Evaluating Scale and Technical Efficiency among Farms and Ranches with a Local Market Orientation

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Abstract

In recent years, the growth in local food marketing channels has been significant. Most of the research in this field examining the economic implication of these trends has focused post-farmgate including supply chain analysis (e.g. Hardesty et al., 2014; King et al., 2010), regional economic impacts (e.g. Brown et al., 2014; Hughes et al., 2008; Jablonski et al., 2016), and consumer values and motivations that have driven demand (e.g. Costanigro, 2014; Lusk and Briggeman, 2009). To date, with the exception of a few case studies examining expenses and sales by channel assessment (LeRoux et al., 2010; Hardesty and Leff, 2010; Jablonski and Schmit 2016) there has been little research that examines the impact on financial viability among farms selling through these markets. The goal of this paper is twofold: first, to identify the factors that have the greatest influence on the efficiency of farmers and ranchers that participate in local food systems, and second, to estimate the relationship between marketing strategy and farm financial efficiency, with a particular focus on variations across farm size. Our estimation of the stochastic production frontier suggests that scale, production enterprise specialty, market outlet choices, land ownership, and management of expenses have the greatest influence on producer financial efficiency. Our model suggests that scale has the largest impact on financial efficiency, providing evidence that, all else constant, the most important factor in the efficiency of direct market producers is scale. When profit is defined as operating profit, results indicate that marketing channel is not an important indicator of efficiency. But when profit is defined as return on assets, marketing channel is an important indicator of efficiency, albeit less than is scale. Results from this analysis indicate there are economies of scale associated with farms and ranches that sell through local and regional markets, and that scale rather than marketing channel has the largest influence on efficiency.

Key words: Local foods, technical efficiency, farm profitability

The 2015 U.S. Department of Agriculture's (USDA) Economic Research Service (ERS) report on Trends in Local and Regional Food Systems reported that in 2012, 7.8 percent of all U.S. farms participated in local food systems, including both direct-to-consumer sales (e.g. farmers' markets) as well as intermediated channels (e.g. farm-to-restaurant), with total sales of $6.1 billion. In recent years, the growth in local food marketing channels has been significant. For example, since 2006, farmers' markets have grown 180 percent and food hubs have increased by 288 percent (Low et al., 2015). Most of the research in this field examining the economic implication of these trends has focused post-farmgate including supply chain analysis (e.g. Hardesty et al., 2014; King et al., 2010), economic impact studies (e.g. Brown et al., 2014; Hughes et al., 2008; Jablonski et al. 2016), and studies focused on the consumer-oriented factors that have driven the demand for local food (e.g. Costanigro, 2014; Lusk and Briggeman, 2009).

Though there are a handful of case studies that examine differential farm expenditures and sales by market channel (Le Roux et al. 2010, Hardest and Leff 2010; and Jablonski and Schmit 2016), no research has systemically examined the impact on financial viability among farms selling through these markets. These three previous studies examined the differential expenditures per unit of sales by market channel, paying particular attention to labor and fuel utilization. However, the sample size is small in each of these studies as they required primary data collection based on individual case studies. Thus it was not possible for these authors to use rigorous methods to analyze the data. Jablonski and Schmit (2016) did compare their case studies to ARMS data, however it was only for NYS, for which the ARMS sample is relatively small.

Given the sample size limitations, these previous studies could not address questions such as: how does the financial performance of farms utilizing local food markets compare to their peers? Does the optimal size vary among farmers depending on the nature of how they participate in local food system? Is there an optimal diversification strategy with respect to market orientation, or is that dependent on other factors (scale, region, primary commodity)? The goal of this paper is twofold: first, to identify the factors that have the greatest influence on the efficiency of farms and ranches that participate in local food systems; and second, to estimate the relationship between marketing strategy and farm profitability and productivity, with a particular focus on farm size.

Farmers and ranchers, the USDA, and private foundations that fund regional food systems have an interest in understanding how new markets influence the resiliency of farms, particularly, beginning or smaller operations for whom more traditional commodity oriented markets may have larger barriers to entry or advantage larger-scale operations. For farmers and ranchers, very little "peer" data is available that allows for comparison with similar farms or to provide a roadmap for growth. Access to and consideration of this information will provide them with an opportunity to understand their competitive position, and if needed, see factors that may allow them to increase profitability.

