitutes, while negative values suggest that they are complements. Note that these elasticities are not symmetric; that is, $\varepsilon_{ij} \neq \varepsilon_{ji}$ since $\varepsilon_{ij} = \widehat{s_j}\delta_{ij}$ while $\varepsilon_{ji} = \widehat{s_i}\delta_{ij}$. While they are different in magnitude, the signs must be the same since they depend on the Allen-Uzawa partial elasticities (δ_{ij}).

It is also important to estimate Morishima elasticity of substitution since the Allen-Uzawa elasticity are conceptually relevant to the cases involving only two inputs (Blackorby and Russell 1989). The Morishima elasticity of substitution are computed as

$$M_{ij} = \varepsilon_{ij} - \varepsilon_{jj} \tag{9}$$

iii. Technological progress is calculated using $\varepsilon_{ct} = -\partial \ln cv/\partial t$, which is equal to

$$\varepsilon_{ct} = -\left(\alpha_t + \alpha_{tt}t + \sum_i \rho_{ti} \ln P_i + \rho_{tY} \ln\left(\frac{Y}{K}\right)\right) \tag{10}$$

and can be decomposed into neutral $(-\alpha_t - \alpha_{tt}t)$, biased $(-\sum \rho_{ti}\ln P_i)$ and scale-augmenting $-\left(\rho_{ty}\ln(Y/K)\right)$. Technological progress entails the downward shift in long-run average cost and measures growth in total factor productivity.

iv. Following Morrison (1988) and Paul (1999), capacity utilization (CU) is computed as

$$\text{CU} = \frac{\varepsilon_{cY}}{\alpha_Y + \beta_K}, \tag{11}$$

where $\alpha_y + \beta_k$ is the long-run returns-to-scale, and the elasticity of short-run cost with respect to output (ε_{cy}) is given by Eq. 5. Then, the elasticity of capacity utilization with respect to a variable input price depends on ρ_{yi}, calculated as

$$\varepsilon^{CU} = \frac{\partial CU}{\partial P_i} \cdot \frac{P_i}{CU} = \frac{\rho_{yi}}{CU}, \tag{12}$$

where ${\varepsilon_i}^{cu}$ is the elasticity of capacity utilization with respect to the price of a variable input i. Since $\rho_{yi} = -\rho_{ki}$, a positive ρ_{yi} implies that capital and input i are substitutes. In other words, the elasticity of capacity utilization with respect to the price of a variable input depends on the relationship between the variable input and capital.

Data and estimation method

Statistics Canada's KLEMS (capital, labor, energy, materials, and services) data set is used for this analysis. The data set provides information on input prices, total expenditure on each input, as well as output and input quantity indexes. Summary statistics are provided in Table 1. Since the regression is based on real variables, the summary statistics are for the ratios of the respective value to the output price index.

Figure 5 shows trends in the log values of real input prices. The graph shows that real input prices have been relatively stable since the early 1980s, except for the period

Table 1 Summary statistics for the variables used in estimation

Variables (in logs)	Notations	Mean	SD	Minimum	Maximum
Variable Cost	VC	536.87	122.84	304.54	820.34
Unit cost of labor inputs	Pl	0.86	0.13	0.58	1.15
Unit cost of energy inputs	Pe	0.69	0.23	0.35	1.14
Unit cost of materials inputs	Pm	1.31	0.24	1.00	1.85
Unit cost of Services	Ps	0.92	0.08	0.78	1.10
Output	Y	73.69	20.19	36.50	109.82
Capital	K	72.72	23.79	32.96	108.49
Shares in the short-run cost					
Labor cost	Sl	0.17	0.01	0.15	0.20
Energy cost	Se	0.02	0.003	0.11	0.02
Raw materials cost	Sm	0.73	0.03	0.68	0.79
Services cost	Ss	0.09	0.02	0.06	0.13

Number of observations is 54 (1961–2014). The variable cost and input prices are deflated using the outprice index. Output and Capital inputs are indexes

