Sources and Measurement of Agricultural Productivity and Efficiency in Canadian Provinces: Crops and Livestock

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This paper measures and assesses the variation in total factor productivity (TFP) growth among Canadian provinces in crops and livestock production over the period 1940–2009. It also determines if agricultural productivity growth in Canada has recently slowed down as indicated by earlier studies. The paper uses the stochastic frontier approach that incorporates inefficiency to decompose TFP growth into technical change (TC), scale effect (SE), and technical efficiency change. The results indicate that productivity changes were mainly driven by TCs for crops, while the productivity changes in livestock was mainly driven by SEs and technical progress. Though change in technical efficiency is mainly positive (except for New Brunswick and Nova Scotia), its contribution to productivity growth was very little for the provinces. We also found that over the entire period, the productivity growth rates for the crop subsector are on average higher for the Prairie provinces than for the Eastern and Atlantic provinces. On the other hand, the productivity growth rates in the livestock subsector are on average higher in the Eastern and Atlantic provinces than in the Prairie region with the exception of Manitoba. Finally, we found that though there is some evidence of a recent decline in productivity growth for the crops subsector, there is no such evidence in the livestock subsector.

Dans le présent article, nous examinons l'écart de croissance de la productivité totale des facteurs (PTF) entre les provinces canadiennes dans les secteurs des cultures et de l'élevage pour la période 1940–2009. Nous tentons également de déterminer si la croissance de la productivité agricole au Canada a ralenti comme l'ont indiqué des études antérieures. Nous avons utilisé le modèle de frontière stochastique qui inclut l'inefficience afin de décomposer la croissance de la PTF en divers éléments tels que le progrès technologique, l'effet d'échelle et l'efficience technique. Selon les résultats de notre étude, les écarts de productivité dans le secteur des cultures sont principalement déterminés par le progrès technologique tandis que dans le secteur de l'élevage, ils sont déterminés par l'effet d'échelle et le progrès technologique. Bien que l'écart d'efficience technique soit principalement positif (à l'exception du Nouveau-Brunswick et de la Nouvelle-Écosse), sa contribution à la croissance de la productivité compte pour peu dans les provinces. Au cours de cette même période, le taux de croissance de la productivité du sous-secteur des cultures a été en moyenne plus élevé dans les provinces des Prairies que dans les provinces de l'Est et de l'Atlantique. En revanche, le taux de croissance de la productivité du sous-secteur de l'élevage a été plus élevé dans les provinces de l'Est et de l'Atlantique que dans

Canadian Journal of Agricultural Economics 64 (2016) 49–70
DOI: 10.1111/cjag.12061

les provinces des Prairies, à l'exception du Manitoba. Finalement, bien qu'il existe des signes de ralentissement récent de la croissance de la productivité dans le sous-secteur des cultures, il ne semble pas en exister dans le sous-secteur de l'élevage.

INTRODUCTION

This paper uses Canadian provincial data from 1940 to 2009 to measure and assess variation in total factor productivity (TFP) growth in the crops and livestock subsectors. Measuring agricultural productivity growth is a difficult task, but very important for various reasons. First, agricultural productivity growth is an important indicator for the analysis of the overall economic growth, improvement of living standards, and international competitiveness. Second, agricultural productivity growth is an important concept in the discussions on global food security and poverty alleviation, especially in the developing world. Bruinsma (2009) stated that by 2050 the world population is expected to grow by 40% and allowing for increase in income and changes in diet, global demand for food and fiber is expected to grow by 70%. Hence, agricultural productivity growth would have to keep pace with the expected global demographic changes in order to avoid global food security problems and make significant progress toward poverty alleviation in the developing world.

Against this background, there have been some recent discussions on the direction of global agricultural productivity growth in the literature. Alston et al (2010a, 2010b) used a range of partial productivity measures to examine productivity growth in the world. They found that with the exception of China and Latin America, agricultural productivity growth rates in most of the world have slowed down since the early 1990s. They also concluded that in some part of the world the decline in agricultural productivity growth rates have been substantial and widespread. Fuglie (2008, 2010) concluded differently when he examined long-run productivity trends in the global agriculture sector using an index number (IN) approach. He found that there was no evidence of a general decline in agricultural productivity, at least through 2007. He stated that the growth rates in agricultural TFP have actually accelerated in recent decades because of rapid productivity gains in several developing countries, led by Brazil and China, and more recently due to a recovery of agricultural growth in the countries of the former Soviet Bloc. In the case of Canada, Rao et al (2008) and Agriculture and Agri-Food Canada (2009) have indicated that agricultural productivity growth has significantly slowed down and lagged behind that of the United States and many Organisation for Economic Co-operation and Development (OECD) countries. Stewart et al (2009) have also concluded that TFP growth rates for crops and livestock in the Prairies have slowed down considerably. Veeman and Gray (2009) agreed with Stewart et al (2009) by concluding that productivity growth in crops production has slowed down since 1990. On the contrary, de Avillez (2011a, 2011b) concluded that over the period 1961–2007, the primary agriculture sector in Canada experienced impressive productivity growth. He also reported that the productivity growth performance in the agricultural sector by far exceeded productivity growth in the Canadian business sector as a whole.

From the studies discussed above, and to some extent, the general agricultural productivity literature, it could be concluded that the methodologies and assumptions used in measuring agricultural productivity growth could affect the magnitude of the estimated productivity growth rates and the direction of effects. For example, most agricultural productivity studies have the underlying assumption that farms are fully efficient. If this assumption is incorrect, then the productivity measures could be misleading. Though some studies have allowed for inefficiencies at the farm level, those that focused on Canada have mainly used data on a specific crop or type of livestock production within a specific province (Amara and Romain 1990; Weersink et al 1990; Cloutier and Rowley 1993; Amara et al 1999; Giannakas et al 2001; Samarajeewa et al 2012) or used data on crops and livestock sectors for a few provinces (Stewart et al 2009). None of these studies used data on all the provinces for both the crop and livestock subsectors.

The main focus of this paper is to address the concerns raised above by using provincial level data on the crops and livestock subsectors for the period 1940–2009 and a stochastic frontier approach that incorporates inefficiency, to decompose the TFP growth in the Canadian agricultural sector into technical change (TC), scale effect (SE), and technical efficiency change (TEC).[1] The paper also determines if agricultural productivity growth in Canada has recently slowed down as claimed by earlier studies. To the best of our knowledge, this is the first paper that examines TFP growth decomposition for all provinces (except for Newfoundland) in Canada for both the crops and livestock subsectors. The use of provincial data is very essential in measuring productivity growth in order to reveal any possible provincial idiosyncrasies for the design and implementation of appropriate policies.

