Journal of Agricultural and Applied Economics (2020), **52**, 177–193
doi:10.1017/aae.2019.41

CAMBRIDGE UNIVERSITY PRESS

RESEARCH ARTICLE

Greenhouse Gas Emissions and Technical Efficiency in Alberta Dairy Production: What Are the Trade-Offs?

Stephanie Le, Scott Jeffrey* and Henry An

Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta, Canada
*Corresponding author. Email: scott.jeffrey@ualberta.ca

Abstract:
The impact of greenhouse gas (GHG) reduction on the efficiency of Alberta's dairy industry is assessed through a technical efficiency analysis over the period 1996–2016, with and without emissions included as a "bad" output. Environmentally adjusted technical efficiency and technical efficiency estimates are highly correlated; thus, reducing GHG emissions may not result in decreased efficiency. Increased milk per cow, a southern Alberta location, and increased use of forage are associated with greater environmentally adjusted technical efficiency. The opportunity cost of foregone milk revenue associated with reduced emissions is Can$308.29 per metric ton of GHG. The results imply possible policy strategies to reduce emissions.

Keywords: Dairy production; greenhouse gas emissions; stochastic distance function; technical efficiency

JEL Classifications: D24; Q12; Q54

1. Introduction

The dairy sector is a significant contributor to Canada's agricultural economy and the Canadian diet—more than 8 billion kg of milk are produced in Canada annually (Canadian Dairy Information Centre, 2019). However, dairy production has a significant carbon footprint; at the farm level, approximately 1 kg of carbon dioxide (CO_2) equivalents is released per kilogram of milk produced in Canada (Vergé et al., 2007). Anthropogenic greenhouse gas (GHG) emissions are widely accepted as a key contributor to climate change, which in turn is predicted to have negative ecological, social, and economic effects (Haines et al., 2006). In response to societal concerns, government policy is increasingly emphasizing the reduction of environmental impacts from agriculture. Under Alberta's Agricultural Carbon Offset Program, for example, farmers adopting GHG mitigation practices can receive carbon offset credits (Alberta Environment, 2010).

There is a large body of research showing that GHG mitigating practices in the dairy industry can also increase production levels. Typically, these practices indirectly affect per unit emissions through increasing/improving milk yield, feed efficiency, or animal health. For example, reductions in replacement rates, culling rates, or calving interval for dairy cows have been shown to decrease GHG emissions (Weiske et al., 2006). In addition, production of enteric methane, which comprises the majority of dairy farm–level GHG emissions, represents a loss of energy that could have been used toward production. Strategies to inhibit methanogens include feeding lipids, more digestible diets, and antimicrobials such as ionophores, nitrates, dicarboxylic acids, and bacteriocins (Cottle and Wiedemann, 2011).

Because of the complexity of the dairy system, many practices that reduce GHGs in one part of the farming enterprise create higher emissions in another part. Feeding lipids, for example, can decrease enteric methane from ruminants but may increase overall GHG emissions because of resulting changes in cropping practices (Williams et al., 2014). In addition, although some GHG mitigation practices can increase milk production, their cost can be prohibitive, and this is especially true for the use of many feed additives (Eckard, Grainger, and de Klein, 2010). If the dairy enterprise is thus considered within the larger context of the overall farm business, what is the effect of reducing GHG emissions on total farm economic performance? A relevant avenue of investigation to address this question is to assess the relationship between whole farm GHG emissions and the technical efficiency of dairy producers.

Many previous studies have examined the technical or economic efficiency of dairy farms, using both stochastic frontier analysis (SFA) and data envelopment analysis (DEA) frameworks (e.g., Cloutier and Rowley, 1993; Hailu, Jeffrey, and Unterschultz, 2005; Johansson, 2005; Weersink, Turvey, and Godah, 1990). When considering environmental externalities and efficiency, earlier studies have mainly focused on nitrogen surpluses (e.g., Mamardashvili, Emvalomatis, and Jan, 2016; Reinhard, Knox Lovell, and Thijssen, 1999). Only a small number of technical efficiency studies have examined GHGs (e.g., Njuki and Bravo-Ureta, 2015; Shortall and Barnes, 2013) and knowledge gaps still remain to be filled. For example, information is needed to assess whether technically efficient producers are more or less "efficient" when considering GHG emissions and what types of producer or management factors affect this relationship. This knowledge would be relevant for policy makers in terms of informing debate about whether incentives are required to move producers toward reduced emissions.

The primary objective of this study is to estimate the technical efficiency for a sample of Alberta dairy farms, calculated with and without consideration of GHG emissions. In doing so, this study contributes to the relatively sparse literature concerning the effects of GHG emissions on technical efficiency. An additional contribution is the calculation of the opportunity cost of improved "environmental performance," measured as the shadow price of GHG emissions. As the relationship between GHG emissions and farm-level efficiency is largely unexplored, these results can assist in creating economically viable GHG mitigation policies, aid producer decision making in response to policy initiatives, and provide methodological contributions for the inclusion of a detrimental output in efficiency analysis.

2. Methodology

2.1. Theoretical framework

A production frontier describes the maximum amount of output that can be produced from a specified amount of inputs, given production technology. A producer operating on the frontier is said to be fully technically efficient (Coelli et al., 2005). Frontiers may be considered to be deterministic or stochastic. In the case of a stochastic frontier, deviations from the frontier are assumed to be because of a combination of random shocks and producer inefficiency. Given that variability in milk production is because of a combination of management and environmental factors, it is appropriate to model technical efficiency by estimating a stochastic frontier. A stochastic frontier may be represented as follows:

$$\ln y_i = \ln f(x_i; \beta) e^{(v_i - u_i)}, \tag{1}$$

where y_i is the output produced by the ith farm, x_i is a vector of inputs, β is a vector of parameters to be estimated, v_i is the stochastic error term, and u_i is the nonnegative inefficiency term.

This study considers dairy production in terms of generating multiple outputs: two "good" outputs and one "bad" output. Thus, a standard production function would be inadequate as it typically allows for only one positive output. Instead, a distance function frontier is defined and estimated. There are alternative types of distance functions that may be considered for this type of analysis. Following Cuesta, Knox Lovell, and Zofío (2009), an enhanced hyperbolic distance function is used. The hyperbolic distance function allows for the asymmetric treatment of beneficial and detrimental outputs by considering equiproportional contraction (expansion) of bad (good) outputs in a multiplicative manner. The enhanced model also considers the

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

proportional contraction of inputs (Cuesta and Zofío, 2005). Given an underlying behavioral assumption of profit maximization, the results from the enhanced hyperbolic distance function are comprehensive economic performance measures that consider the ability of the producers to simultaneously maximize beneficial outputs, minimize detrimental outputs, and minimize inputs.