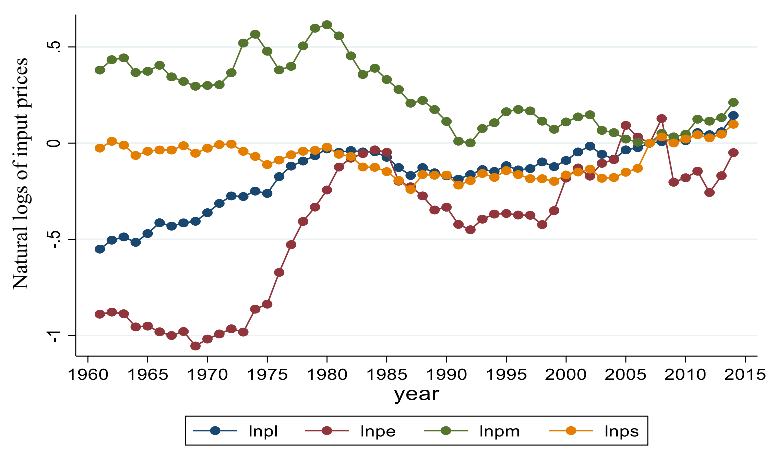

Fig. 5 Trends in log real input prices

when oil prices spiked between 1970 and early 1980s, causing labor and energy prices to rise. We then observe an upswing in real raw material input prices after 2005.

The cost and share equations are jointly estimated using the seemingly unrelated regression (SUR) method because it generates more efficient estimators when the errors are correlated (Greene 2012). The method is implemented by denoting the vector of the error terms as $\xi_t = (\xi_{C,t}, \xi_{L,t}, \xi_{E,t}, \xi_{M,t})'$, where the subscripts C, L, E, M respectively, denote cost, labor, energy, and materials, and t denotes the time subscript. The errors vector is assumed to have zero mean and a co-variance matrix of $E\left(\xi_t \xi_t'\right) = \Omega$. The SUR estimator is given as

$$\beta_{sur} = \left(X'\Gamma^{-1}X\right)^{-1} X'\Gamma^{-1}Y, \tag{13}$$

where β_{sur} and X are the stacked vectors of coefficients and regressors, respectively; Y is a stacked vector of unit variable cost and the respective cost shares for labor, energy, and material, and $\Gamma = \Omega \otimes I$ where I is identity matrix. The estimation is carried out

Table 2 Estimation results for restricted cost function

Variable	Coefficient	Estimates	SE	|*t*-ratio|	*P* > |*t*-ratio|
Constant	α_0	2.57	0.46	5.63	0.00
lnPl	α_l	0.30	0.01	30.67	0.00
lnPe	α_e	0.02	0.002	9.10	0.00
lnPm	α_M	0.59	0.01	54.42	0.00
lnPs	α_s	0.17	0.16	1.07	0.29
lnY	α_y	0.46	0.28	1.65	0.01
lnK	β_K	0.40	0.31	1.30	0.19
t	α_t	− 0.02	0.006	− 3.58	0.00
tsqr	α_{tt}	0.001	0.0001	6.30	0.00
tln(Y/K)	ρ_{ty}	0.0003	0.008	0.05	0.96
tlnPl	ρ_{tl}	− 0.02	0.003	− 6.27	0.00
tlnPe	ρte	0.001	0.001	1.14	0.26
tlnPm	ρ_{tm}	0.01	0.002	3.60	0.00
tlnPs	ρ_{ts}	− 0.003	0.004	0.71	0.48
lnPlsqr	α_{ll}	0.15	0.01	13.96	0.00
lnPesqr	α_{ee}	0.01	0.001	10.55	0.00
lnPmsqr	α_{mm}	0.22	0.01	16.95	0.00
lnPssqr	α_{ss}	0.05	0.01	6.35	0.00
lnPllnPe	ρ_{le}	− 0.01	0.002	6.81	0.00
lnPllnPm	ρ_{lm}	− 0.14	0.01	13.55	0.00
lnPllnPs	ρ_{ls}	0.02	0.01	2.83	0.01
lnPelnPm	ρ_{em}	− 0.002	0.002	1.16	0.25
lnPelnPS	ρ_{es}	0.01	0.003	2.15	0.03
lnPmlnPS	ρ_{ms}	− 0.08	0.01	12.09	0.00
ln(Y/K)lnPl	ρ_{yl}	− 0.04	0.01	2.90	0.00
ln(Y/K)lnPe	ρ_{ye}	0.01	0.003	0.50	0.62
ln(Y/K)lnPm	ρ_{ym}	0.02	0.02	1.14	0.25
Ln(Y/K)lnPs	ρ_{ys}	− 1.77	0.85	2.07	0.04
Breusch–Pagan test of independence			$X^2_{(6)} = 116.34$ $(P > \chi^2 = 0.00)$		
Wald Chi-square test for overall significance			$X^2_{(24)} = 561{,}766.32$, $(P > \chi^2 = 0.00)$		