The rest of the paper is organized as follows. Section "Review of Productivity Growth and Efficiency Studies" provides a brief overview of productivity and efficiency studies. Section "Methodology" describes the theory behind the stochastic frontier approach used to decompose the TFP growth and provides a brief description of the data used in the estimation (detail descriptions of the data are relegated to the Appendix). Section "Estimation Procedure" describes the estimation procedure, while Section "Estimation Results" presents and discusses the main estimation results. Concluding remarks and policy implications are given in the last section.

REVIEW OF PRODUCTIVITY GROWTH AND EFFICIENCY STUDIES

The literature on productivity growth and efficiency is vast in both theoretical and applied fields. Hence, the purpose of this section is not to provide a comprehensive review of the literature, but to provide a summary of relevant literature that is closely related to our analysis below. A comprehensive review of this literature is given in recent work by Darku et al (2013), and interested readers can refer to their paper for more complete review. The

[1] We decomposed TFP into three components: technological progress; SE; and technical efficiency. Technological progress captures the idea that production function can shift overtime. It refers to the situation in which a firm can achieve more output from a given combination of inputs or equivalently, the same amount of output from fewer inputs. SE refers to the proportionate increase in output due to a given proportionate increase in all inputs in the production process. Technical efficiency is the situation where it is impossible for a firm to produce with a given technology either (i) more output from the same inputs or (ii) the same output with less of one or more inputs without increasing the amount of other inputs. Hence, technical inefficiency indicates the amount by which actual output falls short of the maximum possible output.

approaches used in the analysis of productivity growth and efficiency can be classified into three main groups: (i) the regression approach, such as stochastic frontier analysis (SFA) which can be parametric or nonparametric;[2] (ii) linear programming approach, such as deterministic data envelopment analysis (DEA) that is purely nonparametric; and (iii) the IN and/or growth-accounting approach.[3]

The SFA approach was originally and independently proposed by Aigner et al (1977) and Meeusen and Van den Broeck (1977). The approach utilizes a standard regression equation with a two-component error term. The first component is a two-sided symmetric error term representing random shocks (e.g., weather) and the second component is a one-sided error term representing technical inefficiency. The basic formulation of the stochastic frontier approach was extended by Pitt and Lee (1981), and Schmidt and Sickles (1984) for the panel data case. Battese and Coelli (1992) introduced further enhancements where the technical inefficiency term was modeled to be time variant. The SFA approach has been applied to agricultural studies by Aigner et al (1977), Battese and Tessema (1993), Färe et al (1994), Abdulai and Huffman (1998), Seyoum et al (1998), and Giannakas et al (2001) just to name a few. Recent studies, such as Constantin et al (2009) and Pires and Garcia (2012), have used the SFA framework and the "Bauer-Kumbhakar" technique to decompose TFP into technical and allocative efficiency, TC, and SE.

Another strand of studies dubbed *the efficiency literature* has mostly used the DEA technique to determine technical efficiency level of firms or industries. This literature began with Charnes et al (1978), who used the DEA technique to pursue Farrell's (1957) approach to technical efficiency measurement. They simply extended the measurement of technical efficiency from a single output and multiple input case to a multiple output and multiple input case. Färe et al (1994) utilized the DEA approach to decompose TFP into TCs and TECs. At the same period that the DEA technique became popular in measuring agricultural productivity, the indexing approach to measuring productivity and efficiency also gained importance with the introduction of the Malmquist index. Caves et al (1982), Shephard (1970), and Färe (1988) calculated the Malmquist TFP index as geometric mean of output and input Malmquist indexes, and found that the TFP can be decomposed into TCs and TECs. Hsu et al (2003) and Nin Pratt and Yu (2008) have also used the DEA technique to decompose TFP into TCs and TECs. Further, development in the efficiency literature has led to the combination of the Malmquist index and the DEA techniques to yield the Malmquist DEA method. This approach has been applied in some studies to evaluate TCs and TECs using variety of data set and countries (Lambert and Parker 1998; Hsu et al 2003; Coelli and Walding 2005; Tipi and Rehber 2006; Ludena 2010).[4]

[2] By nonparametric we mean the functional form of the frontier is left unspecified.

[3] There are other approaches that combine DEA with some sort of regressions analysis to overcome the deterministic nature of DEA (this approach is known as stochastic DEA), and others that combine IN with production or cost regression in order to decompose the TFP growth into various components.

[4] However, the Malmquist index has been criticized by O'Donnell (2009, 2010) who indicated that the Malmquist TFP index is not complete and using it for decomposition yields bias estimate of TCs and TECs. He then used the Hicks Moorsteen and Fisher indexes to construct complete and recognizable TFP indexes and decomposed them into meaningful measures of TCs and TECs. In a series of further papers, O'Donnell (2012a, 2012b) demonstrated that like other multiplicative

Bravo-Ureta et al (2007) used metaregression analysis of previous 167 frontier studies of technical efficiency in the agricultural sectors to determine the commonalities and trends within that set of literature, and try to explain the patterns that emerge in efficiency levels. They concluded that the methodological characteristics (estimation technique) and other study-specific characteristics (functional form, sample size, product analysis, and geographical region) affect the empirical estimates of technical efficiency. The mean technical efficiency of all the 167 frontier studies was 76.6%, suggesting that farms are not fully efficient.

