Greenhouse gas emissions and productive efficiency in Alberta dairy production: What are the trade-offs?

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Abstract

Societal concern and consumer demand for products with a low carbon footprint are growing (Forbes et al. 2009). To assess the impact of GHG reduction on the economic performance of Alberta's dairy industry, results from production frontiers estimated with and without considering GHG emissions are compared. Technical efficiency is defined as the efficiency derived from the frontier not considering GHGs, while environmental efficiency is estimated from a frontier that incorporates GHGs as a "bad" output. This study examines technical and environmental efficiency, relevant elasticities, and shadow prices. Hyperbolic distance functions are estimated using a restricted translog for an unbalanced panel of dairy producers from 1996-2015. Inefficiency models are jointly estimated using maximum likelihood. The results indicate that environmental and technical efficiency estimates are highly correlated, suggesting that the objective of minimizing GHGs aligns with increasing technical efficiency. It is also seen that increasing milk yield per cow, decreasing butterfat, decreasing paid labour proportion, and decreasing purchased feed ratio improves environmental efficiency. Forage and capital inputs are associated with higher GHG emissions, while labour and "other" inputs can reduce GHGs. The opportunity cost of foregone milk revenue associated with reduced GHG (calculated as a shadow price) is $417.59 per tonne of GHG. The results provide possible policy implications regarding economically viable strategies to reduced GHG emissions.

Introduction

The dairy sector is a significant contributor to Canada's agricultural economy and the Canadian diet– over eight billion kilograms (kgs) of milk are produced in Canada annually (Canadian Dairy information Centre 2017). However, dairy production has a significant carbon footprint, with approximately one kg of carbon dioxide (CO_2) equivalents released per kg of milk produced in Canada at the farm level (Verge et al. 2007). Anthropogenic greenhouse gas (GHG) emissions are widely accepted as a key contributor to climate change, which 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. For example, under Alberta's Agricultural Carbon Offset Program, farmers adopting GHG mitigation practices can receive carbon offset credits (AAF 2014).

Much research has been done on GHG mitigation practices that do not have a negative impact on milk production. Such practice include, for example, increasing feed efficiency, improving animal health, and feeding anti-methanogenic supplements (Weiske et al. 2006). However, due to the complexity of the dairy system, many practices that reduce GHGs in one aspect of the supply chain may create higher emissions in another sector. Feeding lipids, for example, can decrease enteric methane from ruminants but may increase overall GHG emissions due to the resulting changes in cropping practices (Williams et al. 2014). In addition, while some GHG mitigation practices can increase milk production, their cost can be prohibitive, and this is especially true for many feed additives (Eckhard et al. 2010). The question then is– what is the effect of reducing GHG emissions from the entire dairy enterprise on farm economic performance? One way to assess this impact is to examine the relationship between GHG emissions and the technical efficiency of Alberta dairy producers, which is the objective of this study.

Many previous studies have examined the technical efficiency of dairy farms (e.g., Cloutier and Rowley, 1993; Weersink et al, 1990) as well as economic efficiency (e.g., Johansson, 2005), using both stochastic frontier analysis (SFA) and data envelopment analysis (DEA) frameworks. When considering environmental factors in efficiency, earlier studies mainly focused on nitrogen surpluses (e.g., Mamardashvili et al. 2016, Reinhard et al, 1999) and only a small number of technical efficiency studies examine GHGs (e.g., Shortall and Barnes, 2013; Njuki and Bravo-Ureta, 2015). Studies specifically focusing on the effect of GHG reduction on technical efficiency in an SFA context are lacking for dairy farms, and addressing this area is one of the contributions of this study. 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.