To further examine the impact of considering GHG emissions on the economic performance of farmers, results from two versions of the enhanced hyperbolic distance function are compared: one including GHGs as a detrimental output and one without GHGs. The enhanced hyperbolic distance function with a negative output is represented by

$$D_H(x, y, b) = \inf\left\{\theta > 0 : \left(x\theta, \frac{y}{\theta},\ b\theta\right) \in T\right\}, \tag{2}$$

where T is the production possibility set that denotes the conversion of the input vector (x) into the beneficial output vector (y) and the detrimental output scalar (b) by the production technology. A representation of T is provided by equation (3):

$$T = \{(x, y, b) : (x, y, b) \in \mathrm{R}_+,\ x \text{ can produce } (y, b)\}. \tag{3}$$

Without the negative output, equation (2) can be written as follows:

$$D_H(x, y) = \inf\left\{\theta > 0 : \left(x\theta, \frac{y}{\theta}\right) \in T\right\}. \tag{4}$$

Interpreted in the context of efficiency, the value of the distance function (θ) represents the level of technical efficiency. The distance function has a range of $0 < D_H(x, y, b) \leq 1$, where 1 represents complete technical efficiency. If the customary production function axioms are satisfied by the technology, the hyperbolic distance function has the following properties (Cuesta, Knox Lovell, and Zofío, 2009):

1. Almost homogeneity: $D_H(\mu^{-1}x, \mu y, \mu^{-1}b) = \mu D_H(x, y, b)$, $\mu > 0$
2. Nondecreasing in beneficial outputs: $D_H(x, \alpha y, b) \leq D_H(x, y, b)$, $\alpha \in [0,1]$
3. Nonincreasing in detrimental outputs: $D_H(x, y, \alpha b) \leq D_H(x, y, b)$, $\alpha \geq 1$
4. Nonincreasing in inputs: $D_H(\alpha x, y, b) \leq D_H(x, y, b)$, $\alpha \geq 1$

2.2. Empirical model

With the almost homogeneity property, the hyperbolic distance function can be represented using a translog functional form. Equation (5) represents the model considering N producers ($i = 1, 2, \ldots, N$), T time periods ($t = 1, 2, \ldots, T$), K inputs ($k = 1, 2, \ldots, \mathrm{K}$), M beneficial outputs ($m = 1, 2, \ldots, M$), and one bad output (b):

$$\begin{aligned}\ln D_{Hit} = {} & \alpha_0 + \sum_{k=1}^{K}\alpha_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\alpha_{kl}\ln x_{kit}\ln x_{lit} + \sum_{m=1}^{M}\beta_m \ln y_{mit} \\ & + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\beta_{mn}\ln y_{mit}\ln y_{nit} + \delta\ln b_{it} + \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km}\ln x_{kit}\ln y_{mit} \\ & + \sum_{m=1}^{M}\theta_{mb}\ln y_{mit}\ln b_{it} + \sum_{k=1}^{K}\theta_{kb}\ln x_{kit}\ln b_{it}.\end{aligned} \tag{5}$$

Returning to the almost homogeneity condition, μ is chosen to be the inverse of one of the good outputs (y_M):

$$D_H\left(xy_M, \frac{y_m}{y_M},\ by_M\right) = \frac{D_H(x, y, b)}{y_M}. \tag{6}$$

The transformed function becomes

$$\ln\left(\frac{D_{Hit}}{y_M}\right) = \alpha_0 + \sum_{k=1}^{K}\alpha_k \ln x^*_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\alpha_{kl}\ln x^*_{kit}\ln x^*_{lit} + \sum_{m=1}^{M-1}\beta_m \ln y^*_{mit}$$
$$+\frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1}\beta_{mn}\ln y^*_{mit}\ln y^*_{nit} + \delta \ln b^*_{it} + \sum_{k=1}^{K}\sum_{m=1}^{M-1}\gamma_{km}\ln x^*_{kit}\ln y^*_{mit} \quad (7)$$
$$+\sum_{m=1}^{M-1}\theta_{mb}\ln y^*_{mit}\ln b^*_{it} + \sum_{k=1}^{K}\theta_{kb}\ln x^*_{kit}\ \ln b^*_{it}, (i = 1, 2, \ldots, N; t = 1, 2, \ldots, T),$$

where: $x^*_{kit} = x_{kit}\, y_M,\quad b^*_{it} = b_{it}\, y_M,\quad y^*_{mit} = \frac{y_{mit}}{y_{Mit}}$.

Moving $\ln D_{Hit}$ to the right-hand side of the equality allows it to be interpreted as the inefficiency component of the error term (i.e., u_{it}), and the function can be written as follows:

$$-\ln y_{Mit} = \text{Translog}\left(x^*_{kit},\ y^*_{mit},\ b^*_{it}\right) + (v_{it} - u_{it}), \quad (8)$$

where $x^*, y^*,$ and b^* are "adjusted" values for inputs, other beneficial output (i.e., livestock), and detrimental output, respectively, as defined in equation (7). The distribution of v_{it} is assumed to be *iid* (independent and identically distributed) $N\left(0,\ \sigma_v^2\right)$. Following Battese and Coelli (1995), the inefficiency term is assumed to follow a nonnegative truncated normal distribution:

$$u_{it} \sim N\left(z_{it}\varphi,\ \sigma_u^2\right), \quad (9)$$

where the mean $z_{it}\varphi$ is a function of a vector of farm-specific variables (z_{it}), and φ is a vector of parameters to be estimated jointly with the production frontier. To obtain the technical efficiency estimates, the following equation is estimated[1] as follows:

$$TE_{it} = E\left[e^{(-u_{it})}|(v_{it} - u_{it})\right]. \quad (10)$$

The production frontier and efficiency results for the hyperbolic distance function that do not consider GHGs are estimated and calculated (respectively) in the same manner, with the exception being that terms with b_{it} are not included. Maximum likelihood methods are used to estimate the stochastic frontiers and joint inefficiency models.[2] Specifically, "frontier" software, developed by Coelli and Henningsen (2019) for R, is used for this analysis.

2.3. Data

Data from Alberta Agriculture and Forestry's Dairy Cost Study over the period 1996–2016 are used for this study. The Dairy Cost Study is an annual survey of a sample of Alberta dairy producers (Van Biert, 2017). The data generated from the surveys provide benchmarks for provincial milk pricing policy and cost and return information for use by individuals and organizations in the dairy sector. Study administrators strive to obtain a representative sample of the dairy producer population. Participation in the survey varies from year to year, so the data represent an unbalanced panel of producers.[3]

The survey includes information on farm expenses, milk output, livestock numbers, feed components, and farm-specific characteristics such as years farming and farm location. For this study, beneficial outputs are milk and livestock. Milk production is standardized to 4% butterfat using a method from the International Dairy Federation (2015). Livestock output is composed of the

[1]Given the structure of the inefficiency term, technical efficiency is assumed to be time varying in nature.

[2]In estimating the production frontier, symmetry was imposed on the model parameters. No other properties were imposed a priori.

[3]Although there is a panel dimension to the data set, it is sufficiently unbalanced (i.e., over two-thirds of the firms have five or fewer observations) that a panel modeling approach is not used.

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

value of sales of different types of dairy stock (i.e., cows, heifers, calves, etc.) aggregated using the Fisher price index, with the base year being 1996 (Diewert, 1992). Observations from the year 2008 are removed for this study as the Canadian dairy industry shifted to a total production quota system from a two-tiered quota system that year, which changed the data coding system such that recorded production levels may not be accurate for that year. The resulting data set used in the analysis consisted of 1,075 observations for 210 farms.

The detrimental output is GHG emissions in kilograms of CO_2 equivalents. GHG emissions for the sample producers are not directly observable and instead are calculated using algorithms adapted from Agriculture and Agri-Food Canada's Holos model. Holos is an emissions simulation model based on the Intergovernmental Panel for Climate Change Tier 2 and 3 methodologies, which are the country-specific guidelines, and tailors the algorithms for regions within Canada (Little et al., 2008). Holos calculates whole farm GHG emissions, which include soil nitrous oxide (N_2O) emissions from cropping practices, manure N_2O, manure methane (CH_4), enteric CH_4, and CO_2 from farm energy use. For parameters required by Holos that are not directly available from the Dairy Cost Study, values were obtained through expert opinion[4] and a review of relevant literature. The use of this type of approach is consistent with previous literature examining GHG emissions as a detrimental output (e.g., Njuki and Bravo-Ureta, 2015; Shortall and Barnes, 2013; Wettemann and Latacz-Lohmann, 2017).