There is benefit from estimating the equations jointly since they are not independents as ascertained by the Brueuch and Pagan (1980) test

iteratively, beginning with an estimation of each equation by the ordinary least square (OLS) method to obtain estimates of the error terms and use them to construct the joint co-variance matrix, Ω. Starting with this step, iterative estimation implies repetition of the procedure by using the errors computed from the preceding regression to compute the elements of Ω to be used in each subsequent step, continuing until the values of the parameters converge. This method, known as the iterative seemingly unrelated regression (ISUR), is preferred since iteration until convergence yields maximum likelihood estimates, which are invariant to the choice of the share equation to be deleted due to the requirement of the adding up restriction (Kmenta and Gilbert 1968). The estimation is carried out by imposing the relevant cross equation restrictions as well as the specific restrictions presented above. As shown in Fig. 5 below, the variables are non-trending

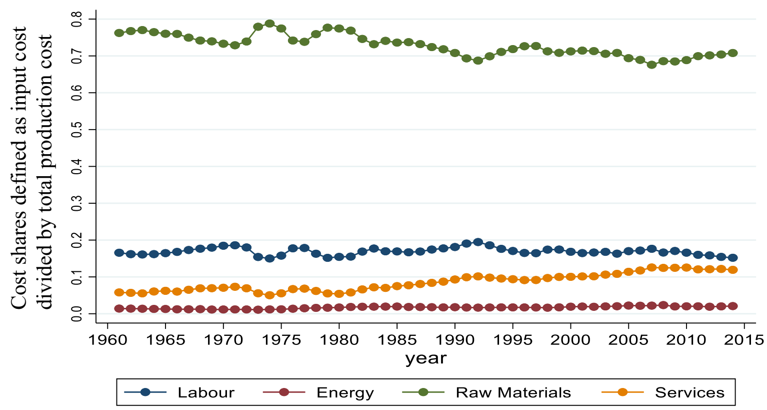

Fig. 6 Trends in estimated cost shares for variable inputs

once they are presented relative to output price. This allows us to ignore the time series properties of the data in our estimation.

Estimation results

Summary of estimation results

The estimated coefficients are presented in Table 2. The results indicate that the specified model has an excellent fit to the data and passes several robustness checks. For example, the Wald test for overall significance is highly significant both for the cost and the share equations. The Breusch–Pagan test for cross-equation correlations suggests that estimation of the cost equation along with the share equations has contributed to the generation of efficient standard errors. Moreover, the use of an iterative, seemingly unrelated regression procedure ensures consistency of the estimated parameters. I have also carried out tests for alternative specifications by imposing a restriction implied by Hicks neutral production technology. The tests favor the model with non-neutral technical change, which suggests the existence of price-induced technical changes. Accordingly, the estimate for technical progress captures neutral, biased, and scale-augmented technical changes.

Lastly, I checked whether the estimated model passed the monotonicity restrictions, which is based on the requirement that estimated shares must be non-negative at all data points. In rather sophisticated works that involve computer programming, such requirements are imposed as one of the a priori restrictions, like the restrictions that I have considered. In this study, I didn't pre-impose these restrictions, but it is comforting that the estimation results do not violate monotonicity restrictions. This is confirmed by the trends in the predicted shares provided in Fig. 6. These results can, therefore, be used to compute the various metrics that this study is set out to undertake.

Estimated capacity utilization and productivity growth

The estimated capacity utilization reveals some important facts. First, capacity utilization has always been below one, revealing the food industry is experiencing capacity underutilization almost every year except for a couple of occasions when capacity utilization is above one. This result suggests the advantage of cost-based estimation, which could capture capacity overutilization. The most important observation from the results