Methodology

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). In a SFA framework, deviations from the frontier are due to a combination of random shocks and producer inefficiency. The frontier can be represented by:

$$y_i = f(x_i; \beta) + v_i - u_i \quad (1)$$

where y_i is the output produced by the i^{th} farm, x_i is a vector of inputs, β is a vector of parameters, v_i is the stochastic error term, and u_i is the non-negative inefficiency term. As this study considers multiple beneficial outputs and a detrimental output, a standard production function would be inadequate as it typically allows for only one positive output. Thus, following Cuesta et al. (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 proportional contraction of inputs, and the underlying behavioral assumption is profit maximization, while for the regular model, revenue maximizing behavior is assumed (Cuesta and Zofio 2005). As such, 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. For dairy farmers in Alberta, where milk production follows a quota under supply management, profit maximization is a more feasible behavioral assumption than revenue maximization, and the enhanced model will be used for this study.

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

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

where T, the production possibility set, denotes the conversion of the input vector x into the output vectors, both beneficial, y, and detrimental, b, by the production technology (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:

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

The distance ranges from: $0 < D_H(x, y, b) \leq 1$, where 1 is full technical efficiency. If the customary production function axioms are satisfied by the technology, the hyperbolic distance function has the following properties: (Cuesta et al. 2009)

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

Empirical Model

With the almost homogeneity property, the hyperbolic distance function can be represented in a translog functional form. Equation 5 represents the model considering N producers, T time periods, K inputs, M beneficial outputs, and GHGs (b):

$$\begin{aligned} lnD_H = {} & \alpha_0 + \sum_{k=1}^{K} \alpha_k lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl}\, lnx_{kit} lnx_{lit} + \sum_{m=1}^{M} \beta_m lny_{mit} + \\ & \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_m\, lny_{mit} lny_{nit} + \delta lnb_{it} + \sum_{k=1}^{K}\sum_{n=1}^{M} \gamma_{km}\, lnx_{kit} lny_{mit} + \\ & \sum_{m=1}^{M} \theta_{mb} lny_{mit} lnb_{it} + \sum_{k=1}^{K} \theta_{kb} lnx_{kit}\ lnb_{it}, (i = 1,2, \ldots, N; t = 1,2, \ldots, T) \end{aligned} \tag{5}$$

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

$$D_H(xy_M, \frac{y_m}{y_M}, by_M) = \frac{D_H(x,y,b)}{y_M} \quad (6)$$

The transformed function becomes:

$$ln(\frac{D_H}{y_M}) = \alpha_0 + \sum_{k=1}^{K} \alpha_k lnx^*_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl}\, lnx^*_{kit} lnx^*_{lit} + \sum_{m=1}^{M} \beta_m lny^*_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_m\, lny^*_{mit} lny^*_{nit} + \delta lnb^*_{it} + \sum_{k=1}^{K}\sum_{n=1}^{M} \gamma_{km}\, lnx^*_{kit} lny^*_{mit} + \sum_{m=1}^{M} \theta_{mb} lny^*_{mit} lnb^*_{it} + \sum_{k=1}^{K} \theta_{kb} lnx^*_{kit}\ lnb^*_{it}, (i = 1,2, \dots, N\ ; t = 1,2, \dots, T) \quad (7)$$

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

Moving lnD_H to the right hand side of the equality, it can be interpreted as the inefficiency component of the error term, and the function can be written:

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

The distribution of v_{it} is assumed to be i.i.d $N(0, \sigma_v^2)$. Following Battese and Coelli (1995), the inefficiency term is assumed to follow a non-negative truncated normal distribution: $u_{it} \sim N(m_{it}, \sigma_u^2)$, where m_{it} is a function of a vector of farm-specific variables (z_{it}), such that $m_{it} = z_{it}\varphi$ and φ is a vector of parameters to be estimated jointly with the production frontier. To obtain the technical efficiency estimates, the below equation is used:

$$TE_{it} = exp(-u_{it}) \quad (9)$$

The production frontier and efficiency results for the hyperbolic distance function that does not consider GHGs are calculated 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. Specifically, the package 'frontier' developed by Coelli and Henningsen (2017) for R is used for this analysis.