The literature on agricultural efficiency for Canadian farms is limited but growing. These studies have mostly used various methodologies identified in the literature to determine the level of efficiency of Canadian crop farms. Haghiri et al (2004) used nonparametric stochastic frontier model to estimate technical efficiency between dairy farmers in Ontario and New York. They concluded that Ontario dairy farmers are less efficient than their New York counterpart. Mbaga et al (2003) used parametric and nonparametric approaches to measure the level of technical efficiency of Quebec dairy farmers. The analysis revealed that Quebec dairy farmers are very homogenous in terms of efficiency. Cloutier and Rowley (1993) used the DEA and found the same result for Quebec dairy farmers. Amara et al (1999) used the deterministic statistical frontier production function to measure production efficiency using data on potato farmers in Quebec. They found that farming experience and the adoption of concentration technologies are both significant variables for improving technical efficiency. They also found that environmental factors such as farmers awareness of environmental degradation as a problem and his/her attitude toward technological innovation determine technical efficiency. Samarajeewa et al (2012) used the SFA technique and data on cow-calf farmers in Alberta to conduct an analysis similar to Amara et al (1999). They found that farmers are generally not fully efficient and that government support, smaller herd size, lower share of family labor, and lower expense for bedding material reduced efficiency. Hailu et al (2005) used SFA to compare the cost efficiency of Alberta and Ontario dairy farms. Their results indicated that Ontario dairy farms may be more cost efficient than Alberta dairy farms, but the statistical evidence was inconclusive. Slade and Hailu (2011) extended Hailu et al's (2005) analysis on Ontario and New York dairy farms by using stochastic DEA analysis to examine allocative and cost efficiency. They concluded that efficiency generally increased with farm size in both regions. However, New York benefited more from the presence of larger dairy farms. Farms operating under the system of supply management were found to make poorer allocative decision when compared to farms in a competitive environment.

Although the above studies focused on one or two provinces for their productivity and efficiency analysis, other studies have used data on all the provinces to study Canadian agricultural productivity. Echevarria (1998) used provincial data on agriculture to compute the TFP growth rates across all the 10 provinces. Her results indicated that the Canadian agriculture sector is less labor intensive than both services and manufacturing sectors, though the level of capital intensity is similar in the three sectors. In addition, the

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complete TFP indexes (Laspeyres, Paache, Fisher, and Tornqvist), the Hicks-Moorsteen index has some weakness in terms of satisfying some important axioms. He proposed a new TFP index (the Lowe TFP index) that satisfies all axioms and used it to decompose TFP into TCs and TECs.

average TFP growth rate in the agriculture sector is approximately 0.3% that is similar to that of the Canadian manufacturing sector. Beside the provincial-level studies, Fantino and Veeman (1997) and Veeman and Gray (2009, 2010) have used national level data to analyze Canadian agricultural productivity.

A few Canadian studies have undertaken TFP decomposition analysis. Giannakas et al (2001) used stochastic decomposition method to determine the level and driving force of technical efficiency using data on Saskatchewan dairy farmers. They found that TFP contributed significantly more to output growth than input usage. They also found that TC contributed almost twice as much as technical efficiency to TFP growth. Stewart et al (2009) used the Prairie region (Alberta, Saskatchewan, and Manitoba) agriculture data on crops and livestock along with four factors of production (capital, labor, land, and materials) for the period 1940 to 2004 to decompose TFP growth into technological progress and SEs. Their approach is based on Tornqvist-Theil indexing procedure coupled with econometric estimation of a Translog cost system. They found that productivity growth rate in the Prairie agriculture sector was 1.56% per year, and that the productivity growth rate in crops is significantly higher than that of livestock. Furthermore, their results indicated that, whereas the productivity growth in the crops sector was mainly driven by technological progress, economies of scale was the main source of productivity growth in the livestock sector.

METHODOLOGY

The method used in this paper is based on the stochastic production frontier approach originally proposed by Aigner et al (1977) and Meeusen and Van den Broeck (1977). The specification of a stochastic production frontier function can be generally written as:

$$Y_{it} = f(X_{it}, t; \beta)\exp(v_{it} - u_{it}) \tag{1}$$

where Y_{it} denotes the output of province i at time t, X_{it} is a $k \times 1$ vector of input factors used in the production process, t is a time trend that captures the TC, β is a $k \times 1$ vector of unknown parameters to be estimated, v_{it} is an independent and identically distributed (i.i.d.) symmetric random disturbance such that $v_{it} \sim N(0, \sigma_v^2)\, u_{it} \geq 0$ is an *i.i.d.* nonnegative random variable representing technical inefficiency and the function $f(.,.)$ is the production technology that takes a specific form. The idea behind Equation (1) is that, for a given technology and at any point in time the provinces are not fully efficient in implementing the best possible practice from the stock of knowledge. Following the stochastic frontier literature, we assume that $u_{it} \sim |N(0, \sigma_u^2)|$ albeit other nonnegative distributions, such as exponential and gamma, could be considered. However, it is known that the estimation results are not sensitive to the distributional assumption on u_{it}; see Greene (2003).

Let $y_{it} = \ln Y_{it}$ and $x_{it} = \ln X_{it}$. Assuming that price information is available, we can follow Kumbhakar and Knox Lovell (2000) to decompose TFP changes into four components: TC, SE, TEC, and changes in allocative inefficiency (AEC). To do this, let $\dot{z}$ denotes the growth rate of a variable Z that is, $\dot{z} = \partial \ln Z/\partial t$ and define TFP growth as output growth unexplained by input growth. That is:

$$T\dot{F}P = \dot{y} - \sum_{j=1}^{k} s_j \dot{x}_j \tag{2}$$

where s_j is the jth input share of production cost and $\dot{x}_j = \partial lnX_j/\partial t$. By using Farrell's (1957) definition of technical efficiency, Equation (2) can be rewritten as:[5]

$$T\dot{F}P = TC + (\varepsilon - 1)\sum_{j=1}^{k}\left(\frac{\varepsilon_j}{\varepsilon}\right)\dot{x}_j + T\dot{E} + \sum_{j=1}^{k}\left(\frac{\varepsilon_j}{\varepsilon} - s_j\right)\dot{x}_j \tag{3}$$

where ε_j is the output elasticity with respect to input j and $\varepsilon = \sum_j \varepsilon_j$. The first term on the right-hand side of Equation (3) measures the TC that relates to the technological progress, including not only advances in physical technologies, but also innovation in the overall knowledge base that lead to better decision making and planning. It captures the upward shift of the production function. The second term on the right-hand side of Equation (3) measures the SE that refers to the proportionate increase in output due to proportionate increase in all inputs in the production process. Note that in the presence of constant returns to scale, $\varepsilon = 1$ this term vanishes. The third term on the right-hand side of Equation (3) measures the changes in TEC and the last term measures AEC that refers to the deviation of each input value of marginal productivity from output normalized cost. The AEC will vanish if the provinces/regions/farms are allocatively efficient. However, in the present study, we do not make adjustment for the AEC since input prices data are incomplete.

The data used in this paper come from Statistics Canada (2011a, 2011b). We used nine provinces' data in this study. Newfoundland and Labrador, Yukon, and the Northwest Territories are excluded because there are many missing observations from their data. The period chosen for this study is from 1940 to 2009. The length of this data series is unique since few studies of Canadian agricultural productivity have used approximately 70 years of data. This enables us to make assessment of provincial agriculture growth and productivity performances both for a relatively long period of time and for different time periods.