From the standpoint of the USDA and private foundations that provide funding in this area, understanding the factors that influence efficiency will enable them to better target their resources and support local and regional food system development. As one example, the Farm Service Agency is striving to provide more capital to farms participating in these markets, but needs to understand the underlying factors that allow farms to be viable (and repay their loans). Additionally, in 2015 the USDA Risk Management Agency began piloting Whole-Farm Revenue Protection, a program that provides an insurance plan for diversified producers selling through local and regional food markets. In both cases, there is more to learn in order for financing and risk management programs to be structured effectively; understanding the determinants of efficiency will be one important aspect.

Part of the challenge has been that until recently, these types of questions were not possible to answer on a national level due to a lack of available data. Although national data on direct-to-consumer sales has been available since 1976, nationally representative data on intermediated sales by farm operators (the largest segment of local food sales) has only been available since the 2008 U.S. Department of Agriculture, Agricultural Resource Management Survey (ARMS). ARMS is currently the primary source of nationwide farm financial information (Low & Vogel, 2011). The ARMS now provides a sufficiently large sample of financial data for producers participating in local food systems at the national level, allowing for financial evaluation of this subset of U.S. farmers. To our knowledge, there have been no studies that focus on the financial performance and efficiency of farming operations that participate in local food system and few studies of this kind on a national scale.

Empirical Approach

The most common approach to estimating production or financial efficiency across the farm sector is stochastic frontier analysis (SFA), whereby a production function is estimated with an error composed of both a productive inefficiency component and a random component. It is assumed that the production function is the theoretical production ideal, so any deviation from this function is the result of an inefficiency (Green, 2012). Although there have been no studies that evaluate the efficiency of regional food system participants, there have been a number of studies that use stochastic frontier analysis to evaluate the efficiency of other types of U.S. farming and ranching operations (e.g. Key & McBride, 2014; Mayen, Balagatas & Alexander, 2010; Morrison Paul & Richard Nehring, 2005), as well as international farming and ranching operations (e.g. Barath & Ferto, 2015; Bokusheva, Hockmann, & Kumbhakar, 2012).

Another common approach to estimate efficiency is data envelop analysis (DEA). Although DEA can be seen as superior to SFA because it does not require an assumption of the functional form the production function must take, because of its reliance on all data points to estimate the efficient frontier, it is very sensitive to outliers and inconsistencies in the data. For this reason, SFA is the preferred choice when estimating efficiency in the agricultural sector.

SFA allows us to estimate the maximum attainable output (or other profitability measure) for a given set of inputs and prices. By including farm characteristics in our model beyond inputs and prices, we are able to determine the full set of factors that influence a producer's ability to reach this ideal. Based on previous literature, one of the most influential factors in efficiency is scale (e.g. Morrison Paul and Nehring, 2005; Hoppe, 2014). In the U.S., the majority, 75%, of production is produced by midsize and large scale farms (defined by the USDA ERS as >$350,000 in gross cash farm income), while the remaining 25% is from small scale farms. This is despite the fact that over 90% of farms are small scale farms. Of the small scale farms, over two-thirds have profitability measures that fall in the critical zone, i.e. ROA less than 1% and/or operating profit margin less than 10%) (Hoppe, 2014). Yet for those producers participating in direct marketing channels, research has suggested they may be more economically viable and likely to survive, regardless of their scale (Low et al., 2015).

Using SFA will allow us to disentangle the effect of scale on efficiency from the many other factors that influence efficiency. In our study, we use gross cash farm income to proxy scale. Marketing channel and scale can be interdependent factors, as larger producers in local food systems generally sell through intermediated marketing channels while smaller producers usually sell through direct-to-consumer marketing channels only. To disentangle the effect scale has on efficiency when marketing channel is held constant, and vice versa, the model will be estimated with both marketing channel and scale included, and then again with only the marketing channel variables. In addition to marketing channel, primary commodity may also have an influence on efficiency and only scale included. While fruit and vegetable producers make up the majority of sales for producers in local food systems (Low & Vogel, 2011) profitability has been shown to vary across output types (Detre et al., 2011).