Data

Data from Alberta Agriculture and Forestry's Dairy Cost of Production Survey for an unbalanced panel of producers over the period 1996-2015 are used for this study. 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 methodology from IDF (2010). Livestock output is composed of the 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.

The detrimental output is GHG emissions in kg of CO_2 equivalents calculated using algorithms adapted from Agriculture and Agri-Food Canada's Holos model. Holos uses 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 available from the Dairy Cost Study, values were obtained through expert opinion and a review of relevant literature.

The inputs used in the production frontier are: forage, concentrate, capital, labour, and "other". With the exception of labour, Fisher price indices are used to aggregate the separate expenses into an implicit quantity by dividing total expenses by the price index.

Due to potential measurement error from assuming a price for family and operator labour, the total number of hours of paid, family, and operator labour is used instead. The forage input variable consists of hay, silage, greenfeed, straw, and alfalfa pellets. Concentrate consists of the higher energy feeds such as grains, supplements, minerals, molasses, and brewer's grain. Capital input is derived following Dayananda (2016), where capital includes machinery, dairy equipment, dairy buildings, land, livestock, and supplies. The “other” input variable includes expenditures for inputs such as insurance, bedding, veterinary expenses, utilities, milk hauling and miscellaneous expenses. Linear and quadratic time trend variables are also included in the production frontier to capture technical change.

Variables included in the inefficiency model were selected based on insights from previous studies as well as availability in the data set. Typical variables included in past efficiency studies include farming intensity, livestock quality, age and education of farmer, and access to technology (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 labour, proportion of purchased feed, debt to asset ratio, a regional dummy for a farm located in North or South Alberta, and a time trend. Herd size is measured in the number of head of lactating and dry cows, and is hypothesized to have a positive effect on efficiency due to scale effects. Milk yield, in liters of fat corrected milk per cow per day, directly reflects the productivity of the cow, and is expected to be positively related to farm efficiency. Butterfat percentage is also expected to have a positive effect, as it can represent management ability, especially as dairy quota is calculated in kg of butterfat (Alberta Milk 2017). Years farming and the time trend are hypothesized to have a positive effect on efficiency due to benefits of increased experience and technological improvements, respectively. The proportion of total hours of labour that is from paid labour, the proportion of total feed that is purchased, as well as the debt to asset ratio all impose additional costs to the producers, and thus may negatively affect efficiency. A regional dummy is also included, since farms in Southern Alberta have different farming practices and environmental factors; for example, feeding more corn silage compared to Northern Alberta (Statistics Canada 2014). Descriptive statistics for the variables are provided in Table 1.

Results and Discussion

Efficiency Estimates

To prevent problems with model convergence, the production frontier variables are normalized by their geometric mean. Due to the presence of econometric issues (i.e., autocorrelation), bootstrapped standard errors generated with 2000 replications are used. In addition, due to high multicollinearity between the variables, a restricted translog is estimated with the terms $forage * forage,\ concentrate * concentrate, labour * labour, concentrate * capital, labour * capital, capital * capital, livestock * concentrate, GHG * GHG, GHG * forage, GHG * capital. GHG * other$ being removed. The parameter estimates for both models are reported in Table 2. For simplicity, the efficiency from the model estimated with GHGs is denoted environmental efficiency and the efficiency from the model without GHGs as technical efficiency.

The efficiency estimates are summarized in Table 3. Overall, the models with and without considering GHGs are very similar, as seen in the scatterplot (Figure 1), with a mean environmental efficiency of 0.931 and a mean technical efficiency of 0.934. The distributions are also highly similar, with most producers having very high efficiency (Figure 2). In addition, the efficiencies are highly correlated, with a Pearson's correlation coefficient of 0.9608 and a Spearman's correlation coefficient of 0.9180. This suggests that minimizing GHG emissions aligns with the objective of maximizing output for given levels inputs. One possible explanation of the high correlation is that GHG emissions are a loss in energy; for example, enteric methane 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. 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 et al. 1999, Shortall and Barnes 2013)