Most of the data were retrieved from Canadian Socio-Economic Information Management System (CANSIM) and in some situations multiple tables had to be combined in order to cover the time period of interest, as some tables had been terminated. The census data (Census years 2001 and 2006) that were required for input allocation were retrieved from CANSIM. Data from the census years 1940–96 were retrieved from printed Census of Agriculture documents found in the University of Lethbridge Library. Census data are available online through CANSIM for the census years between 1991 and 2006. Other selected historical data were also available.

The outputs considered in this paper are the aggregate crops and livestock outputs deflated by the appropriate Farm Product Price Index (FPPI; 1997 = 100) in order to remove the price effect. Inputs are aggregated into the four main input categories: capital

[5] See Kumbhakar and Knox Lovell (2000) for detailed derivation.

(K), including machinery and equipment, and livestock inventory; labor (L), including paid and unpaid labor; land and buildings (LB), including cropped land, pasture, summer fallow, and buildings; and materials (M), including fertilizer, seed, pesticides, feed, fuel, electricity, irrigation, and other miscellaneous expenses. To minimize aggregation bias, inputs of different qualities were valued by the price of each input-quality type. Brief descriptions of the data for crops and livestock are provided in the Appendix.

ESTIMATION PROCEDURE

For the estimation purpose, we need to specify a functional form for the production function f (.). In this paper, we used the flexible Translog form:

$$y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j x_{jit} + \gamma_1 t + \frac{1}{2}\gamma_2 t^2 + \sum_{m=1}^{8} \delta_m D_{mit} + \frac{1}{2}\sum_{j=1}^{4}\sum_{l=1}^{4} \beta_{jl} x_{jit} x_{lit}$$

$$+ \sum_{j=1}^{4} \beta_{tj} t x_{jit} + \sum_{m=1}^{8} \delta_{mt} t D_{mit} + \sum_{m=1}^{8}\sum_{j=1}^{4} \alpha_{mj} D_{mit} x_{jit} + v_{it} - u_{it} \tag{4}$$

where D_{it} represent the provincial dummy. The specification in Equation (4) is quite flexible and it allows for general form of nonneutral TC. In addition, it contains the Cobb–Douglas production with neutral TC as a special case when $\beta_{jl} = \beta_{tl} = \gamma_2 = 0$ or all j and t.

Estimation of Equation (4) is carried out using maximum-likelihood (ML) method. To write down the log-likelihood function, let $e_{it} = v_{it} - u_{it} = y_{it} - \ln f\,(X_{it}, t, \beta)$. Under the distributional assumptions of v_{it} and u_{it}, the conditional probability density function of e_{it} is given by:

$$f\,(e_{it}|x_{it}) = \frac{2}{\sigma}\phi\left(\frac{e_{it}}{\sigma}\right)\Phi\left(-\frac{\lambda e_{it}}{\sigma}\right), \quad -\infty < e_{it} < +\infty$$

where $\sigma^2 = \sigma_v^2 + \sigma_u^2 \lambda = {}^{\sigma_u}/_{\sigma_v}\, \phi\,(.)$ and $\Phi\,(.)$ are the probability density function and cumulative distribution function of a standard normal variable. In order to avoid nonnegativity restrictions on the variance parameters σ^2 and λ, we choose to reparameterize them as $\tilde{\sigma}^2 = \ln(\sigma^2)$ and $\tilde{\lambda} = \ln(\lambda)$. The conditional log-likelihood function for a sample of NT observations is given by:

$$\ln L\,(\theta) = -\frac{NT}{2}\left(\ln 2\pi + \ln \tilde{\sigma}^2\right) - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{\frac{(y_{it} - \ln f(X_{it}, t, \beta)}{\sigma}\right\}^2$$

$$+ \sum_{i=1}^{N}\sum_{t=1}^{T} \ln \Phi \left\{-\frac{\tilde{\lambda}}{\tilde{\sigma}}\,[y_{it} - \ln f\,(X_{it}, t, \beta)]\right\} \tag{5}$$

where $\theta = (\beta, \tilde{\sigma}^2, \tilde{\lambda})$. By maximizing Equation (5) with respect to θ, the ML estimates of θ can be written as:

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmax}} \ln L(\theta) \tag{6}$$

It must be noted that the log-likelihood function in Equation (5) is highly nonlinear and requires some types of numerical algorithm and starting values in the optimization process. In this paper, we used the corrected ordinary least squares (see, e.g., Kumbhakar and Knox Lovell 2000) estimates of Equation (4) as the starting values in the optimization process along with David–Fletcher's algorithm. The convergence criterion is set at 10^{-5}. In the estimation process, no numerical (i.e., convergence) problems were encountered while using a standard conjugate gradients algorithm to maximize the log-likelihood function. The parameter estimates converged fairly quickly.

Once the parameter estimates are obtained, the technical inefficiency term u_{it} could be predicted via Jondrow et al (1982) prediction formula:

$$\hat{u}_{it} = E\left(u_{it}|e_{it}\right) = \frac{\hat{\sigma}\hat{\lambda}}{1+\hat{\lambda}^2}\left\{\frac{\phi(\hat{\lambda}\hat{e}_{it}/\hat{\sigma})}{\Phi(\hat{\lambda}\hat{e}_{it}/\hat{\sigma})} - \frac{\hat{\lambda}\hat{e}_{it}}{\hat{\sigma}}\right\} \tag{7}$$

where $\hat{e}_{it}$, $\hat{\sigma}$, and $\hat{\lambda}$ are the ML estimates of e_{it}, σ, and λ, respectively. As common in the frontier models, if the variables are measured in logs, a point estimate of the technical efficiency is then provided by $E\hat{F}F_{it} = \exp\left(-\hat{u}_{it}\right) \in [0, 1]$. Given the Translog specification in Equation (4), the estimates of TFP change, TC, SE, and TEC can be computed as follow:

(i) $\widehat{TC} = \hat{\gamma}_1 + \hat{\gamma}_2 t + \sum_{j=1}^{4} \hat{\beta}_{tj} x_{jit} + \sum_{m=1}^{8} \hat{\delta}_{mt} D_{mit}$
(ii) $\widehat{SE} = (\hat{\varepsilon} - 1) \sum_{j=1}^{4} (\hat{\varepsilon}_j/\hat{\varepsilon}) \Delta x_{jit}$

where $\hat{\varepsilon}_j = \hat{\beta}_j + \hat{\beta}_{tj} t + \sum_{l=1}^{4} \hat{\beta}_{jl} x_{lit} + \sum_{m=1}^{8} \hat{\delta}_{mt} D_{mit},\ j = 1, \cdots, 4$ and $\hat{\varepsilon} = \sum_{j=1}^{4} \hat{\varepsilon}_j$

(iii) $\Delta\widehat{TE} = \Delta \exp(-\hat{u}_{it})$
(iv) $\Delta\widehat{TFP} = \widehat{TC} + \widehat{SE} + \Delta\widehat{TE}$

and the "^" denotes the ML estimates. Note that, we have used $\Delta x_{jit} = x_{jit} - x_{jit-1}$ to approximate the time derivative $\dot{x}_{jit}$ and similarly for $\dot{TE}$.