The inputs used in the production frontier are forage, concentrate, capital, labor, and "other." With the exception of labor and capital, input expenditures are used to quantify inputs. This is done in part to reflect differences in input quality as well as for input aggregation purposes (e.g., forage, concentrate). Fisher price indices are used to aggregate the separate expenses into an implicit quantity by dividing total expenses by the price index, with the base year being 1996. The forage input variable consists of hay, silage, greenfeed, straw, and alfalfa pellets. Concentrate consists of feeds with higher energy content such as grains, supplements, minerals, molasses, and brewer's grains. The "other" input variable includes expenditures for inputs such as insurance, bedding, veterinary expenses, utilities, milk hauling, and miscellaneous expenses.

Because of potential measurement error from assuming a price for family and operator labor, total hours of paid, family, and operator labor are used as the labor input variable. Capital input is derived following equation (11):

$$Capital = Value\ of\ total\ assets * User\ cost + Repairs + Rent, \tag{11}$$

where the value of total assets includes machinery, dairy equipment, dairy buildings, land, dairy animals, and supplies. User cost is calculated following Slade and Hailu (2016). The implicit interest rate from the Dairy Cost Survey is used as the price of debt, and the 5- to 10-year marketable Government of Canada bond rate as the price of equity (Statistics Canada, 2019a). Linear and quadratic time trend variables are also included in the production frontier to capture technical change.

Variables included in the inefficiency model (i.e., z_{it} as defined in equation 9) are selected based on a combination of evidence from the empirical literature (i.e., previous dairy efficiency studies) as well as data availability. Typical variables hypothesized to influence efficiency include farming intensity, livestock quality, age and education of farmer, and access to technology (e.g., Jiang and Sharp, 2014; Mosheim and Lovell, 2009; Weersink et al., 1990). For this study, the variables included in the model are herd size, milk yield, butterfat, years farming, proportion of paid labor, proportion of purchased feed, debt-to-asset ratio, a regional dummy for a farm located in North or South Alberta, linear and quadratic time trends, and proportion of forage in the diet.

Herd size is measured as the number of lactating and dry cows and is hypothesized to have a positive effect on efficiency because of scale effects. Milk yield (liters of fat-corrected milk per cow per day) directly reflects the productivity of the cow and is included as a proxy for underlying

[4]Expert opinion refers to information received through consultations with individuals who are familiar with Alberta dairy production and production practices. These include Alberta Agriculture and Forestry staff, dairy nutritionists, and dairy researchers.

genetic quality. It is expected to be positively related to farm efficiency. Butterfat percentage is also expected to have a positive effect, as it can reflect management ability, especially as dairy quota is calculated in kilograms of butterfat (Alberta Milk, 2019).

Years farming and the time trend are hypothesized to have a positive effect on efficiency because of benefits of increased experience and technological improvements, respectively. The proportion of total hours of labor that is from paid labor, the proportion of total feed that is purchased, and the debt-to-asset ratio all impose additional costs or constraints to the producers and thus may negatively affect efficiency. A regional dummy is also included, as farming practices and environmental factors differ between northern and southern producers.[5] For example, southern Alberta producers feed more corn silage compared with producers in northern Alberta (Statistics Canada, 2017). Finally, the proportion of the forage in the diet is predicted to have a negative effect on efficiency as forage is a lower-energy feed that increases GHG emissions relative to concentrate (Beauchemin et al., 2008) and so is included in the inefficiency model.

As noted earlier, the final data set used in the production frontier and inefficiency model estimation consisted of 1,075 observations for 210 farms. Over the sample period, average herd size more than doubled, from approximately 71 cows in 1996 to more than 159 cows in 2016. This trend, combined with increasing milk per cow,[6] resulted in positive trends for all three outputs: total milk, livestock output, and GHG emissions. Sample farms located in southern Alberta had, on average, larger herd sizes (121.5 vs. 103.1 cows, respectively) and slightly more productive cows (18.7 liters/day vs. 17.7 liters/day, respectively) than farms located in northern Alberta, resulting in greater levels of total milk, GHG emissions, and livestock output. Descriptive statistics for the production frontier and inefficiency model variables are provided in Table 1.

3. Results and discussion

3.1. Efficiency estimates

To prevent problems with model convergence, the production frontier variables are normalized by their geometric mean. To deal with any potential econometric issues (i.e., autocorrelation and heteroscedasticity), bootstrapped standard errors generated with 2,000 replications are used.[7] The parameter estimates for both models are reported in Table 2. For clarity in discussion, efficiency estimates from the model that includes GHGs are denoted as environmentally adjusted technical efficiency, whereas efficiency estimates from the model without GHGs are referred to as technical efficiency.

The efficiency estimates are summarized in Table 3. Overall, the models with and without GHGs are very similar, as seen in the scatter plot (Figure 1), with a mean environmentally adjusted technical efficiency of 0.9367 and a mean technical efficiency of 0.9252. The distributions are also highly similar, with most producers having very high efficiency (Figure 2). In addition, technical and environmentally adjusted technical efficiency are highly correlated with each other; the Pearson's correlation coefficient is 0.8638, and the Spearman's rank correlation coefficient is 0.8367. This suggests that minimizing GHG emissions may not be inconsistent with the objective of maximizing output for given levels of inputs. One possible explanation for the high correlation is that GHG emissions are in part attributable to inefficient use of energy by the animal. Enteric methane, for example, makes up the largest proportion of the GHG emissions (Table 4) and represents a significant loss in feed energy that could have been converted to productive outputs (Beauchemin et al., 2008). This contribution to GHG emissions could therefore be reduced with

[5]For the purposes of the Dairy Cost Study, northern Alberta producers are those located north of Ponoka County (Van Biert, 2017).

[6]Average milk per cow increased at a slower rate than did herd size; average daily production per cow increased from 16.9 liters in 1996 to 21.4 liters in 2016.

[7]The "boot" package in R was used to perform ordinary nonparametric bootstrapping for the standard errors.

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Table 1. Descriptive statistics for model variables (n = 1,075)

	Name	Mean	Standard Deviation	Minimum	Maximum
Positive outputs	Milk output (hL FPCM[a])	7,559.49	5,663.86	1,416.88	41,335.22
	Livestock output[b]	54,029.25	47,096.09	1,054.78	474,394.20
Detrimental output	Greenhouse gas emissions (kg CO_2 eq)	972,236.90	737,320.40	206,722.50	6,525,698.00
Inputs	Forage[b]	108,143.90	99,067.56	14,145.00	979,632.20
	Concentrate[b]	187,287.80	150,277.80	21,160.65	1,173,868.00
	Labor (hours)	6,168.15	3,673.52	1,369.88	35,542.00
	Capital[c]	1,294,967.00	2,694,390.00	63,576.98	30,380,290.07
	Other[b]	78,160.84	58,851.92	16,239.74	583,759.80
Inefficiency model variables	Milking herd size (number of cows)	112.92	88.36	26.58	834.25
	Milk yield per cow (L/day)	18.23	2.78	9.43	26.83
	Butterfat (%)	3.76	0.27	2.68	5.30
	Years farming	19.94	11.77	0.00	57.00
	Paid labor (proportion of total)	0.2413	0.26	0.00	0.92
	Purchased feed (proportion of total)	0.6407	0.21	0.03	1.00
	Debt-to-asset ratio	0.0201	0.02	0.00	0.12
	Proportion of forage in the diet	0.3783	0.10	0.12	0.75
	North/south dummy (north = 1)	North = 501 observations		South = 574 observations	

[a]Fat- and protein-corrected milk, where milk is standardized to 4% fat and 3.3% milk protein (International Dairy Federation, 2015).
[b]The quantity is the implicit quantity obtained by dividing the value of sales (or expenses) by the implicit price (Fisher price index with 1996 as the base year).
[c]The quantity of capital is proxied by the annual cost of capital.

more efficient energy use by the cow. Previous studies have also found high correlation between environmental and technical efficiencies, with Spearman rank correlations ranging from 0.418 to 0.920 (Dayananda, 2016; Reinhard, Knox Lovell, and Thijssen, 1999; Shortall and Barnes, 2013).