Overall, the average efficiency level of Alberta dairy farms is very high, suggesting that many Alberta dairy farms are close to the frontier. Other dairy technical efficiency studies also reveal fairly high average technical efficiency scores, with Mbaga et al. (2003)'s study testing a variety of SFA models and finding average scores for Quebec dairy farmers around 0.95, and Cabrera et al. (2010) with an average score of 0.88 for Wisconsin dairy farmers. The flexibility of the enhanced hyperbolic function may also contribute to this result as greater efficiency can be achieved through decreasing inputs and negative output, or by increasing the positive outputs (Cuesta et al. 2009, Mamardashvili et al. 2016). While average technical efficiency and environmental efficiency values are numerically similar, the two efficiency scores are significantly different ($p < 0.001$) with environmental efficiency (i.e., considering GHG minimization) being lower, likely due to the additional constraint. Overall, when considering GHGs, Alberta dairy farms have the potential to increase milk and livestock outputs by 7.41% ($\frac{1}{0.9310} - 1 = 0.0741$), while simultaneously reducing input use and GHG emissions by 6.90% ($1 - 0.9310 = 0.069$).

Inefficiency Model

The regression estimates for both models, including those from the inefficiency model, are presented in Table 2. For the inefficiency model, a positive signed coefficient indicates a positive effect of the variable on inefficiency (u_i); that is, a negative effect on efficiency. The signs on coefficients are the same for both versions of the inefficiency model. However, several of the variables are significant for environmental efficiency but have no statistically significant effect on technical efficiency; specifically, time trend, years farming, and proportion of paid labour. One possible reason is that the hyperbolic distance function considering GHGs is a significantly better fit of the data compared to the distance function without GHGs (likelihood ratio test $\chi^2 = 288.57,\ p < 0.001$). For years farming, which has a negative effect on environmental efficiency, one possible explanation is younger farmers may be more aware of new innovations and technology which may have a smaller carbon footprint. Proportion of paid labour also has a negative effect on efficiency, and it is possible family and operator labour is higher quality and more focused on areas with a larger impact on GHG minimization; for example, maintaining animal health. The time trend shows that environmental efficiency is decreasing at a decreasing rate. The trend where inefficiency rises for a portion of time may be due to farmers adjusting to structural changes such as converting to a total production quota system from a two quota system in 2008, as well as the phasing in of the Canadian Quality Milk program, which became mandatory for all dairy producers in 2009 (Heikkila and Van Biert 2014).

The remaining farm characteristics affect environmental efficiency and technical efficiency in a similar fashion. Consistent with previous analyses, increasing milk yield per cow and decreasing the proportion of purchased feed increases efficiency (Cabrera et al. 2010, Weersink et al. 1990). Possible explanations are higher milk yield cows may have higher feed utilization efficiency and overall productivity, and homegrown feed can be of higher quality and require less resources overall i.e. for feed transportation. There are also differences from this analysis to other studies– the region, herd size, and debt to asset ratio have no effect on efficiency, while butterfat levels decrease efficiency levels for this study (Mosheim and Lovell 2009, Weersink et al. 1990). These results suggest that scale effects on efficiency may not exist; as seen earlier, increasing paid labour and purchased feed can decrease efficiency, and larger farms are typically associated with these two factors. For butterfat levels, generally there is a inverse relationship between milk yield and butterfat levels (Fuller 2004), and lower milk yield may decrease efficiency.

Elasticities

As the data is normalized by the mean, the first order coefficients can be interpreted as the elasticities 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 elasticities at the frontier and at the mean should be very small. A summary of the production elasticities can be found in Table 5. Livestock and milk production elasticities are similar in sign for both the with and without GHG models; however, the milk production elasticities have much higher statistical significance. As a result, for the beneficial outputs, only the milk production elasticities will be discussed. Between the GHG and no GHG models, the milk production elasticities are also quite similar, with the exception of capital and concentrate. Capital is negative for the GHG model where a 1% increase in capital will decrease milk output by 0.12%, while for the model without GHGs, a 1% increase in capital does not have a statistically significant impact on milk output. This suggests that capital is a large contributor to GHG emissions because increasing capital while maintaining the same GHG emissions decreases milk production. Indeed, total livestock units are aggregated into the capital variable for this study, and as mentioned earlier, enteric methane comprises the bulk of GHG emissions.