ESTIMATION RESULTS

For brevity, we report only a subset of the ML parameter estimates, including the parameters associated with the variances from each of the noise components of the production frontier specified in Equation (4) for both crops and livestock (since there are more than 50 parameters for each sector) stemming from our Translog production function.[6] Table 1 presents these estimates for crops and livestock for the entire period from 1940 to 2009. Before discussing the results, it is important to note that the parameters of the Translog

[6] The full set of ML parameter estimates is available from the authors upon request.

Table 1. Subset of estimated production function parameters

Crops			Livestock		
Variable	Coefficient	(SE)	Variable	Coefficient	(SE)
Cons.	4.4127***	(0.1316)	Cons.	3.4112***	(0.1457)
l	0.2392***	(0.0498)	*l*	0.2014***	(0.0521)
m	0.4273***	(0.1056)	*m*	0.1163***	(0.0425)
k	0.5932***	(0.0894)	*k*	0.5168***	(0.0988)
lb	0.1093***	(0.0364)	*lb*	0.3175**	(0.1503)
t	0.0497*	(0.0291)	*t*	0.0540*	(0.0311)
ll	−0.0873***	(0.0115)	*ll*	−0.0932***	(0.0166)
mm	−0.1015***	(0.0156)	*mm*	−0.0325***	(0.0098)
kk	−0.1373***	(0.0146)	*kk*	−0.1124***	(0.0126)
lblb	−0.0152***	(0.0049)	*lblb*	−0.1412***	(0.0199)
tt	−0.0042	(0.0038)	*tt*	−0.0031	(0.0033)
lm	0.0263**	(0.0113)	*lm*	0.0066	(0.0144)
lk	0.0086	(0.0122)	*lk*	0.0132**	(0.0064)
llb	0.0018	(0.0023)	*llb*	0.0038	(0.0087)
lt	0.0011	(0.0015)	*lt*	0.0019	(0.0056)
mk	0.0727***	(0.0094)	*mk*	0.0029	(0.0042)
mlb	0.0031	(0.0042)	*mlb*	0.0016	(0.0051)
mt	−0.0016	(0.0037)	*mt*	−0.0034	(0.0066)
klb	0.0063**	(0.0038)	*klb*	0.0072***	(0.0028)
kt	−0.0022	(0.0044)	*kt*	0.0011	(0.0055)
lbt	0.0031	(0.0032)	*lbt*	0.0049	(0.0079)
σ_u	0.4965***	(0.0413)	σ_u	0.2548***	(0.0621)
σ_v	0.1462***	(0.0136)	σ_v	0.1548***	(0.2516)

Notes: $l = \ln L$, $lk = (\ln L)(\ln K)$ and other variables are similarly defined.
Significance: ***1% level; **5% level; *10% level.

function do not have any direct economic interpretation. However, most of the estimated parameters are statistically significant at the 1% or 5% significance levels, and could be used in conjunction with the estimated technical inefficiency to estimate additional measures of interest, such as TC, return to scale, and TFP growth. We also conducted specification test for the Cobb–Douglas frontier using the likelihood ratio (LR) statistics. The LR value was 82.6 with an asymptotic p-value of 0.0000. Hence, we rejected the Cobb-Douglas specification as the correct specification for our data set.

The results from Table 1 show that in term of the noise components, the estimates of $\mathcal{S}_u^2$ are statistically significant at 1% for both crops and livestock, indicating that the use of the stochastic frontier model is appropriate. The means and standard deviations of the estimated technical efficiency measure for each province are displayed in Table 2. The means of technical efficiency are different from province to province for both crops and livestock, albeit relatively small. For crops, the most technically efficient province is Manitoba (83.97%) and the least technically efficient is New Brunswick (79.34%).

Table 2. Mean and standard deviation of technical efficiency[a]

Province	Crop	Livestock
AB	0.8216	0.8321
	(0.0913)	(0.0895)
BC	0.8115	0.8238
	(0.1028)	(0.1105)
MAN	0.8397	0.8462
	(0.899)	(0.0812)
NB	0.7934	0.8024
	(0.1243)	(0.1105)
NS	0.7988	0.8067
	(0.1320)	(0.1227)
ON	0.8198	0.8485
	(0.1089)	(0.1141)
PEI	0.7969	0.8094
	(0.1425)	(0.1312)
QC	0.8178	0.8594
	(0.1066)	(0.1091)
SK	0.8345	0.8421
	(0.0855)	(0.0903)

Note: [a]Standard deviations are given in parentheses.

Table 3. TFP growth rates: Crop

Province	1980–99	1990–2009	1940–2009
AB	1.16	1.12	1.57
BC	1.09	1.05	1.01
MAN	2.39	2.38	2.03
NB	0.64	0.67	0.63
NS	0.73	0.75	0.69
ON	1.18	1.14	1.21
PEI	0.90	0.92	0.89
QC	1.03	1.00	1.05
SK	1.92	2.06	1.69

For livestock, the most technically efficient province is Quebec (85.94%) and the least technically efficient province is New Brunswick (80.24%).

We now turn our attention to the results of the TFP growth and its decompositions. The average annual TFP growth rates for crops and livestock for the entire period are reported in Tables 3 and 4, respectively. For comparison purposes, we also provided the average annual TFP growth for two overlapping periods of 1980–99 and 1990–2009. This enables us to determine if there has been decline in agricultural productivity growth in Canada as indicated by other studies.[7] From 1940 to 2009, the TFP growth rates are on

[7] We would like to thank an anonymous referee for suggesting this to us.