Given the nature of the "environmental efficiency" measure (i.e., environmentally adjusted technical efficiency), it represents a mix of environmental efficiency and regular technical efficiency. However, higher levels of environmentally adjusted technical efficiency are associated with lower GHG emission intensity, defined as GHG emissions per hectoliter of milk (Figure 3). The Pearson's correlation coefficient is −0.761.

The high average efficiency level for the sampled Alberta dairy farms is an indication that in this sample most producers are very similar in terms of their efficiency. Because efficiency is measured relative to the most efficient producer(s), this results in a high average. Other dairy technical efficiency studies also reveal fairly high average technical efficiency scores. For example, Mamardashvili, Emvalomatis, and Jan (2016) estimated an average technical efficiency level of 0.966 for Swiss dairy farms, and Cabrera, Solis, and Del Corral (2010) found an average technical efficiency score of 0.88 for Wisconsin dairy farmers. In a Canadian context, Mbaga et al.'s (2003) study of Quebec dairy farmers estimated a variety of SFA models and found average efficiency scores to be approximately 0.95. Singbo and Larue (2016) decomposed total factor productivity into scale and efficiency effects for a sample of Quebec dairy farmers and estimated the average

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Table 2. Maximum likelihood parameter estimates: hyperbolic distance function with and without greenhouse gas (GHG) emissions (n = 1,075)

	GHGs		Without GHGs	
	Estimate[a]	Standard Error[b]	Estimate[a]	Standard Error[b]
Intercept	−0.0090	0.0152	0.0822***	0.0159
Forage[c]	0.0116	0.0088	−0.0376***	0.0118
Conc	−0.0241***	0.0089	−0.0706***	0.0108
Capital	−0.0483***	0.0119	−0.1916***	0.0106
Labor	−0.0251***	0.0069	−0.0514***	0.0091
Other	−0.0350***	0.0075	−0.0834***	0.0097
LvstkSales	0.0174***	0.0057	0.0244***	0.0073
Time trend	−0.0062**	0.0025	−0.0117***	0.0027
(Time trend)^2	−0.0002	0.0001	−0.0006***	0.0001
LvstkSales*LvstkSales	0.0024	0.0160	0.0046	0.0143
LvstkSales*Forage	−0.0782***	0.0192	−0.0145	0.0220
LvstkSales*Conc	0.0057	0.0235	−0.0112	0.0263
LvstkSales*Labor	−0.0100	0.0156	−0.0079	0.0169
LvstkSales*Capital	0.0413	0.0267	0.0060	0.0285
LvstkSales*Other	0.0268***	0.0100	−0.0100	0.0117
Forage*Forage	−0.0330	0.0222	0.0310	0.0252
Forage*Conc	−0.0360***	0.0108	−0.0207	0.0134
Forage*Labor	0.0248	0.0206	0.0392*	0.0233
Forage*Capital	0.0045	0.0179	−0.0247	0.0234
Forage*Other	0.0503***	0.0133	0.0606***	0.0173
Conc*Conc	−0.0024	0.0273	−0.0412	0.0333
Conc*Labor	0.0167*	0.0097	0.0207**	0.0096
Conc*Capital	−0.0451***	0.0172	−0.0741***	0.0239
Conc*Other	0.0586***	0.0163	0.0433*	0.0231
Labor*Labor	0.0078	0.0056	0.0078	0.0071
Labor*Capital	−0.0030	0.0142	0.0142	0.0166
Labor*Other	−0.0137	0.0130	0.0004	0.0146
Capital*Capital	−0.0750***	0.0250	−0.0700**	0.0299
Capital*Other	0.0137	0.0122	0.0224	0.0185
Other*Other	−0.0129	0.0163	0.0189	0.0200
GHG	−0.3642***	0.0201		
GHG*GHG	0.0214	0.0533		
GHG*LvstkSales	0.0754***	0.0291		
GHG*Forage	0.0306	0.0456		
GHG*Conc	0.0809**	0.0315		

(*Continued*)

Table 2. (*Continued*)

	GHGs		Without GHGs	
	Estimate[a]	Standard Error[b]	Estimate[a]	Standard Error[b]
GHG*Labor	−0.0312	0.0435		
GHG*Capital	0.0009	0.0296		
GHG*Other	−0.1279***	0.0456		
Joint inefficiency model				
Intercept	0.5416***	0.0676	0.6803***	0.1015
Herd size	0.0001	0.0001	0.0001	0.0001
Milk yield	−0.0281***	0.0020	−0.0333***	0.0038
Time trend	0.0063	0.0040	0.0013	0.0041
(Time trend)^2	0.0000	0.0002	0.0005**	0.0002
Butterfat	−0.0063	0.0149	−0.0429*	0.0242
Years farming	0.0005	0.0004	0.0010**	0.0005
Prop. paid labor	0.0060	0.0134	0.0182	0.0173
Prop. purchased feed	0.0072	0.0150	0.0698**	0.0283
D/A ratio	0.0588	0.2097	0.5159	0.3202
N/S dummy (north = 1)	0.0153**	0.0063	0.0010	0.0095
Prop. forage in diet	−0.1703***	0.0577	−0.0857	0.0837
$\sigma_u{}^2$	0.0023***	0.0007	0.0038***	0.0012
$\sigma_v{}^2$	0.0005***	0.0001	0.0013***	0.0002
γ	0.7993***	0.0582	0.7417***	0.0645
Log likelihood ratio	1,961.982		1,619.716	

[a]Asterisks (*, **, and ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b]Standard errors derived from bootstrapping with 2,000 replications.
[c]With the exception of the intercept, inefficiency model variables, and time trends, all variables are natural logarithms.
Notes: Conc, concentrates; D/A, debt-to-asset ratio; LvstkSales, livestock sales; N/S, north/south; Prop, proportion.

Table 3. Efficiency results: descriptive statistics

Model	Mean	Standard Deviation	Minimum	Maximum
Environmentally adjusted technical efficiency	0.9367	0.0453	0.7599	0.9948
Technical efficiency	0.9252	0.0545	0.6922	0.9925

level of technical efficiency to be approximately 0.88. Another contributing factor to the high average efficiency values in the case of Canadian studies is likely the supply management system and its influence on producer incentives.

The flexibility inherent in the enhanced hyperbolic function may also contribute to higher efficiency scores through the potential scaling from decreasing inputs or the negative output, or by increasing the positive outputs (Cuesta, Knox Lovell, and Zofío, 2009; Mamardashvili, Emvalomatis, and Jan, 2016). Although average technical efficiency and environmentally adjusted technical efficiency values are numerically similar, a t-test of the two estimated efficiency scores reveals them to be significantly different ($P < 0.001$) in statistical terms. Overall, Alberta dairy farms have the potential to increase milk and livestock outputs by

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Table 4. Contribution of different sources of greenhouse gas emissions to total emissions (average across data set)

Emission Type (kg CO_2 equivalent/year)	Mean Value	Proportion of Total
Cropping N_2O	86,516.90	0.0912
Enteric CH_4	469,585.69	0.4950
Manure CH_4	109,590.14	0.1155
Manure N_2O	69,617.63	0.0734
Energy CO_2	213,298.61	0.2249
Total emissions	948,608.96	

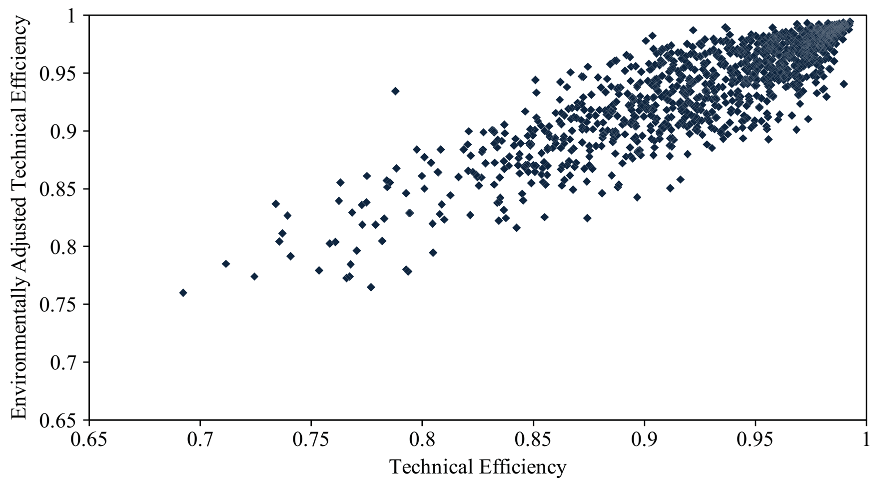

Figure 1. Scatter plot of technical and environmentally adjusted technical efficiency estimates by observation.