The milk production elasticity for concentrate is significant for the model without GHG, where a 1% increase in concentrate will increase milk production by 0.14%. Conversely, it does not have a statistically significant effect on the model considering GHGs. A possible explanation is that concentrate may also be a large contributor to GHGs as increasing concentrate while allowing GHGs to increase freely will increase milk production, but when GHGs are constrained to remain constant, milk production does not increase. One possible reason can be the more resource intensive cropping practices required for concentrate feed products (Little et al. 2008). Typically, inputs have a positive production elasticity as increasing inputs will increase outputs. However, forage is negative for livestock and milk outputs for both models. The estimates suggest that when keeping other outputs and inputs constant, increasing forage use will decrease milk or livestock output, indicating an association between high forage farms with low production. This is likely due to the inefficiency of converting forage to beneficial outputs, where a large proportion of feed energy is released as methane (Beauchemin et al. 2008).

In the case of the production elasticities for the detrimental output, GHGs, the results confirm the inferences above where increasing forage and capital inputs will increase GHG emissions. On the other hand, increasing labour and other will decrease GHG emissions while maintaining the same level of beneficial outputs. One possible reason for the GHG reducing potential of these inputs is that the increased labour and "other" inputs can be used towards animal care, as improving animal health is a large contributor to increasing milk yield and reducing overall environmental impact (Weiske et al 2006).

Shadow prices

As there is no market for GHGs (i.e., the negative output), 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 (MRT) between the good outputs and GHGs is given an economic valuation. Following Vardanyan and Noh (2006) and Mamardashvili et al. (2016), the shadow price (s) can be calculated as:

$$s = -p_m \frac{\frac{\partial D_H}{\partial b}}{\frac{\partial D_H}{\partial y_m}} \tag{8}$$

where p_m is the price of the beneficial output. As the data used in this study are normalized, the results are for the mean of the data rather than at the frontier. However, since 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. Using the average price of milk for Alberta dairy farmers standardized to 2015 Canadian dollars, it is estimated that the cost to reduce one tonne of GHGs is $417.59 worth of milk. Past studies studying the shadow price of GHGs from dairy farms show a similar value– Wetteman and Latacz-Lohmann (2017) found an abatement cost using DEA of 165 euros/tonne, and Njuki and Bravo-Ureta (2015) found a range of shadow prices from $43/tonne to $950/tonne for different counties across the United States using a parametric directional distance function approach. The shadow value from this study appears to be on the higher end, and it is due to slightly higher dairy prices in Canada. As such, pollution reduction can be a costly endeavour for dairy farmers, especially those close to the frontier.

A shadow price of GHGs can also be derived from livestock, and it appear that for a one tonne reduction in GHGs, $69.33 of livestock revenue will be given up. The large discrepancy in shadow values between the two beneficial outputs indicate that Alberta dairy farmers are not allocatively efficient, because farms with full allocative efficiency are expected to have the same shadow prices with respect to the output (Mamardashvili et al. 2016). This may be due to the focus of management efforts being on the dairy enterprise instead of livestock production, as livestock revenue may be considered a "by-product" by many dairy farmers.