Table 4. TFP growth rates: Livestock

Province	1980–99	1990–2009	1940–2009
AB	0.36	0.31	0.61
BC	0.44	0.42	0.47
MAN	1.88	1.97	1.08
NB	1.77	1.89	1.73
NS	1.85	1.97	1.84
ON	2.59	2.54	2.77
PEI	1.67	1.70	1.68
QC	2.44	2.45	2.43
SK	1.30	1.66	0.73

average higher for crops in each of the Prairie provinces (Alberta, Saskatchewan, and Manitoba) than for the eastern and Atlantic provinces. For example, the annual average TFP growth in Alberta, Saskatchewan, and Manitoba are 1.57%, 1.69%, and 2.03% respectively, compared to 1.21% in Ontario, 1.05% in Quebec, and less than 1% in the Atlantic provinces.

Comparing average productivity growth in the crops sector between the two overlapping periods (1980–99 and 1990–2009), we observe that with the exception of Saskatchewan, the crops productivity growth in the remaining major crops producing provinces—Alberta, British Columbia, Manitoba, Ontario, and Quebec—are lower for the period 1990–2009 than those of the period 1980–99. Our finding suggests some evidence of a recent decline in productivity growth for crops subsector in Canada, at least in the major crop-producing provinces. This result is also qualitatively consistent with recent findings in the literature, at least for the Prairie provinces (see, e.g., Stewart et al 2009; Veeman and Gray 2009, 2010). Specifically, compared to the results of Stewart et al (2009) for the Prairie provinces, our results show that the magnitudes of the average annual TFP growth rates are slightly lower. These differences are perhaps due to the presence of the technical inefficiency term in the model as well as larger sample size.

For livestock, the average annual TFP growth rates for the period 1940–2009 are on average higher in the Eastern and Atlantic provinces than in the Prairie region. Higher productivity growth rates are found in Ontario and Quebec (2.77% and 2.43%, respectively) followed by New Brunswick, Nova Scotia, Prince Edwards Island, and Manitoba. The average annual productivity growth rates for British Columbia and the Prairie provinces with the exception of Manitoba are all less than 1%.

Comparing the results to those of the periods 1980–99 to 1990–2009, we observe that the average livestock productivity growth in Saskatchewan, Manitoba, Quebec, and the Atlantic provinces were higher during the latter 20 years. However, it is noted that Alberta, Ontario, and British Columbia experienced lower livestock productivity growth during the same period. The results suggest that there is no clear evidence to support the claim that TFP growth rates in the livestock sector in Canada has declined during the latter two decades. For the period 1990–2009, the productivity growth rates in the livestock subsector are on the average still higher in the Eastern and Atlantic provinces than in the Prairie region with the exception of Manitoba that has a TFP growth rate similar to those of the Atlantic provinces. As in the case for crops, comparing our results to Stewart et al (2009) for the Prairie provinces shows some qualitative similarities, but reveals some differences in magnitude in the productivity growth rates. Our estimates of productivity growth rates in the crop and livestock sectors for all the Prairie provinces are smaller than those of Stewart et al (2009). This implies that perhaps including the technical inefficiency term in the model is relevant in determining the true magnitudes of productivity growth rates.

The finding of higher productivity growth rates for crops relative to livestock for the Prairie provinces compared to the Eastern and Atlantic provinces could be explained by longer production cycle and slower progress in controlled genetic technology associated with cattle production in the Prairie region, especially in Alberta and Saskatchewan.[8] Manitoba is an exception since traditionally livestock in the province has been more diversified and it is possible that farms have benefited more from faster progress in controlled genetics. Conversely, the finding of higher productivity growth rates for livestock relative to crops in the Eastern and Atlantic provinces compared to the West may be due to improvement of genetics, feed conversion, and exploitation of economies of scale (intensive livestock operations especially regarding feedlots and hog barn) in livestock production. Finally, it was noted that productivity growth in the agriculture sector in Alberta slowed down possibly due to the reallocation of financial and human resources from the agriculture sector to the oil and gas sector.

To get more insights into how crops and livestock productivity growth occurred, we turn our attention to the TFP growth decomposition using data for the entire period (1940–2009). Tables 5 and 6 provide the decomposition of estimated TFP growth into TC, SEs, and TEC for the crops and livestock sectors, respectively.

As seen in Table 5, TC seems to be the dominant component of the estimated productivity growth for crops in all the provinces except Ontario and Quebec. For example, in Alberta, Saskatchewan, Manitoba, New Brunswick, and Nova Scotia, TC contributed 88.5%, 85.2%, 79.3%, 73.0%, and 69.6%, respectively, to the TFP growth. For these provinces, with the exception of Alberta, the role of SEs is also economically important, ranging from 15.8% in British Columbia to 33.3% in New Brunswick. The SE is much less for Alberta crops with only 6.4% contribution to TFP growth. For Ontario and Quebec, both technological progress (44.6% and 43.8%, respectively) and SEs (52.1% and 45.7%, respectively) played important role in the estimated TFP growth. An important implication of these results is that the TFP growth in crops is mainly driven by technological progress. The results reinforce the vital role research and development (the adoption of new seed varieties and cropping practice) and extension activities play in the overall development of the Canadian agriculture sector. The change in technical efficiency is mainly positive (except for New Brunswick and Nova Scotia), but has relatively small contributions to the TFP growth for most provinces. Finally, the residuals that account for the unexplained component of the TFP growth are very small. This indicates that factors such as measurement errors and changes in allocative efficiency play very little role in crops productivity growth.

For the livestock sector, Table 6 shows that the SEs play a significant role in TFP growth for all provinces, especially in the East and the Atlantic region. In addition,

[8] The results are consistent with Stewart et al (2009).

Table 5. TFP decomposition results for crop: 1940–2009[a]

Province	TFP	TC	SEs	TE change	Residual
AB	1.57	1.39	0.06	0.06	0.02
	(100)	(88.5)	(6.4)	(3.8)	(1.3)
BC	1.01	0.81	0.16	0.03	0.01
	(100)	(80.2)	(15.8)	(3.0)	(1.0)
MAN	2.03	1.61	0.34	0.07	0.01
	(100)	(79.3)	(16.7)	(3.4)	(0.5)
NB	0.63	0.46	0.21	−0.05	0.01
	(100)	(73.0)	(33.3)	(−7.9)	(1.6)
NS	0.69	0.48	0.22	−0.04	0.03
	(100)	(69.6)	(31.9)	(−5.8)	(4.3)
ON	1.21	0.54	0.63	0.08	−0.04
	(100)	(44.6)	(52.1)	(6.6)	(−3.3)
PEI	0.89	0.53	0.28	0.05	0.03
	(100)	(59.6)	(31.5)	(5.6)	(3.3)
QC	1.05	0.46	0.48	0.07	0.04
	(100)	(43.8)	(45.7)	(6.7)	(3.8)
SK	1.69	1.44	0.21	0.05	−0.01
	(100)	(85.2)	(12.4)	(3.0)	(−0.6)

Note: [a]Figures in parentheses denote percentage contribution to TFP.