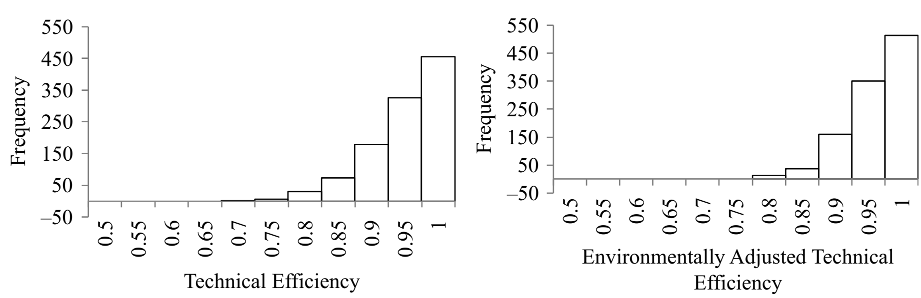

Figure 2. Frequency distributions for technical (without greenhouse gases [GHGs]) and environmentally adjusted technical (with GHGs) efficiency estimates.

6.76% $\left(\frac{1}{0.9367} - 1 = 0.0676\right)$, while simultaneously reducing input use and GHG emissions by 6.33% $(1 - 0.9367 = 0.0633)$.

3.2. Inefficiency model

The inefficiency model parameter estimates for both versions of the distance function (i.e., with and without GHG emissions) are also presented in Table 2. Given the structure of the inefficiency

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

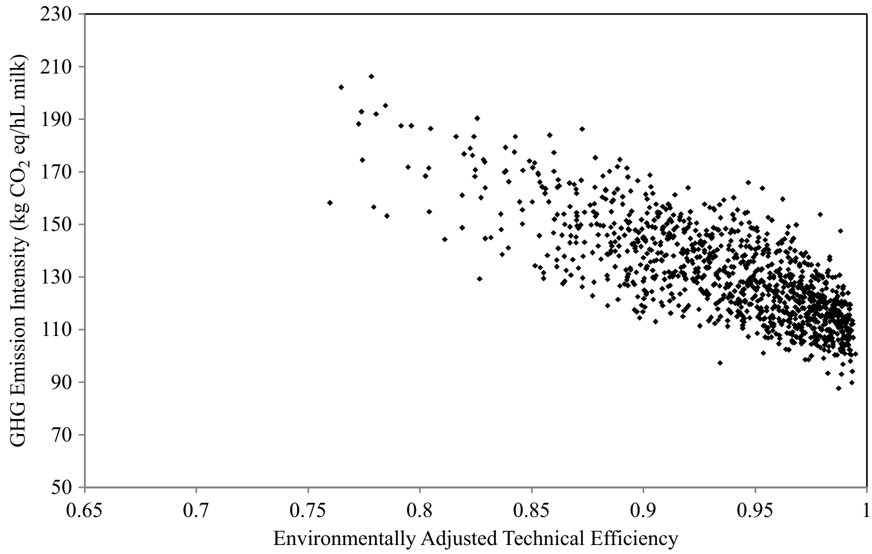

Figure 3. Scatter plot of environmentally adjusted technical efficiency estimates and greenhouse gas (GHG) emission intensity (CO_2 equivalent/hL milk) by observation.

model, positive coefficients indicate that the variable contributes positively to inefficiency (u_i); that is, variables with positive coefficients are negatively related to technical or environmentally adjusted technical efficiency. From Table 2, it can be seen that the signs on coefficients are the same for both versions of the inefficiency model. However, there are differences between the two inefficiency models in terms of statistical significance. The only variable that is statistically significant for both environmentally adjusted technical efficiency and technical efficiency is milk yield per cow (i.e., the proxy for genetic quality). Consistent with previous studies (e.g., Weersink, Turvey, and Godah, 1990), increased milk yield per cow is positively related to efficiency. There are also differences in the inefficiency model results when compared with other studies (e.g., Mosheim and Lovell, 2009; Weersink, Turvey, and Godah, 1990) in that there is no statistically significant relationship between efficiency and herd size, proportion of paid labor, or debt-to-asset values.

Variables significant for technical efficiency but not environmentally adjusted technical efficiency include butterfat, years farming, and proportion of purchased feed. As expected, increased butterfat percentage is positively related to technical efficiency; however, it does not have a significant effect on environmentally adjusted technical efficiency. The nonsignificance for environmentally adjusted technical efficiency may be at least in part because of the lack of availability of detailed nutrition management information in the data set (e.g., forage quality, use of mixed rations) and the potential importance of these factors in explaining methane emissions (e.g., Cameron et al., 2018; Eckard, Grainger, and de Klein, 2010). Years of farming (i.e., experience) is negatively related to technical efficiency. A possible explanation is that younger farmers may be more aware of new innovations and technology that facilitate improved technical efficiency, but that these may not necessarily result in a smaller carbon footprint. Greater use of purchased feed is negatively related to technical efficiency, which could be a result of homegrown feed being of higher quality in terms of nutrient content.

Conversely, the regional dummy and proportion of forage in the diet were significantly related (in statistical terms) to environmentally adjusted technical efficiency but not to technical efficiency. The result for the regional dummy suggests that farms in northern Alberta are less environmentally efficient than those in southern Alberta, although there is no statistically

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Table 5. Production elasticities for estimated models (with and without greenhouse gas [GHG] emissions)[abc]

	Model	Forage	Concentrate	Labor	Capital	Other
Milk	With GHGs	−0.012	0.024***	0.025***	0.048***	0.035***
		(0.0088)	(0.0089)	(0.0069)	(0.012)	(0.0075)
	Without GHGs	0.0376***	0.071***	0.051***	0.192***	0.083***
		(0.012)	(0.011)	(0.0091)	(0.011)	(0.0097)
Livestock	With GHGs	−0.666	1.384***	1.441***	2.769***	2.005***
		(0.42)	(0.505)	(0.500)	(0.752)	(0.621)
	Without GHGs	1.541***	2.894***	2.107***	7.847***	3.415***
		(0.504)	(0.698)	(0.579)	(1.645)	(0.806)
GHGs	With GHGs	0.0319*	−0.0663***	−0.0690***	−0.133**	−0.0960**
		(0.0182)	(0.0204)	(0.0176)	(0.0267)	(0.207)

[a]Asterisks (*, **, and ***) denote statistical significance at 10%, 5%, and 1% levels, respectively.
[b]The elasticities presented here represent the percent increase in output from a 1% increase in a specific input.
[c]Standard errors are presented in parentheses.

significant difference in their technical efficiency. Southern farms may have a smaller environmental impact because of differences in soil, feeding practices (e.g., producers in southern Alberta feed more corn silage), and/or temperatures. For example, temperature differences can affect factors such as crop yields, milk yields, and cattle maintenance energy requirements.