For the trade-offs between milk and livestock, the results between the GHG and without GHG models are very similar. These shadow prices are negative where for every dollar of livestock revenue reduced, milk revenue will increase by $6.56, and for every hL of milk reduced, livestock revenue will increase by $12.82. The negative prices are due to the MRT, where milk and livestock have a negative MRT, and GHGs and the beneficial outputs have a positive MRT. GHG emissions are complementary to milk and livestock production, while milk and livestock compete for the same scarce inputs

Conclusion

This study compared the results from a model that accounted for GHGs and one that did not for an balanced panel sample of Alberta dairy producers from 1996-2015. Stochastic production frontiers using a restricted translog functional form are jointly estimated with inefficiency models using maximum likelihood techniques. Environmental efficiency estimates are highly correlated with technical efficiency, suggesting the goal of emission reduction aligns with reaching full technical efficiency. As technical efficiency, maximizing output while minimizing input, is a natural objective for producers, this suggests that rigorous government interventions such as emission quotas may not be needed. Instead, policies such as education and outreach for topics such as improving farm profitability can be implemented.

Mean efficiency levels for Alberta dairy farms are very high, and many farms are already close to the frontier. Further reductions in GHG reduction or improvements in milk or livestock productivity beyond the technically efficient point may come at a cost. As seen in the results, GHGs and beneficial outputs are complements. Thus, at the frontier, any reduction in GHGs will result in a reduction in beneficial output, which imposes a private cost on the producers for a social benefit. This study found that $417.59 will be given up for every tonne of GHG reduced. Policy instruments involving shared costs between government and farmers may be beneficial (e.g., incentives for clean technology adoption and subsidies). For clean technology, the elasticity analysis revealed that not only forage is the input with the largest contribution to GHG, it is also associated with lower production. However, recommending the reduction of forage use may have detrimental effects on output, as negative animal health effects, such as ruminal acidosis, can result from insufficient forage levels in the diet (Gozho et al. 2007).

More effective strategies may lie in increasing the efficiency of forage utilization such as through feed supplements or genetic improvements to increase the digestibility of feed. Inputs with a positive effect on the beneficial outputs while reducing GHGs are labour and "other". The GHGs are likely reduced through improved animal care, but more research is warranted to identify the mechanism by which these two inputs can reduce GHGs. Other ways GHGs can be reduced while maintaining efficiency can be derived from the inefficiency model, where increasing milk yield per cow and using homegrown feed are seen to have positive effects on the efficiency of dairy producers.

From this study, methodological contributions include the combination of Battese and Coelli's (1995) inefficiency model with an enhanced hyperbolic distance function, and separating the feed variable into forage and concentrate variables. Although previous studies typically combine the feed variables, as seen in this study, there are large differences in their effect on production. Overall, this study extends the limited literature that uses stochastic frontier analysis to study farm-level efficiency and GHGs and provides potential policy implications.

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Appendix 1. Tables

Table 1. Descriptive statistics for model variables (n = 1088)

	Name	Mean	Std. Dev.	Min	Max
Positive Outputs	Milk output (L FPCM)	7222.42	5427.88	1178.07	41335.22
	Livestock output[1]	31493.85	45046.93	0.00	683970.10
Detrimental Output	GHG (kg CO_2 eq)	948609.00	737528.30	229067.50	6418104.00
Inputs	Forage[1]	106721.80	96297.20	14145.00	947044.40
	Concentrate[1]	185747.50	145387.70	21160.65	1058836.00
	Labour (hours)	6101.16	3574.99	1369.88	35542.00
	Capital[1]	41297277.54	3203281.40	1307664.68	1568444810.42
	Other[1]	76963.06	57111.89	16239.74	583759.80
Inefficiency Model Variables	Milking herd size (number of cows)	111.90	86.42	26.58	728.75
	Milk yield per cow (L/day)	17.68	3.12	1.18	25.83
	Butterfat (%)	3.74	0.26	2.68	5.19
	Years farming	19.63	11.60	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
	North/South dummy (N = 1)	0.4654	0.50	0.00	1.00

[1]The quantity is the implicit quantity obtained by dividing the value of sales (or expenses) by the calculated Fisher Price Index

Table 2. Maximum likelihood parameter estimates: Hyperbolic distance function with and without GHGs