Table 6. TFP decomposition results for livestock: 1940–2009[a]

Province	TFP	TC	SEs	TE change	Residual
AB	0.61	0.20	0.31	0.09	0.01
	(100)	(32.8)	(50.8)	(14.8)	(1.6)
BC	0.47	0.13	0.24	0.08	0.02
	(100)	(27.7)	(51.1)	(17.0)	(4.2)
MAN	1.08	0.38	0.56	0.12	0.02
	(100)	(35.1)	(51.9)	(11.1)	(1.9)
NB	1.73	0.59	1.01	0.21	−0.08
	(100)	(34.1)	(58.4)	(12.1)	(−4.6)
NS	1.84	0.64	1.05	0.24	−0.09
	(100)	(34.8)	(57.1)	(13.0)	(−4.9)
ON	2.77	0.72	1.92	0.26	−0.04
	(100)	(29.6)	(69.3)	(9.3)	(−3.3)
PEI	1.68	0.48	1.05	0.18	−0.03
	(100)	(28.6)	(62.5)	(10.7)	(−1.8)
QC	2.43	0.61	1.59	0.20	0.03
	(100)	(25.1)	(65.4)	(8.2)	(1.2)
SK	0.73	0.23	0.41	0.08	0.01
	(100)	(31.5)	(56.2)	(11.0)	(1.3)

Note: [a]Figures in parentheses denote percentage contribution to TFP.

improvement in the degree of technical efficiency is significant for the sector. These results suggest that economies of scale associated with the expansion of aggregate livestock output have been the main driver of the productivity growth during the period 1940 to 2009. Perhaps the main explanation for the role of economies of scale and improvements in the degree of technical efficiency in livestock productivity growth is the shift to more intensive livestock operations, such as improvements in genetics, feedlots conversion, and management practices as aggregate provincial livestock output expands over time.

CONCLUDING REMARKS

Agricultural productivity growth is important with regard to economic efficiency, living standards, international competitiveness, and economic sustainability. Recent studies have concluded that agricultural productivity growth in Canada lags behind that of the United States and many OECD countries. Other research evidence suggests that agricultural productivity growth in Canada has significantly slowed down. However, studies by de Avillez (2011a, 2011b) have showed that the Canadian agricultural sector has experienced significant labor productivity growth. Furthermore, some Canadian studies have used various methodologies to examine agricultural productivity growth and efficiency for a specific crop or type of livestock farm within a specific province or a collection of few provinces. The results from those studies have showed that methodological characteristics (estimation technique) and other study-specific characteristics (functional form, sample size, product analysis, dimensionality, and geographical region) could affect the empirical estimates of productivity growth and technical efficiency.

To the best of our knowledge, there is no study that examines productivity growth using data on crops and livestock production in all the provinces in Canada while allowing for production inefficiencies to further decompose TFP growth into SEs, TEC, and TC. In this paper, we address the above issues by using a stochastic frontier approach that allows for inefficiencies, and provincial-level agricultural data on crops and livestock from 1940 to 2009 to examine and decompose TFP growth into SEs, TEC, and TC. The paper also investigates the claim that agricultural productivity growth in Canada has recently slowed down.

The results indicate that from 1940 to 2009, the productivity growth rates for the crops subsector were on average higher for the Prairie provinces than for the Eastern and Atlantic provinces. During the same period, the productivity growth rates in the livestock subsector were on the average higher in the Eastern and Atlantic provinces than in the Prairie region with the exception of Manitoba where TFP growth has been similar to those of the Atlantic provinces for the period 1990 to 2009. Comparing average productivity growth in both the crops and livestock subsectors for the period 1940–2009 to the periods 1989–99 and 1990–2009, our results indicate that for most of the provinces the recent average productivity growth rate are higher than the overall average for the entire period. However, by looking at the two overlapping periods of 1989–99 and 1990–2009, our results suggest some evidence of a recent decline in crops productivity growth, but the evidence of a recent decline in the livestock subsector is not clear, since half of the major livestock-producing provinces experienced a decline, while the other half show a rise in productivity growth.

The productivity changes in the two subsectors were driven mainly by TCs (such as new seed varieties, progress in controlled genetic technology, better quality machinery and equipment) and SEs (arising from intensive livestock operations and cropping practices). Specifically, TC is the dominant component of the estimated productivity growth for crops in all the provinces except Ontario and Quebec. However, SE is the dominant component of the estimated productivity growth for livestock in all the provinces. The contribution of technical progress to productivity growth in livestock was also significant. Finally, though change in technical efficiency is mainly positive for both sectors (except for New Brunswick and Nova Scotia for the crop sector), its contribution to productivity growth was rather very little for the provinces.

There is no guarantee that the productivity growth rates of the Canadian agricultural sector during the last few decades would continue into the future. A number of recent studies have suggested that agricultural productivity growth rates for developed countries have slowed down significantly over the past decade or two. The decomposition analysis undertaken in this paper showed that technical progress and SE are the two most important determinants of productivity growth among Canadian provinces. Therefore, government policies directed toward increasing funding for agricultural research that improves technical progress and enables farms to benefit from scale of operations should form an essential part of the overall agriculture policies. For instance public investment in agricultural science and technological innovations, such as increasing investment in innovation (improving the stock of knowledge/basic research, new seed varieties, progress in controlled genetic technology, cost-effective cropping practices, and livestock operations), fostering and facilitating innovation adoption, and improving research and development infrastructure, could be intensified to improve agricultural productivity growth significantly.

There is, however, an important limitation to the analysis in this paper. Given the nature of advances in technology, it would have been reasonable to allow for time-varying parameters in our model. However, with the flexible form, allowing for time-varying coefficients often creates problems in the estimation process because the parameters become much more difficult to estimate. We could have used a more restrictive form of the production function to deal with the situation. However, our specification test rejected the simpler form of the frontier (the Cobb–Douglas form). We could have also used the standard random coefficients model. The problem with that approach is the identification of the variance parameters in the model since we would have more than two error terms. We therefore leave this for future research.