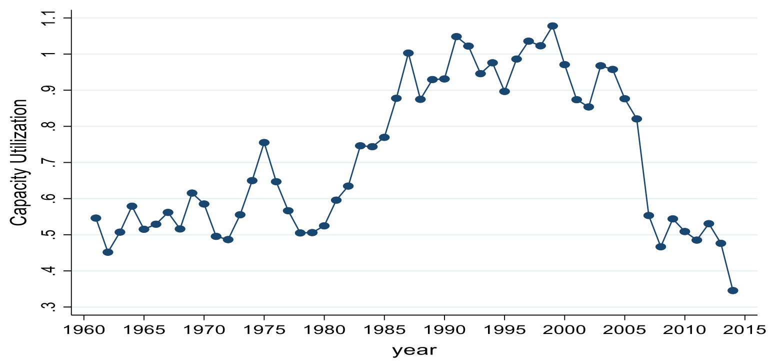

Fig. 7 Estimated cost-based capacity utilization

Table 3 Capacity utilization (CU), TFP growth, and price elasticity of CU

	Mean	Maximum	Minimum	SD
Capacity utilization	0.712	1.08	0.350	0.210
Price elasticity of CU				
Labor	− 0.065	− 0.039	− 0.122	0.019
Energy	0.002	0.004	0.001	0.001
Raw materials	0.035	0.066	0.021	0.010
Services	0.027	0.051	0.016	0.008
TFP growth	− 0.010	0.013	=0.063	0.017

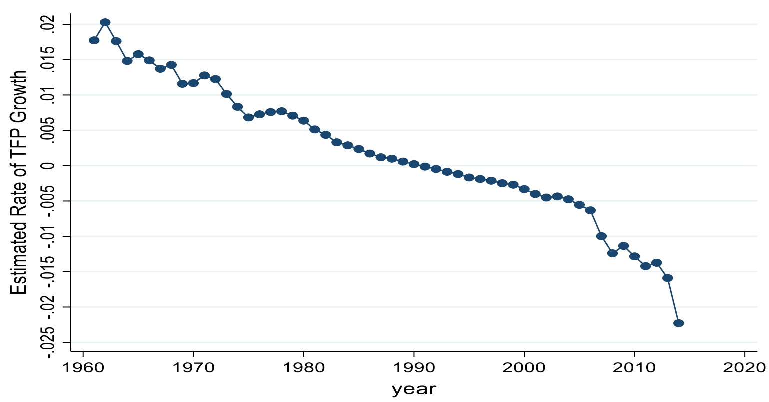

Fig. 8 Estimated productivity growth rate

is that capacity utilization was rising in the 1990s. Such constraints could have spurred investment, which might have contributed to the significant drop in capacity utilization in more recent years. It is, however, notable that the significant drop in capacity utilization has taken place after the surge in raw material costs. One can clearly see a downward trend in the 2000s in general, but the drop after 2005 is substantial (Fig. 7). Capacity utilization is estimated to be around 35% in 2014, the most recent year studied, but the all-time average is 71% (Table 3).

One of the key implications of low-capacity utilization is a decline in productivity growth. We find that productivity growth is generally sluggish and is even negative

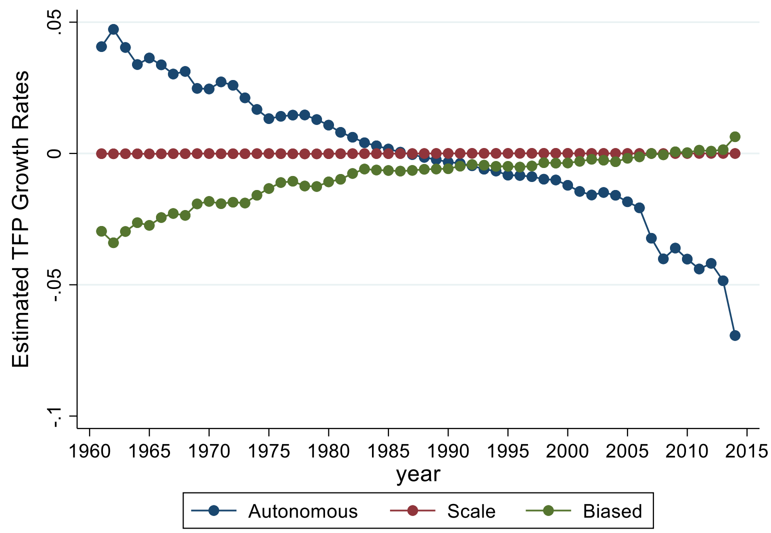

Fig. 9 Decomposition of TFP growth rates

since 1980. The trend after 2005 is unique. As shown in Fig. 8, productivity growth has dropped significantly following the trend in capacity utilization. Given that productivity growth has generally followed a downward trend, I provide its decomposition into neutral, biased, and scale-augmenting technical changes to highlight the main driver of the downward trend. Figure 9 reveals an interesting result: that the decline in technological progress is not due to capacity underutilization but primarily due to unexplained (autonomous) technical deceleration in the food industry. This is an interesting topic to further investigate, but not pursued in this study. Another important piece of information is that there is a price-induced improvement in productivity in general. The little spike in this component after the surge in raw materials costs could be interpreted to imply that the increased cost might have induced cost-saving technical changes to a certain extent.