Previous literature also points to the impact that farm characteristics such as operator age, operator education and reliance on off-farm income may have on efficiency. Younger operators have higher debt than older operators and typically finance farming operations through borrowed capital (Mishra et al., 2002). Park (2014) found that younger farmers were more likely to participate in direct marketing channels than older farmers, likely due to the fact that accessing local and regional food markets may require less production volume and/or capital than traditional marketing channels.

In studies of producers using traditional market outlets, operator education typically increases farm household income (e.g. Mishra et al., 2002). In local and regional food systems there is a greater reliance on aggressively managed marketing and operations compared with traditional market outlets. Operator education is likely to have an impact on these producers in local and regional food systems, and possibly even more so than those producers utilizing traditional marketing channels. Park (2014) finds that operators with a broader portfolio of marketing skills are more likely to increase farm sales relative to farmers who are using fewer marketing skills, indicating the importance of education on efficiency. More than half of all U.S. farm households have household member that works off-farm (Mishra et al., 2002) and the same is true for producers participating in local and regional food systems (Low & Vogel, 2011). Given the reliance on off-farm income, it is likely to be an important factor in determining profitability, but may also compete with time spent focused on the agricultural enterprise, thereby representing a challenge to managerial efficiency.

We use profit as our dependent variable for this analysis[1] and choose to define it in two ways: operating profit margin and return on assets (ROA). Operating profit margin is calculated by subtracting unpaid labor and management provided by provided by principal operator and other persons from net farm income; this calculation assumes that unpaid labor and management provided are opportunity costs and should be accounted for in the calculation of profit (Hoppe, 2014). Secondly, we use ROA to define profit, measuring how efficiency a firm can create profit using their assets in a given year. Much as operating profit margin accounts for the opportunity cost of labor, ROA accounts for the opportunity cost of money.

The use of a "standardized" measure like ROA, may allow some expected and interesting cases (such as lean farms with few owned assets that are aggressively pursuing high end produce and product markets) to emerge more clearly. In contrast, gross measures, such as operating profit margin, may mask some interesting aspects of farms participating in direct markets. Estimating the efficiency frontier using both definitions of profit will enable us to provide a better-rounded picture of local food farmers and ranchers. Explanatory variables include variable and fixed expenses expressed as a percent of total variable and fixed expenses, respectively,

[1] Cost was not chosen as the dependent variable because the direct marketing sector is largely reliant on higher prices for their products rather than low cost of production.

operator age, education, market outlet, scale, type of output, and percent of farm land that is owned[2].

Econometric Model

We estimate the factors that have the greatest impact on the technical efficiency of local food system participants using stochastic frontier analysis, first proposed by Aigner, Lovell and Schmitt (1977) and Meeusen and van den Broeck (1977). The model has the form:

(1) $$\ln(\pi_i) = f(x_i, \beta) + v_i - u_i$$

where π_i is the profit for producer *i*, and $f(x_i, \beta)$ is the maximum profit that can be obtained with the vector of logged inputs, x_i, and the technology described by the parameters β. Deviation from the maximum profit for an individual can either be from a random shock, v_i, or due to a production inefficiency, u_i, where $u_i \geq 0$. The production function for an individual is specified as a Cobb-Douglas production function such that $f(x_i, \beta) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{i,j})$, where β_0 is the constant and β_j are the coefficients for each of the k independent variables.

The technical efficiency for an individual producer is defined as the ratio of the observed ROA of an individual producer to the maximum observed ROA:

(2) $$TE_i = \frac{\pi_i}{\exp\left(f(x_i, \beta) + v_i\right)} = \exp\left(-u_i\right)$$

[2] When off-farm income as a share of total sales was included in the model, it was unable to solve, and is therefore not included in the analysis. When included as a dummy variable for positive off-farm income, results did not change.

where $0 \le TE_i \le 1$. When $TE_i = 1$, the producer is on the efficiency frontier while for any $TE_i < 1$ the producer falls below the efficiency frontier.

We assume the commonly utilized normal/half-normal distribution in which v_i is distributed $N(0, \sigma_v^2)$, u_i is distributed $N^+(0, \sigma_u^2)$, v_i and u_i are statistically independent of each other, and v_i and u_i are independent and identically distributed across observations. Given this distribution $E[u] = \sigma_u \sqrt{2/\pi}$ and $\mathrm{var}[u] = \sigma_u^2 [(\pi - 2)/\pi]$, where $0 < u_i < \infty$.