The proportion of forage has the opposite sign than expected; increased forage in the diet increases environmentally adjusted technical efficiency with no statistically significant effect on technical efficiency. This is unexpected as high forage diets are associated with greater enteric methane emissions (Boadi et al., 2004). However, the use of proportionally more forage in the diet for a given level of milk production is likely accomplished through feeding higher-quality forages. There is evidence that increased forage quality (and specifically digestibility) results in reduced GHG emission intensity in ruminants (e.g., Beauchemin et al., 2011; Guyader et al., 2017; Knapp et al., 2014), and this is a plausible explanation for the inefficiency model result.

3.3. Elasticities

As the data are normalized by the mean, the first-order coefficients may be interpreted as production elasticities evaluated at the mean (Mosheim and Lovell, 2009). As noted earlier, the mean efficiencies suggest that most farmers in the sample are quite close to the frontier, so any differences between the values of elasticities at the frontier and evaluated at the mean should be very small. A summary of the production elasticities is provided in Table 5. Production elasticities between milk and livestock outputs have the same signs and significances. However, the livestock production elasticities are much higher (numerically) than the milk production elasticities for both models (with and without GHG). This is likely because of production decisions focusing on dairy revenue rather than on the value of livestock production. As such, the remainder of the discussion on production elasticities focuses on the milk output.

Between the GHG and no GHG models, the milk production elasticities follow a similar pattern with respect to sign and significance, with the exception of the elasticity for forage. Specifically, the production elasticities for inputs other than forage are positive and statistically significant at the 1% level. However, the elasticities are consistently larger for the non-GHG model (i.e., when GHGs are not held constant). This suggests that the marginal productivity of inputs would be constrained if a certain level of GHGs were to be maintained. The largest difference is for capital,

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

suggesting that this input is a relatively larger contributor to GHG emissions. This may be because of the aggregation of livestock input into the capital input, given that enteric methane comprises the bulk of GHG emissions (Table 4).

For the forage input, both the sign and significance of the production elasticity differ between the two models (Table 5). If GHG emissions are not considered, a 1% increase in forage will increase milk output by 0.038% (evaluated at the mean). However, when GHGs are included in the model a 1% increase in forage input, for a given level of emissions, does not have a statistically significant effect on milk production. This difference (i.e., shifting from significantly positive to insignificantly negative) is likely because of the contribution of forage to higher enteric methane emissions (Beauchemin et al., 2008).

In the case of the production elasticities for the detrimental output (GHG), a 1% increase in forage will increase GHG emissions by 0.032%. This is not surprising given the relationship (noted earlier) between forage consumption and enteric methane emissions. The GHG production elasticities for the other inputs are all negative; an increase in any of these inputs decreases GHG emissions. The decrease in GHGs is expected for nonmaterial inputs such as labor and "other," because use of these inputs is not typically associated with production of emissions. In addition, increased labor and "other" inputs can be used toward animal care, and improved animal health is a large contributor to increased milk yield and reduced overall environmental impact (Weiske et al., 2006). For capital, which has the largest marginal effect on GHG reduction, it may be the case that investing in machinery and equipment can contribute to more efficient feeding, milking, and general farm operations. Similarly, an increase in concentrate, keeping all other inputs and outputs constant, is predicted to decrease GHG emissions. Although concentrate is a material input, it has been found that increasing concentrate in the diet can reduce the feed energy that is converted to methane because of the resulting decrease in ruminal pH (Beauchemin et al., 2008).

3.4. Shadow prices

As there is no market for GHGs, the duality between distance functions and revenue and profit functions is exploited to derive the shadow price of GHGs. The shadow price can be interpreted as the opportunity cost of reducing GHGs where the marginal rate of transformation between the good outputs and GHGs is valued in economic terms. Following Vardanyan and Noh (2006) and Mamardashvili, Emvalomatis, and Jan (2016), the shadow price for the mth beneficial output (s_m) can be calculated as follows:

$$s_m = -p_m \frac{\frac{\partial D_H}{\partial b}}{\frac{\partial D_H}{\partial y_m}}, \tag{12}$$

where p_m is the price of the beneficial output. As the data used in this study are normalized, the resulting shadow prices are representative of the mean of the data rather than at the frontier. However, given that mean efficiency is very high, the marginal rate of transformation at the mean should be similar to that for the frontier.

Table 6 reports the output prices and shadow prices. The price of the beneficial output (milk) is calculated as the average price of milk received by the sampled Alberta dairy farmers over the 1996–2016 period, expressed in 2015 Canadian dollars. Using this value, it is estimated that the opportunity cost of reducing GHG emissions in terms of foregone milk revenue is Can$308.29 per metric ton of emissions.

Previous studies have estimated the shadow price of GHGs from dairy farms. For example, Wettemann and Latacz-Lohmann (2017) estimated the abatement cost (using DEA) to be €165 per metric ton, equivalent to approximately $234 in 2015 Canadian dollars (Bank of Canada, 2017). Using a parametric directional distance function approach Njuki and Bravo-Ureta (2015) found a range of shadow prices from US$43 to US$950 per metric ton for different

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Table 6. Shadow prices[a] for livestock and greenhouse gas (GHG) emission outputs

Output	Model	Market Price[b]	Shadow Price for GHGs (Can$/metric ton)
Milk	GHGs	$111.95/hL	$308.29
Livestock	GHGs	$603.41/head	$895.84

[a]The shadow price is the value of the output in the leftmost column given up for a one unit reduction of the outputs in the right-hand columns.
[b]Prices are expressed in 2015 Canadian dollars (Statistics Canada, 2019b).

counties across the United States. From these results, it can be seen that there is no consensus on the opportunity cost of reducing emissions. The shadow value from this study is within the range found by Njuki and Bravo-Ureta (2015), although toward the higher end. This may be attributable to slightly higher dairy prices in Canada. Alternatively, it may be that dairy producers are already very efficient with and without consideration of GHGs, and as a result, reducing GHGs is equivalent to deviating from efficient behavior, thus leading to a significant associated cost. As such, pollution reduction can be a costly endeavor for dairy farmers, especially for those close to the frontier.

The estimated shadow price for milk production cannot be interpreted to represent the minimum cost of reducing GHG emissions by producers. It may well be the case that changes in other production practices (i.e., changing rations, culling practices, etc.) may be less costly in terms of managing emissions. However, the shadow price can inform policy in the sense that it provides an indication of the magnitude of cost that would be borne by producers if they were required to reduce output in order to meet GHG emission regulations.

A shadow price of GHGs is also derived for livestock production (Table 6); that is, the value of sale of livestock by the dairy producer. Using the 1996–2016 average selling price of livestock for the sampled producers, expressed in 2015 Canadian dollars, the opportunity cost of GHG emission reductions is Can$895.84 per metric ton of foregone livestock revenue. The large discrepancy in shadow values between the two beneficial outputs (milk and livestock) suggests that Alberta dairy farmers are not allocatively efficient. It would be expected that producers who are allocatively efficient would have equal shadow prices associated with both outputs (Mamardashvili, Emvalomatis, and Jan, 2016). The discrepancy between the two shadow prices may be because of the focus of management efforts being on the dairy enterprise instead of livestock production, because livestock revenue would likely be considered a "by-product" for many commercial dairy operations. It is also possible that more inputs associated with livestock production are less substitutable, creating constraints that make it costlier to reduce GHG emissions. This would be similar to findings by Arandia and Aldanondo-Ochoa (2011) for organic farms; specifically, they found higher shadow prices for organic farms than for conventional operations, which they attribute to the effect of additional regulatory restrictions.

4. Conclusion

This study examines the impact on productive efficiency of incorporating GHG emissions as a detrimental output in a multiproduct analysis. Using a sample of Alberta dairy producers from 1996–2016, stochastic production frontiers using a translog functional form are jointly estimated with inefficiency models using maximum likelihood techniques. Environmentally adjusted technical efficiency estimates are highly correlated with technical efficiency, suggesting the goal of emission reduction aligns with reaching full technical efficiency. Given that striving for technical efficiency (i.e., maximizing output from a given level of inputs) is consistent with an objective of profit maximization, this suggests that stringent government interventions (e.g., emission quotas) may not be needed. Instead, policies such as education and outreach for topics such as improving farm profitability can be implemented.