	GHG		Without GHG	
	Estimate[1]	Std. Error[2]	Estimate[1]	Std. Error
(Intercept)	4.994***	0.352	4.351***	0.509
forage[3]	0.237***	0.085	0.309**	0.139
concentrate	-0.0399	0.0561	-0.137**	0.069
capital	0.124*	0.071	-0.097	0.065
labour	-0.120**	0.059	-0.191*	0.107
other	-0.384***	0.112	-0.457**	0.193
livestock	0.305**	0.134	0.305*	0.166
linear time trend	-0.0126***	0.0028	-0.0080*	0.0048
quadratic time trend	0.0004***	0.0001	0.0003	0.0003
(forage)(concentrate)	-0.0594***	0.0187	-0.0304	0.0205
(forage)(labour)	-0.0354	0.0220	-0.0580**	0.0276
(forage)(capital)	0.0288**	0.0141	0.0248	0.0218
(forage)(other)	0.0361*	0.0186	0.0228	0.0241
(concentrate)(labour)	-0.0095	0.0244	0.0549**	0.0231
(concentrate)(other)	-0.0282	0.0173	-0.0154	0.0200
(labour)(other)	0.0287	0.0229	0.0187	0.0305
(capital)(other)	-0.0527***	0.0143	-0.0340	0.0215
(other)(other)	0.0265*	0.0148	0.0245	0.0230
(livestock)(livestock)	0.0080	0.0052	0.0116	0.0086
(livestock)(forage)	-0.0097	0.0140	-0.0124	0.0167
(livestock)(labour)	-0.0591***	0.0188	-0.0662***	0.0251
(livestock)(capital)	0.0540**	0.0265	0.0476*	0.0279
(livestock)(other)	0.0205	0.0151	-0.0004	0.0268
(GHG)(GHG)	-0.493***	0.129	---	---
(livestock)(GHG)	-0.0382	0.0318	---	---
(GHG)	-0.0496**	0.0246	---	---
(GHG)(concentrate)	0.100***	0.028	---	---

(GHG)(labour)	0.0261	0.0361	---	---
Joint Inefficiency Model				
Herd size	0.0001	0.0001	0.00002	0.00007
Milk yield	-0.0320***	0.0055	-0.0343*	0.0193
Linear time trend	0.0212***	0.0051	0.0176	0.0108
Quadratic time trend	-0.0009***	0.0003	-0.0008	0.0005
Butterfat	0.109***	0.019	0.0955*	0.0542
Years farming	0.0014***	0.0004	0.0015	0.0010
Proportion of paid labour	0.0355*	0.0184	0.0630	0.0429
Proportion of purchased feed	0.0855***	0.0244	0.1567*	0.0918
Debt to asset ratio	-0.335	0.270	-0.1236	0.3472
North/South dummy	0.0066	0.0073	0.0003	0.0106
Log likelihood	1748.89		1604.605	

[1] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[2] standard errors derived from bootstrapping with 2000 replications
[3] with the exception of the intercept, inefficiency model variables, and time trends, the variables are natural logarithms

Table 3. Efficiency results: Descriptive statistics

Model	Mean	Std. Dev.	Min	Max
With GHG	0.9310	0.0679	0.4927	0.9939
Without GHG	0.9343	0.0703	0.3974	0.9924

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

Emission type (kg CO_2 equivalent/year)	Mean value	Proportion of total
Cropping N_2O	86516.90	0.0912
Enteric CH_4	469585.69	0.4950
Manure CH_4	109590.14	0.1155
Manure N_2O	69617.63	0.0734
Energy CO_2	213298.61	0.2249
Total emissions	948608.96	

Table 5. Production elasticities for estimated models (with and without GHG)[1,2,3]