The log-likelihood function is as follows:

(3) $$\ln L(\pi \mid \beta, \lambda, \sigma^2) = N \ln\left(\frac{\sqrt{2}}{\sqrt{\pi}}\right) + N \ln \sigma^{-1} + \sum_{i=1}^{N} \ln\left[1 - F\left(\varepsilon_i \lambda \sigma^{-1}\right) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \varepsilon_i^2\right]$$

where $\varepsilon_i = \pi_i - x_i^{'} \beta$, $\lambda = \sigma_u / \sigma_v$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and F is the standard normal CDF (Aigner, Lovell, & Schmidt, 1977). The main parameter of interest, u_i, is the technical efficiency of each individual, which is a component of the estimated error, $\varepsilon_i = v_i + u_i$. Because u_i is not directly estimable, to estimate the technical efficiency for an individual enterprise, we estimate the expected value of u_i given ε_i as proposed by Jondrow et al., 1982:

(4) $$E(u_i \mid \varepsilon_i) = \frac{\sigma\lambda}{1 + \lambda^2}\left[\frac{f\left(\varepsilon\lambda / \sigma\right)}{1 - F\left(\varepsilon\lambda / \sigma\right)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right]$$

where f is the standard normal density.

Data

Data are taken from the 2013 Phase III ARMS to estimate the parameters of the model. The data include gross cash farm income, marketing channels utilized, primary commodity, fixed and variable expenses, assets, debt, and farm and operator characteristics. The ARMS is a nationally representative survey that targets about 30,000 farms annually and utilizes a complex survey design (e.g. complex stratified, multiple-frame, and probability-weighted). The ARMS mission is to provide annual, national-level data on farm business with a particular focus on 15 core agricultural states. Therefore, it may provide a relatively small sample of a niche group, such as direct market producers, particularly in the non-core agricultural states. Although the ARMS is not designed to collect data on agricultural sectors such as direct marketing, it remains the best source of nationally representative data available for this type of analysis (Low and Vogel, 2011; Low et al., 2015).

Given this survey design, if the purpose of the analysis is to describe the population, then the estimates must be weighted (using a jackknife weighting scheme). But if the purpose is to describe variability within a sample, which in our case is farms and ranches selling through local food marketing channels, then weighting the sample will distort the results by forcing this sample to appear more like the average farm or ranch (Dubman, 2000). If the goal is to compare farms and ranches selling through local food markets to those farms and ranches utilizing traditional marketing channels, then it is necessary to weight estimates. But, as is the case in this paper, if the comparison is within local food marketing channels, then no weighting is necessary.

By not using the jackknife weighting scheme to standardize the sample analyzed, this paper assumes that; 1) local food producers would not be shown as representative using the criteria commonly used to create more representative farms in the ARMS sampling scheme; 2) the ARMS sampling scheme is representative of all farms so comparisons of our targeted set of producers to the sample still offers some important inferences. We did not modify the targeted sample to normalize it to a representative US farm population because we expect it is those farms' variance from being "representative" which is interesting for comparisons.

In the ARMS data collection protocol, sales through local food markets are asked in two ways (similar to how questions are asked in the Census of Agriculture). First, participants are asked to respond (yes/no) if they produced, raised, or grew commodities for human consumption that were sold directly to: (1) individual consumers, (2) retail outlets, and (3) institutions. Subsequently, they are asked to provide how much money was receive for the cash market, open market, or marketing contract sales from selling (1) directly to consumers at farmers markets, (2) directly to consumers from on-farm store, u-pick, roadside stands, CSA's, (3) to a local retail outlet such as a restaurant or grocery store, (4) to a regional distributor such as a food hub, (5) to a local institutional outlet such as a school or hospital. We define local food system participants by all those that reported positive sales in any of the five direct marketing channels listed above.