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

The results from the distance function estimation indicate that mean efficiency levels for Alberta dairy farms (at least for those producers in the sample) are very high; that is, many farms are already close to the frontier. Thus, there are limited opportunities for reducing GHG emissions through further improvements in efficiency. Given this result, further reductions in GHG emissions would likely necessitate reducing total milk output, imposing a significant private cost on producers in return for generating a social benefit. Based on shadow price estimates, this study estimates the cost at more than Can$300 per metric ton of reduced emissions, in terms of reduced milk revenue. Given these results, it may be the case that policy instruments that involve cost sharing between government and dairy producers may need to be considered (e.g., incentives for clean technology adoption and subsidies) to achieve further reductions in emissions.

The elasticity analysis revealed that increasing use of inputs may reduce GHG emissions, with the exception of forage where its increased use will raise total GHG emissions, holding all other inputs and outputs constant. However, reduced use of forage may have detrimental effects on output because of negative animal health effects, such as ruminal acidosis, that can result from insufficient forage levels in the diet (Gozho, Krause, and Plaizier, 2007). In addition, the inefficiency model suggests that increasing the ratio of forage in the diet can actually improve environmentally adjusted technical efficiency. Thus, more effective strategies may lie in increasing the efficiency of forage utilization such as through use of feed supplements or genetic improvements to increase the digestibility of feed or through the use of higher-quality forages.

The inefficiency model results also indicate that increased milk yield per cow can improve environmentally adjusted technical efficiency; that is, reduce GHG emissions while maintaining economic viability. However, management strategies to achieve increased milk yield independently of changes to factors modeled in the analysis (i.e., input levels) would likely require longer-term investments in genetics.

This study makes methodological contributions, including the combination of Battese and Coelli's (1995) inefficiency model with an enhanced hyperbolic distance function. In addition, the analysis separates feed into forage and concentrate variables. Previous studies typically combine the feed variables, but, as seen in this study, there are significant differences in their effect on GHG production. The analysis in the study also serves to identify areas of further research. For example, the GHG emissions used in the econometric estimation are imputed rather than observed, and so measurement error is an issue. Furthermore, there may be efficiency effects attributable to differences in production environment that are not captured by the regional dummy. This could be addressed through use of a stochastic metafrontier approach (Battese, Prasada Rao, and O'Donnell, 2004; Jiang and Sharp, 2015). It would also be useful to examine the question of emissions from dairy production within a pure environmental efficiency framework. Overall, however, this study extends the limited literature that uses SFA to study farm-level efficiency and GHGs and identifies policy-relevant implications.

Acknowledgments. The authors wish to thank Aklilu Alemu, Pauline van Biert, Shukun Guan, Manikarnika Kanjilal, Roland Kroebel, Shannan Little, and Sheilah Nolan for their assistance with this project. The authors would also like to thank two anonymous reviewers for their comments and constructive suggestions on the manuscript.

Financial support. This work was supported by Alberta Agriculture and Forestry Strategic Research and Development Program (formerly Alberta Livestock and Meat Agency) under research grant 2015F026R, and by the Canadian Dairy Commission through their graduate scholarship program.

Conflict of interest. None.

References

Alberta Environment. "Quantification Protocol for Emission Reductions from Dairy Cattle." 2010. Internet site: https://open.alberta.ca/dataset/9780778588221 (Accessed October 29, 2019).

Alberta Milk. *Alberta Milk Producer Policy Handbook. Alberta Milk*, 2019. Internet site: https://albertamilk.com/wp-content/uploads/2018/02/2018-Producer-Policy-Handbook-Final.pdf (Accessed October 29, 2019).

Arandia, A., and A. Aldanondo-Ochoa. "Pollution Shadow Prices in Conventional and Organic Farming: An Application in a Mediterranean Context." *Spanish Journal of Agricultural Research* **9**, 2(2011):363–76.

Bank of Canada. "Historical Noon and Closing Rates." 2017. Internet site: http://www.bankofcanada.ca/?p=190915 (Accessed October 29, 2019).

Battese, G.E., and T.J. Coelli. "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* **20**, 2(1995):325–32.

Battese, G.E., D.S. Prasada Rao, and C.J. O'Donnell. "A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating under Different Technologies." *Journal of Productivity Analysis* **21**, 1(2004):91–103.

Beauchemin, K.A., H.H. Janzen, S.M. Little, T.A. McAllister, and S.M. McGinn. "Mitigation of Greenhouse Gas Emissions from Beef Production in Western Canada – Evaluation Using Farm-Based Life Cycle Assessment." *Animal Feed Science and Technology* **166–167**(June 2011):663–77.

Beauchemin, K.A., M. Kreuzer, F. O'Mara, and T.A. McAllister. "Nutritional Management for Enteric Methane Abatement: A Review." *Animal Production Science* **48**, 2(2008):21–27.

Boadi, D., C. Benchaar, J. Chiquette, and D. Massé. "Mitigation Strategies to Reduce Enteric Methane Emissions from Dairy Cows: Update Review." *Canadian Journal of Animal Science* **84**, 3(2004):319–35.

Cabrera, V.E., D. Solis, and J. Del Corral. "Determinants of Technical Efficiency among Dairy Farms in Wisconsin." *Journal of Dairy Science* **93**, 1(2010):387–93.

Cameron, L., M.G.G. Chagunda, D.J. Roberts, and M.A. Lee. "A Comparison of Milk Yields and Methane Production from Three Contrasting High-Yielding Dairy Cattle Feeding Regimes: Cut-and-Carry, Partial Grazing and Total Mixed Ration." *Grass and Forage Science* **73**, 3(2018):789–97.

Canadian Dairy Information Centre. "Canada's Dairy Industry at a Glance." 2019. Internet site: http://www.dairyinfo.gc.ca/index_e.php?s1=cdi-ilc&s2=aag-ail (Accessed October 29, 2019).

Cloutier, L.M., and R. Rowley. "Relative Technical Efficiency: Data Envelopment Analysis and Quebec's Dairy Farms." *Canadian Journal of Agricultural Economics* **41**, 2(1993):169–76.

Coelli, T., and A. Henningsen. frontier: Stochastic Frontier Analysis. R package version 1.1-2. 2019 Internet site: https://CRAN.R-Project.org/package=frontier (Accessed October 29, 2019).

Coelli T.J., D.S. Prasada Rao, C.J. O'Donnell, and G.E. Battese. *An Introduction to Efficiency and Productivity Analysis*. 2nd ed. New York: Springer Science, 2005.

Cottle, D.J., and S.G. Wiedemann. "Ruminant Enteric Methane Mitigation: A Review." *Animal Production Science* **51**, 6(2011):491–514.

Cuesta, R.A., C.A. Knox Lovell, and J.L. Zofío. "Environmental Efficiency Measurement with Translog Distance Functions: A Parametric Approach." *Ecological Economics* **68**, 8–9(2009):2232–42.

Cuesta, R.A., and J.L. Zofío. "Hyperbolic Efficiency and Parametric Distance Functions: With Application to Spanish Savings Banks." *Journal of Productivity Analysis* **24**, 1(2005):31–48.

Dayananda, C. "Technical and Environmental Efficiencies of Ontario Dairy Farming Systems." Master's thesis, University of Guelph, Guelph, ON, 2016.

Diewert, D.E. "Fisher Ideal Output, Input, and Productivity Indexes Revisited." *Journal of Productivity Analysis* **3**, 3(1992):211–48.