Input price elasticity of capacity utilization is used to identify how this variable reacts to changes in input prices. Thus, this is a very important metric to show how industries react to increasing input costs. The computed elasticities are presented in Table 3. What it reveals is that elasticities are small in magnitude, but their signs signal important information. The results show that only wages (labor costs) affect capacity utilization negatively, while all others are positive effects. The price of raw materials has the highest positive elasticity. As stated earlier, the elasticity of CU with respect to the variable input prices is reflective of their substitution relationship with capital, and positive elasticity means capacity and the input are substitutes. Accordingly, a rise in raw material input prices could increase capacity (capital acquisition), which contributes to a decline in capacity utilization rate, all else remaining the same. The elasticity calculation, therefore, signals that the increased cost of raw materials could have contributed to the estimated drop in capacity utilization and TFP growth.

Elasticity and factor substitution

The price elasticities show that factor demands are inelastic with respect to their own and other input prices. The Morishima cross-elasticities, on the other hand, reveal that

Table 4 Elasticities

	Allen-Uzawa price elasticities[a,b]				Morishima Cross-Price Elasticities			
	L	**E**	**M**	**S**	**L**	**E**	**M**	**S**
L	*− 0.143*	**− 0.049**	**0.107**	**0.085**				
E	**− 0.517**	*− 0.324*	**0.756**	**0.080**	− 0.374			
M	**0.025**	**0.169**	*− 0.014*	**− 0.046**	0.168	− 0.155		
S	**0.129**	**− 0.480**	**− 0.484**	*− 0.049*	0.305	− 0.160	− 0.47	

The bold values are the elasticities of substitutions

[a] The values below the main diagonal are the elasticity of the price of the inputs in the rows with respect to the price of the input in the column. Similarly, the values above the main diagonal are the elasticities of the variables indicated in the columns with respect to the prices of the variables indicated in the rows. Note that cross-price elasticities are not symmetric because they are share-weighted

[b] Similarly, the values above the main diagonal are elasticities of the variables indicated in the columns with respect to the prices of the variables indicated in the rows. Note that cross-price elasticities are not symmetric because they are share-weighted

raw material input is a substitute for labor but complementary with energy and services. Thus, besides the effects on capacity utilization reported above, an increase in raw material input prices could induce cost-saving measures through labor substitutions to a limited extent (Table 4).

Conclusions

Sparling and LeGrow noted that food processing companies in Canada are engaged in consolidation and restructuring as well as investing in upgrading facilities and invigorating innovation, productivity, and efficiency in the wake of the unprecedented rise in raw material input prices. This study is motivated by this conclusion and attempts to unravel some of the key economic features of the industry. I employed the cost-based measure of capacity utilization to estimate its trends and assess how it behaved during the period characterized by a spike in raw material prices. I found that capacity utilization dropped significantly after 2005. This has also translated to low productivity growth. Since the industry appeared to have been at full capacity before the spike in the raw material input prices, there could have been more investments aimed at capacity building. This might have contributed to the significant drop in capacity utilization in the aftermath. This observation is consistent with the description that shows that firms were consolidating, which implies that there could be stranded assets. This requires further investigation.

Further analysis in this study reveals that capacity utilization reacts positively to raw material input prices. The results pertaining to the factor-bias of technological progress entail a similar story in that it is labor, energy, and raw materials input saving. Accordingly, a rise in the cost of raw materials would lead to improvements in factor-saving technological progress. These two results suggest that part of the negative consequences of the recent rise in raw material input costs could be offset via raw material-saving technological progress and improvements in capacity utilization emanating from harnessing economies of scale. The ultimate implication of these two results is an improvement in cost-efficiency, which helps the producers cope with the rising cost of production. This is consistent with the report by (Sparling and LeGrow 2015) who noted that food processing companies in Canada are engaged in consolidation and restructuring as well as investing to upgrade facilities and invigorate innovation, productivity, and efficiency. It is important that these changes are strengthened via government policy measures.