Following Low et al. (2015), sales to individual household consumers are classified as direct-to-consumer sales, while sales to retail outlets and institutions are classified as intermediated sales. Of the total sample, 16,461 (94%) reported no local food sales, 1,013[3] (6%) responded that they had positive sales in local food marketing channels. For all those respondents who reported positive sales in local food marketing channels, 664 (66%) had positive direct-to-consumer sales only, 136 (13%) had positive intermediates sales only, and 213 (21%) had positive sales to both outlets. Table 1 provides summary statistics for the main variables used in the study, across all sales categories as well as broken out by sales category.

[3] Note that 63 producers reporting direct market sales production specialty was reported as nursery and not included in the SFA.

Table 1. Summary Statistics for Local Food Farmers and Ranchers

	All Mean (Std. Dev)	$1K-$75K Mean (Std. Dev)	$75K-$350K Mean (Std. Dev)	$350K + Mean (Std. Dev)
Return on Assets (ROA) ($)	-27 (426)	-55 (583)	2.14 (35.90)	13.97 (32.45)
Operating profit ($)	126,553 (981,527)	-28,226 (33,867)	-13,898 (94,607)	699,067 (2,052,901)
Total fixed expense	56,715 (226,559)	6,681 (12,192)	21,774 (19,687)	232,286 (455,287)
Total variable expense	442,793 (2,316,296)	17,143 (21,569)	112,700 (81,040)	1,966,531 (4,784,753)
Labor expense ($)	83,503 (645,001)	2,462 (8,951)	28,738 (42,888)	778,263 (3,301,224)
Age class (1: <=34, 2: 35-44, 3: 45-54, 4 :55-34, 5: 65+)	3.74 (1.12)	3.81 (1.08)	3.53 (1.24)	3.73 (1.08)
Portion of total acres owned to farmed	0.99 (1.56)	1.14 (1.74)	0.90 (1.71)	0.69 (0.97)
Direct-to-consumer sales only (0/1)	0.66 (0.48)	0.78 (0.42)	0.53 (0.50)	0.43 (0.50)
Intermediated sales only (0/1)	0.13 (0.34)	0.08 (0.27)	0.16 (0.37)	0.26 (0.44)
Direct-to-consumer and intermediated sales (0/1)	0.21 (0.41)	0.14 (0.35)	0.31 (0.46)	0.32 (0.47)
Primary commodity: fruit and/or vegetable (0/1)	0.33 (0.47)	0.34 (0.47)	0.34 (0.47)	0.35 (0.48)
Primary commodity: field crop (0/1)	0.19 (0.40)	0.14 (0.35)	0.24 (0.43)	0.28 (0.45)
Primary commodity: livestock and/or dairy (0/1)	0.41 (0.49)	0.47 (0.50)	0.35 (0.48)	0.28 (0.45)
Operator education (1: less than high school, 2: completed high school, 3:some college, 4: completed 4 years of college or more)	3.02 (0.96)	3.06 (0.95)	2.90 (1.00)	3.08 (0.91)
Observations	1,013	534	213	211

Source: 2013 USDA-ERS ARMS. More information on ARMS can be found at http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices.aspx

As a whole, farms participating in direct marketing channels show a broad range of profitability with higher performers reporting return on assets of over 23%, a strong result for a generally low margin industry such as agriculture. On average operating profit is positive, but when broken out by sales category, only those with over $350,000 in sales have positive profits, on average. Fixed expense as a portion of total expenses decrease with scale, ranging from 28% for producers with sales between $1,000 and $75,000 to 11% for producers with sales over $350,000. This is what we would expect and demonstrates one of the benefits from scaling up. Variable expense as a portion of total expense increases with scale, ranging from 72% for the smallest producers to 89% for the largest producers. On average, producers are in the age range of 45-54 and have completed some level of college education. The portion of acres owned to farmed is 1.14 for the smallest scale producers; these producers own more land than they farm. As scale increases, producers own less and lease more land, providing evidence that most producers scale up by leasing land rather than purchasing new land.

On average, 66% of producers participate in direct-to-consumer marketing channels only, 13% in intermediated only, and 21% in both. Scale and participation in market channels show expected results; small scale producers mostly participate in direct-to-consumer marketing channels and as scale increases producers begin to also participate in intermediated marketing channels. On average, 33% of producers sell fruits and vegetables as their primary commodity, 19% field crops, and 41% livestock. The portion of fruit and vegetable production is constant across scales, but small scale producers are more likely to produce livestock whereas larger producers are more likely to producer field crops.