Eckard, R., C. Grainger, and C.A.M. de Klein. "Options for the Abatement of Methane and Nitrous Oxide from Ruminant Production: A Review." *Livestock Science* **130**, 1–3(2010):47–56.

Gozho, G.N., D.O. Krause, and J.C. Plaizier. "Ruminal Lipopolysaccharide Concentration and Inflammatory Response during Grain-Induced Subacute Ruminal Acidosis in Dairy Cows." *Journal of Dairy Science* **90**, 2(2007):856–66.

Guyader, J., S. Little, R. Kröbel, C. Benchaar, and K.A. Beauchemin. "Comparison of Greenhouse Gas Emissions from Corn- and Barley-Based Dairy Production Systems in Eastern Canada." *Agricultural Systems* **152**(March 2017):38–46.

Hailu, G., S.R. Jeffrey, and J. Unterschultz. "Cost Efficiency for Alberta and Ontario Dairy Farms: An Inter-regional Comparison." *Canadian Journal of Agricultural Economics* **53**, 2–3(2005):141–60.

Haines, A., R.S. Kovats, D. Campbell-Lendrum, and C. Corvalan. "Climate Change and Human Health: Impacts, Vulnerability and Public Health." *Public Health* **120**, 7(2006):585–96.

International Dairy Federation. *A Common Carbon Footprint Approach for the Dairy Sector: The IDF Guide to Standard Life Cycle Assessment Methodology*. Bulletin of the International Dairy Federation 479/2015. 2015. Internet site: https://www.fil-idf.org/wp-content/uploads/2016/09/Bulletin479-2015_A-common-carbon-footprint-approach-for-the-dairy-sector.CAT.pdf (Accessed October 29, 2019).

Jiang, N., and B. Sharp. "Cost Efficiency of Dairy Farming in New Zealand: A Stochastic Frontier Analysis." *Agricultural and Resource Economics Review* **43**, 3(2014):406–18.

Jiang, N., and B. Sharp. "Technical Efficiency and Technological Gap of New Zealand Dairy Farms: A Stochastic Meta-Frontier Model." *Journal of Productivity Analysis* **44**, 1(2015):39–49.

https://doi.org/10.1017/aae.2019.41 Published online by Cambridge University Press

Johansson, H. "Technical, Allocative, and Economic Efficiency in Swedish Dairy Farms: The Data Envelopment Analysis versus the Stochastic Frontier Approach." Paper presented at the *International Congress of the European Association of Agricultural Economists*, Copenhagen, Denmark, August 2005.

Knapp, J.R., G.L. Laur, P.A. Vadas, W.P. Weiss, and J.M. Tricarico. "Invited Review: Enteric Methane in Dairy Cattle Production: Quantifying the Opportunities and Impact of Reducing Emissions." *Journal of Dairy Science* **97**, 6(2014):3231–61.

Little, S., J. Linderman, K. Maclean, and H. Janzen. *Holos – A Tool to Estimate and Reduce Greenhouse Gases from Farms. Methodology and Algorithms for Versions 1.1.x.* Agriculture and Agri-Food Canada, No. A52-136/2008E-PDF, 2008. Internet site: http://publications.gc.ca/pub?id=9.691658&sl=0 (Accessed October 29, 2019).

Mamardashvili, P., G. Emvalomatis, and P. Jan. "Environmental Performance and Shadow Value of Polluting on Swiss Dairy Farms." *Journal of Agricultural and Resource Economics* **41**, 2(2016):225–46.

Mbaga, M.D., R. Romain., B. Larue, and L. Lebel. "Assessing Technical Efficiency of Quebec Dairy Farms." *Canadian Journal of Agricultural Economics* **51**, 1(2003):121–37.

Mosheim, R., and C.A. Lovell. "Scale Economies and Inefficiency of US Dairy Farms." *American Journal of Agricultural Economics* **91**, 3(2009):777–94.

Njuki, E., and B.E. Bravo-Ureta. "The Economic Costs of Environmental Regulation in US Dairy Farming: A Directional Distance Function Approach." *American Journal of Agricultural Economics* **97**, 4(2015):1087–1106.

Reinhard, S., C.A. Knox Lovell, and G. Thijssen. "Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms." *American Journal of Agricultural Economics* **81**, 1(1999):44–60.

Shortall, O.K., and A.P. Barnes. "Greenhouse Gas Emissions and the Technical Efficiency of Dairy Farmers." *Ecological Indicators* **29**(June 2013):478–88.

Singbo, A., and B. Larue. "Scale Economies, Technical Efficiency, and the Sources of Total Factor Productivity Growth of Quebec Dairy Farms." *Canadian Journal of Agricultural Economics* **64**, 2(2016):339–63.

Slade, P., and G. Hailu. "Efficiency and Regulation: A Comparison of Dairy Farms in Ontario and New York State." *Journal of Productivity Analysis* **45**, 1(2016):103–15.

Statistics Canada. Table 004-0213, Census of Agriculture, Hay and Field Crops. CANSIM (database). Using CHASS (distributor). 2017. Internet site: http://dc2.chass.utoronto.ca/chasscansim/ (Accessed October 29, 2019).

Statistics Canada. Table 176-0043, Financial Market Statistics. CANSIM (database). Using CHASS (distributor). 2019a. Internet site: http://dc2.chass.utoronto.ca/chasscansim/ (Accessed October 29, 2019).

Statistics Canada. Table 326-0020, Consumer Price Index. CANSIM (database). Using CHASS (distributor). 2019b. Internet site: http://dc2.chass.utoronto.ca/chasscansim/ (Accessed October 29, 2019).

Van Biert, P.A. *Dairy Cost Study: The Economics of Milk Production in Alberta 2016*. Vol. 76. Alberta Agriculture and Forestry, Economics and Competitiveness Branch, Economics Section, 2017. Internet site: https://open.alberta.ca/dataset/abca66b6-d117-4ee2-8615-248fcb53262c/resource/e29d0a9f-c88a-4d2b-b322-5b72b2d95497/download/16production.pdf (Accessed October 29, 2019).

Vardanyan, M., and D.W. Noh. "Approximating Pollution Abatement Costs via Alternative Specifications of a Multi-output Production Technology: A Case of the US Electric Utility Industry." *Journal of Environmental Management* **80**, 2(2006):177–90.

Vergé, X.P.C., J.A. Dyer, R.L. Desjardins, and D. Worth. "Greenhouse Gas Emissions from the Canadian Dairy Industry in 2001." *Agricultural Systems* **94**, 3(2007):683–93.

Weersink, A., C.G. Turvey, and A. Godah. "Decomposition Measures of Technical Efficiency for Ontario Dairy Farms." *Canadian Journal of Agricultural Economics* **38**, 3(1990):439–56.

Weiske, A., A. Vabitsch, J.E. Olesen, K. Schelde, J. Michel, R. Friedrich, and M. Kaltschmitt. "Mitigation of Greenhouse Gas Emissions in European Conventional and Organic Dairy Farming." *Agriculture, Ecosystems and Environment* **112**, 2–3(2006):221–32.

Wettemann, P.J.C., and U. Latacz-Lohmann. "An Efficiency-Based Concept to Assess Potential Cost and Greenhouse Gas Savings on German Dairy Farms." *Agricultural Systems* **152**(March 2017):27–37.

Williams, S.R.O., P.D. Fisher, T. Berrisford, P.J. Moate, and K. Reynard. "Reducing Methane On-Farm by Feeding Diets High in Fat May Not Always Reduce Life Cycle Greenhouse Gas Emissions." *International Journal of Life Cycle Assessment* **19**, 1(2014):69–78.

Cite this article: Le S, Jeffrey S, and An H (2019). Greenhouse Gas Emissions and Technical Efficiency in Alberta Dairy Production: What Are the Trade-Offs? *Journal of Agricultural and Applied Economics* **52**, 177–193. https://doi.org/10.1017/aae.2019.41