ACKNOWLEDGMENTS

We would like to thank a coeditor, B. P. Saha, and two anonymous referees for invaluable comments and suggestions that led to substantial improvement of the article. We would also like to thank Mike Tsionas for his comments and suggestions. Financial support from CAIRN Network is gratefully acknowledged. Finally, an earlier draft of this article was circulated as a CAIRN Network working paper under the same title.

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APPENDIX: DATA DESCRIPTION

In this Appendix, we provide a brief description of the data used in the paper.

Crops

Crop production in Canada is divided into four categories: field crops, potatoes, fruits, and vegetables. Field crops comprise of the majority of crop cash receipts in Canada with the Prairie provinces having the highest proportions. Saskatchewan has about 98% of total crop cash receipts coming from field crops. Field crops include 18 different types of crops: wheat, barley, rye, mixed grain, corn for grain, buckwheat, dry field peas, and others. A number of smaller specialty crops are not included in total output of field crops. These include Triticale, Canary seed, Fababeans, Coriander, Safflower, Caraway seed, Borage seed, and Chick peas. These were left out of total real production because adequate price information was not available to convert them into real terms. Also, the combined total production of these specialty crops was found to be less than 1% of the total production of all field crops in Canada from 1940 to 2009, and therefore would not affect total production very much. The data for field crops came from CANSIM Table 001–0010 (with the exception of potatoes that came from Statistics Canada Table 001–0014). FPPI is used to deflate the value measures of crop in order to remove the price effect.

Livestock

Livestock output was found using farm cash receipts from 1940 to 2009. The total production of livestock is comprised of the production of cattle, calves, hogs, sheep, lambs, dairy products, poultry, eggs, and other livestock and products. These are the nominal values of livestock production. The FPPI is then used to deflate the value measures of livestock in order to remove the price effect.

The values for individual livestock products (cattle and calves, hogs, poultry, eggs, dairy) from 1971 to 2009 were taken from CANSIM Tables 002–0021 and 002–0068; and the missing values from 1940 to 1971 have been imputed using the predicted scores from an ARMA (1,0) process. The ARMA (1, 0) was chosen based on the Akaike and Schwarz model selection criterions from a more general class ARMA (p, q) process.

Inputs

The input data were organized following Stewart et al (2009). The data are organized into four main categories: capital, land, labor, and materials. Capital contains the value of machinery and equipment used in production, the cost of repairs to machinery and equipment, the depreciation value of machinery and equipment, and the value of livestock inventory. Land is comprised of the value of cropped land, land in summer fallow, pasture land, buildings, building repairs, building depreciation, and property tax. Labor contains unpaid and paid labor. Materials include the cost of fuel, electricity, telephone, custom work, twine, business and crop insurance, fertilizer and lime, pesticides, commercial seed, feed, artificial insemination and vet fees, and miscellaneous other expenses.

Capital inputs came from three different CANSIM tables. Table 002–0007 contained the data needed for machinery and equipment, and livestock inventories. Most of the data for land inputs came from the same tables as capital inputs. Land and building values came from Table 002–0007, depreciation, property tax, and building repair values came from Table 002–0005 and Table 002–0015. Building repairs include any costs of repairing fences as well. Cropped land data were obtained from Table 001–0017, and is calculated as the total area, in acres, of seeded land.

Labor consists of unpaid and paid labor. Paid labor is separated into hired labor and operator labor in the nominal section of labor inputs. Hired labor consists of paid wages to employees and family members and was obtained from Table 002–0015 for the years 1940–70 and Table 002–0005 for 1971–2009. These paid wages include room and board as well as cash wages, and the value before rebates was used. Statistics Canada defines operators as those persons responsible for the management decisions made in the operation of a census farm or agricultural operation, and up to three operators can be reported per farm. The net income received by farm operators from farm production was taken as the value of operator labor obtained from Table 380–0052. Unpaid labor was calculated as 70% of operator labor.

For materials, the data came from Table 002–0005 and Table 002–0015. The cost of containers is included in pesticides from 1940 to 1947.

Allocating Inputs

Allocating inputs between the livestock and crops sectors require the use of census of agriculture data, which is more detailed and separates data by farm type. These farm types are categorized as follows: wheat, fruits and vegetables, field crops, cattle, hogs, poultry, mixed farms, and subsistence farms. To be categorized as one of these, at least 51% (50% prior to 1961) of total output must come from the titled crop (i.e., a farm classified as a cattle farm must have 51% of its total output coming from cattle production). In some census years, mixed farms are subdivided into mixed livestock farms, mixed crop farms, and mixed other. A mixed crop farm is a farm that has 51% of its total production from two or more crop categories (wheat, fruits and vegetables, field crops). For livestock, it was computed as the sum of all farms classified as cattle, hogs, poultry, and mixed livestock. For crops, it was computed as the sum of all farms classified as wheat, fruits and vegetables, field crop, and mixed crop farms.

For cropped land, livestock capital, operator labor, paid labor, and the value of land and buildings, the share of each category was determined for each sector following the methodology outlined by Stewart et al (2009). These sector shares were then used to allocate the inputs between the livestock and crop sectors. The share of machinery and equipment was used to allocate all of the capital inputs except livestock inventory that did not require allocation as it is solely a livestock input. The allocation was completed by simply taking the total input value of capital and multiplying it by the sector share. All land inputs were allocated using the sector share of the value of land and buildings. Some land was only used for one sector. Cropped land and summer fallow land are entirely crop inputs, while pasture land is exclusively a livestock input. Two sector shares were used to allocate labor inputs. The share of operator labor was used to allocate unpaid labor and operator labor, while the share of paid labor was used to allocate paid wages.

Irrigation, fertilizer and lime, pesticides, commercial seed, and crop insurance are solely a crop sector input, while feed, artificial insemination, and vet expenses are livestock sector inputs and thus do not need to be allocated. The remaining materials inputs are allocated using one of the above methods or on the crops and livestock's share of value of total output. Fuel is allocated using the capital shares, electricity using the land and building shares, and telephone using the labor share. Custom work, miscellaneous expenses, business insurance, twine, wire, and containers are allocated using the crop and livestock's share of value of total output.

Finally, all the inputs were valued by the price of each input-quality type to account for changes in qualities over time.