Results

Results from the estimated model are presented in table two and three, with profit defined as operating profit margin and ROA, respectively. In table two, the first column of results (1) is from the model specification with operating profit as the dependent variable and includes both gross cash farm income and market channel, the second column (2) is from the model with operating profit as the dependent variable and includes only gross cash farm income, and the third column (3) is from the model with operating profit as the dependent variable and includes only marketing channels. Table three follows the same model specifications but utilizes ROA as the dependent variable[4]. These model specifications were chosen to disentangle the effects that market channel and scale have on profitability, thereby enabling us to answer the question of whether it is scale or marketing channel that has the largest influence on efficiency.

We chose to use total variable expense, with labor broken out, and total fixed expense rather than individual expense categories in order to retain more of the sample (since some individual categories were not available for all observations). Some expense categories are only incurred by livestock producers and others only by crop producers, so the disaggregated categories resulted in a relatively small sample. Labor is left as a disaggregated category as all producer types have labor expense and there is evidence that labor is one of the largest variable expense categories for direct market producers (Thilmany McFadden, Bauman, Jablonski, 2016).

Because the dependent variable is logged in a production frontier model, we lose all observations with negative profit (which accounts for 80% of the sample). Therefore, this analysis only estimates efficiency for those producers with positive profit. A generalized

[4] We also ran the model assuming heteroscedasticity by scale. This changed parameter values slightly but did not change the significance of any estimates. Because the model with heteroscedasticity was unable to find a solution for some of the model specifications, no results with heteroscedasticity are presented here.

likelihood ratio test to determine if σ_u^2 is statistically significantly different from zero (i.e. the SFA model reduces to an OLS model) was rejected for all model specifications at the 1% level with normal errors; thus validating the stochastic frontier approach.

Table 2. Stochastic frontier estimates for profit defined as operating profit

	(1) Scale and marketing channel	(2) Scale Only	(3) Marketing channel only
Total fixed expense	0.90 (.06)	0.08 (0.06)	0.30*** (0.09)
Total variable expense (minus labor expense)	-0.43*** (.10)	-0.42*** (0.10)	0.20** (0.10)
Labor expense	-0.05 (0.05)	-0.05 (0.05)	0.30*** (0.06)
Age class (1: <=34, 2: 35-44, 3: 45-54, 4 :55-34, 5: 65+)	0.02 (0.05)	0.01 (0.05)	-0.10 (0.07)
Operator education (1: less than high school, 2: completed high school, 3:some college, 4: completed 4 years of college or more)	0.07 (0.06)	0.08 (0.06)	-0.09 (0.09)
Portion of total acres farmed that are owned	0.04 (0.04)	0.06 (0.04)	0.14** (0.07)
Gross cash farm income	1.33*** (0.12)	1.34*** (0.12)	-
Direct-to-consumer sales only (0/1)	0.03 (0.14)	-	-0.52*** (0.20)
Intermediated sales only (0/1)	0.26* (0.15)	-	0.03 (0.24)
Direct-to-consumer and intermediated sales (0/1)	omitted category	omitted category	omitted category
Primary commodity: fruit and/or vegetable (0/1)	0.12 (0.13)	0.18 (0.13)	0.15 (0.21)
Primary commodity: livestock and/or dairy (0/1)	0.46*** (0.14)	0.43*** (0.14)	0.30 (0.21)
Primary commodity: field crop (0/1)	omitted category	omitted category	omitted category
Constant	-0.52 (0.71)	-0.63 (0.67)	4.99*** (0.75)
$\ln\sigma_v^2$ (random error)	-2.01*** (0.52)	-1.88*** (0.46)	-0.52 (0.35)
$\ln\sigma_u^2$ (technical inefficiency)	0.39* (0.22)	0.37* (0.22)	0.68** (0.35)

σ_v	0.37 (0.10)	0.39 (0.09)	0.77 (0.14)
σ_u	1.22 (0.14)	1.20 (0.13)	1.41 (0.25)
$\sigma^2 = \sigma_v{}^2 + \sigma_u{}^2$	1.61 (0.28)	1.60 (0.27)	2.57 (0.53)
$\lambda = \sigma_u / \sigma_v$	3.32 (0.22)	3.07 (0.21)	1.83 (0.37)
Technical Efficiency	0.47	0.48	0.43
Log Likelihood	-222.35	-224.09	-292.71
AIC	472.70	472.18	611.42
BIC	518.16	511.15	653.64
Observations	190	190	190

Notes: standard errors are in parenthesis below the estimate, the asterisk denotes significance at the 10% (*), 5% (**), and 1% (***), all continuous variables are in natural logarithms.