	Model	Forage	Concentrate	Labour	Capital	Other
Milk	With GHG	-0.24*** (0.085)	0.040 (0.056)	0.12* (0.059)	-0.12** (0.071)	0.38*** (0.12)
	Without GHG	-0.31** (0.14)	0.14** (0.069)	0.19** (0.11)	0.097 (0.065)	0.46** (0.19)
Livestock	With GHG	-0.78* (0.43)	0.13 (0.19)	0.39 (0.26)	-0.41 (0.31)	1.26* (0.27)
	Without GHG	-1.01 (0.70)	0.44 (0.33)	0.62 (0.49)	0.32 (0.27)	1.5 (1.03)
GHG	With GHG	0.48* (0.21)	-0.081 (0.12)	-0.24* (0.14)	0.25** (0.13)	-0.78** (0.32)

[1] *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.
[2] The elasticities presented here represent the % increase in output from a one % increase in a specific input.
[3] Standard errors are presented in parentheses

Table 6. Marginal rate of transformation and shadow prices for the outputs

			Shadow Price[1,2]		
Output	**Model**	**Market Price[2]**	**Milk (hL)**	**Livestock ($)**	**GHG (tonnes)**
Milk	GHG	$111.95/hL	---	- $6.56	$417.59
	Without GHG		---	- $6.55	---
Livestock	GHG	$603.41/head	-$12.82	---	$69.33
	Without GHG		-$12.82	---	---

[1] Shadow prices are the value of the output in the leftmost column that is given up for a one unit reduction of the output in the right columns

[2] Prices are adjusted to 2015 price index (Statistics Canada 2017)

Appendix 2. Figures

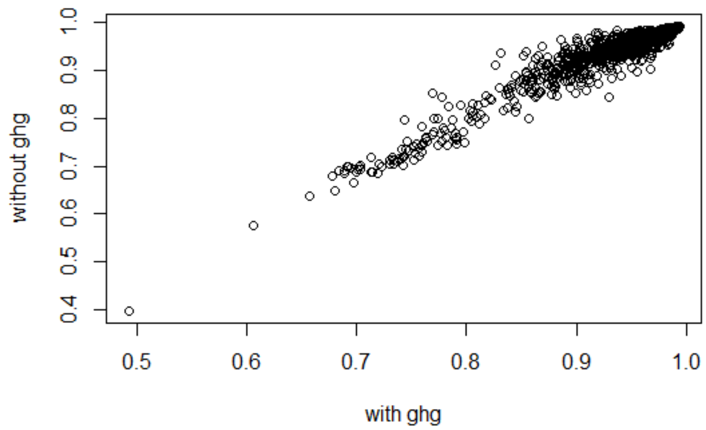

Figure 1. Scatterplot of the efficiency estimates from the two models plotted against each other

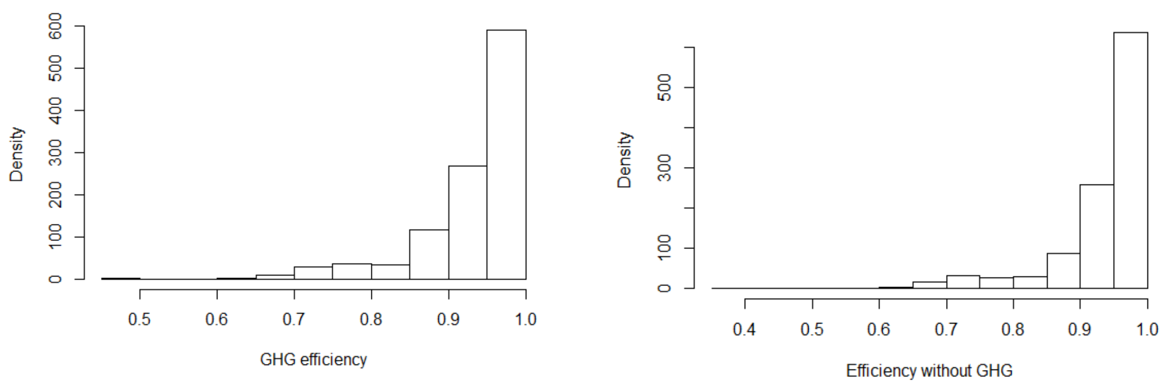

Figure 2. Distribution of the efficiency estimates from both models.