The analysis has revealed that productivity growth is dismal in the food processing industry. This is a major concern, which calls for policies that could stimulate innovations and investments in new technologies. The declining capacity utilization and the resultant low capital productivity also ought to be dealt with. Policies should, therefore, consider ways of stimulating innovations and technological progress through various incentives such as investment tax credits and R&D subsidies.

Abbreviations

CU	Capacity utilization
VC	Variable cost
Pk	Unit cost of capital
Pl	Unit cost of labor
Pe	Unit cost of energy
Pm	Unit cost of raw materials
Y/K	Output-capital ratio
Y	Output
Sl	Share of labor cost
Se	Share of energy cost
Sm	Share of raw materials cos
Ss	Share of services inputs
TFP	Total factor productivity

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Availability of data and materials
The data used in this analysis are available and can be provided, including the estimation commands.

Declarations

Competing interests
I declare that this research is my original research work and has not been submitted elsewhere for publication. As such, there is not any competing interest.

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References

Anderson JD, Coble KH (2010) Impact of renewable fuels standard ethanol mandates on the corn market. Agribusiness 26(1):49–63. https://doi.org/10.1002/agr.20202

Berndt ER, Hess DM (1986) Measuring and assessing capacity utilization in the manufacturing sectors of nine OECD countries. Eur Econ Rev 30:961–989

Berry ST, Roberts MJ, Schlenker W (2013) Corn Production Shocks in 2012 and Beyond: Implications for Harvest Volatility. University of Chicago Press, Chicago, Ill.

Blackorby C, Russell RR (1989) Will the real elasticity of substitution please stand up? A comparison of the Allen-Uzawa and Morishima elasticities. Am Econ Rev 79(4):882–888

Congressional Budget Office (2009) The impact of ethanol uses on food prices and greenhouse-gas emissions. CBO. Accessed from http://www.cbo.gov/sites/default/files/111th-congress-2009-2010/reports/04-08-ethanol.pdf

Greene, W. H. (2012). *Econometric Analysis.* (7th, Ed.) Upper Saddle River, NJ: Prentice Hall.

Hausman C, Auffhammer M, Berck P (2012) Farm acreage shocks and crop prices: an SVAR approach to understanding the impacts of biofuels. Environ Resour Econ 53(1):117–136

Jorgenso DW, Wilcoxen PJ (1993) Reducing US carbon emissions: an econometric general equilibrium assessment. Resour Energy Econ 15(1):7–25

Kennedy C (1964) Induced bias in innovation and the theory of distribution. Econ J 74:541–547

Kmenta J, Gilbert RF (1968) Small sample properties of alternative estimators of seemingly unrelated regressions. J Am Stat Assoc 63(324):1180–1200
Morrison CJ (1985) Primal and dual capacity utilization: an application to productivity measurement in the US Automobile Industry. J Bus Econ Stat 3(4):312–324
Morrison CJ (1999) Scale economy measures and subequilibrium impacts. J Prod Anal 11:55–66
Morrison CJ (1988) Capacity utilization and productivity measurement: an application to the US automobile industry. In: Färe R (ed) Springer
Mueller SA, Anderson JE, Wallington TJ (2011) The impact of biofuel production and other supply and demand factors on food price increases in 2008. Biomass Bioenerg 35(5):1623–1632
Roberts MJ, Schlenker W (2013) Identifying supply and demand elasticities of agricultural commodities: implications for the US ethanol mandate. Am Econ Rev 103(6):2265–2295
Sparling D, Cheney E (2014) The changing face of food manufacturing in Canada: food manufacturing performance. CAPI, Ivey Business School, Western University, London, Ontario. Accessed from URL http://www.capi-icpa.ca/proc-food/proc3a.html
Sparling D, LeGrow S (2015) The changing face of food manufacturing in Canada: an analysis of plant closings, openings, and investments. CAPI, Ivey School of Business, Western University, London, Ontario. Accessed from David Sparling, Sydney LeGrow: The Changing Face ofhttp://www.capi-icpa.ca/proc-food/proc3b.html
The International Council on Clean Transportation (2021) The impact of the U.S. Renewable Fuel Standard on food and feed prices. https://theicct.org/sites/default/files/publications/RFS-and-feed-prices-jan2021.pdf; Accessed on November 10, 2021
US EPA (2010) Renewable Fuel Standard Program (RFS2) Regulatory impact analysis
US Energy Information Adminstration (2020) U.S. fuel ethanol production capacity increased by 3% in 2019. https://www.eia.gov/todayinenergy/detail.php?id=45316#.

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