I will first discuss the parameter results for all three models using operating profit as the dependent variable (table 2, columns 1-3) and then compare overall model statistics. Total fixed expense and labor expense are only statistically significant in the model specification that includes marketing channel only (column 3), where an increase in fixed/labor expense leads to an increase in efficiency. In this case, fixed expense and labor expense are likely acting as a proxy for scale, in which larger scale producers that have higher fixed and labor expenses and are also more efficient. The only expense category that is statistically significant across model specifications is total variable expense (not including labor). In the first two model specifications that both include scale (columns 1 & 2), an increase in variable expense leads to a decrease in efficiency, this is as we would expect. The sign flips in the model specification that includes marketing channel only (column 3), where an increase in variable expense leads to an increase in efficiency. Much as with fixed/labor expense, variable expense is likely a proxy for scale.

The portion of total acres farmed that are owned is only statistically significant in the model that is more parsimonious and only includes marketing channel (column 6), where an increase in ownership leads to an increase in efficiency. This is in line with the traditional thinking that land ownership is a key to financial success. But, the fact that land ownership is not statistically significant in the model specifications in which scale is included (columns 1 & 2) provides evidence that land ownership is not a key determinant of efficiency in the direct marketing sector.

Gross cash farm income (our scale variable) is positive and statistically significant in both models in which it is included (columns 1 & 2). Gross cash farm income has the largest impact on financial efficiency, providing evidence that, all else constant, the most important factor in the efficiency of direct market producers is scale. In the model that includes both scale and marketing channel (column 1), among the marketing channel options, intermediated only is statistically significant at the 10% level but direct-to-consumer is not. Participating in intermediated markets only increases efficiency compared to participating in both intermediated and direct-to-consumer marketing outlets. In contrast, for the more parsimonious model that includes only marketing channel (column 3), direct-to-consumer is statistically significant. Compared to participating in both intermediated and direct-to-consumer marketing outlets, participating in only direct-to-consumer markets decreases efficiency[5]. These three models provide evidence that, all else equal, scale is the largest determinant on efficiency for direct market producers, not market channel.

When comparing farms and ranches that utilize local markets by commodity, we find that those with a primary commodity of livestock are more profitable than both those who sell field crops and fruits and/or vegetables. Field crop producers represent a relatively small market share of the direct market segment and it is to be expected that they are the least profitable given the

[5] Results remain the same when the omitted category is intermediated only

relatively lower margins and fewer opportunities to create value-added extension lines with grains compared to livestock products, fruits, and vegetables. These results show that livestock producers, all else constant, are more efficient than fruit and vegetable producers, an interesting results in a market segment often perceived as being populated primarily by fruit and vegetable producers.

Average technical efficiency ranges from 0.43 to 0.48; most direct market producers are not producing on the efficiency frontier. Comparing model fit, based on the AIC/BIC statistic, the models containing both scale and marketing channel (column 1) as well as scale only (column 2) are very similar, with the model specification with scale only fairing slightly better in terms of fit; moreover, both have a better fit than the model specification with marketing channel only (column 3). We conduct two likelihood ratio tests to compare the goodness of fit between the restricted models (column 2 & 3) and the unrestricted model (column 1). When both scale and marketing channel are included, compared to including scale only, the resulting model fit is not a statistically different model, failing to reject the null (with a p-value of 0.18). The opposite is true when comparing the model that includes only marketing channel, adding scale to this model did statistically significantly improve model fit (with a p-value of 0.00). Results indicate that scale has the largest influence on efficiency and including choice of market channel does not significantly change how precisely we measure efficiency.

Overall, the model specifications that include scale (columns 1 & 2) have relatively few parameters that are significant. The model specification that includes marketing channel only (column 3) has more significant parameters, but it appears they may largely be acting as proxies for the omitted scale variable; overall, this model has a worse fit. It is possible that using operating profit margin as our dependent variable, a gross measure, might be masking some interesting aspects of farms participating in direct markets and is unable to establish some of the components of financial efficiency. Next, the parameter results for all three models using ROA as the dependent variable (table 3) are discussed and then overall model statistics are compared both within the model specifications using ROA as the dependent variable as well as comparing the models with differing dependent variable specifications.

Table 3. Stochastic frontier estimates for profit defined as return on assets (ROA)

	(4) Scale and marketing channel	(5) Scale Only	(6) Marketing channel only
Total fixed expense	-0.31*** (0.09)	-0.35*** (0.09)	-0.09 (0.09)
Total variable expense (minus labor expense)	-0.44*** (0.11)	-0.48*** (0.12)	0.07 (0.10)
Labor expense	-0.09 (0.07)	-0.10 (0.07)	0.20*** (0.06)
Age class (1: <=34, 2: 35-44, 3: 45-54, 4 :55-34, 5: 65+)	-0.12** (0.06)	-0.12* (0.07)	-0.16** (0.07)
Operator education (1: less than high school, 2: completed high school, 3:some college, 4: completed 4 years of college or more)	-0.02 (0.08)	0.00 (0.08)	-0.16* (0.09)
Portion of total acres farmed that are owned	-0.20*** (0.06)	-0.18*** (0.06)	-0.16** (0.07)
Gross cash farm income	1.11*** (0.13)	1.24*** (0.14)	-
Direct-to-consumer sales only (0/1)	-0.51*** (0.18)	-	-0.82*** (0.21)
Intermediated sales only (0/1)	0.19 (0.20)	-	0.13 (0.24)
Direct-to-consumer and intermediated sales (0/1)	omitted category	omitted category	omitted category
Primary commodity: fruit and/or vegetable (0/1)	0.26 (0.18)	0.37** (0.18)	0.23 (0.21)
Primary commodity: livestock and/or dairy (0/1)	0.61*** (0.19)	0.47** (0.20)	0.52** (0.22)
Primary commodity: field crop (0/1)	omitted category	omitted category	omitted category
Constant	-1.95*** (0.80)	-2.96*** (0.82)	2.21*** (0.74)

$\ln \sigma_v^{\ 2}$ (random error)	-1.17*** (0.37)	-0.81*** (0.32)	-0.62* (0.34)
$\ln \sigma_u^{\ 2}$ (technical inefficiency)	0.73*** (0.23)	0.62** (0.28)	0.89*** (0.27)
σ_v	0.56 (0.10)	0.67 (0.11)	0.73 (0.12)
σ_u	1.44 (0.17)	1.36 (0.19)	1.56 (0.21)
$\sigma^2 = \sigma_v^{\ 2} + \sigma_u^{\ 2}$	2.38 (0.40)	2.29 (0.41)	2.97 (0.54)
$\lambda = \sigma_u / \sigma_v$	2.58 (0.25)	2.04 (0.28)	2.13 (0.31)
Technical Efficiency	0.42	0.44	0.40
Log Likelihood	-269.37	-276.59	-299.24
AIC	566.74	577.18	624.48
BIC	612.20	616.14	666.69
Observations	190	190	190

Notes: standard errors are in parenthesis below the estimate, the asterisk denotes significance at the 10% (*), 5% (**), and 1% (***), all continuous variables are in natural logarithms.

In the model that includes both scale and marketing channel (column 4) as well as scale only (column 5), both fixed expense and variable expense (not including labor) are statistically significant; as to be expected, as expenses increase financial efficiency decreases. Interestingly, labor expense is not statistically significant in both models. By comparison, in the model that only includes marketing channel (column 6), labor is statistically significant but both fixed and variable expense are not. In this model, an increase in labor expense leads to an increase in financial efficiency. While we typically expect for an increase in an expense to decrease financial efficiency, in this case, labor expense is likely a proxy for some of the scale effect, where larger producers that have a higher labor expense are also more financially efficient. This result is the same for the previous model specification using operating profit as the dependent variable.

Age class is statistically significant across all model specifications; financial efficiency decreases with age. This is contrary to previous studies that found younger producers typically have higher levels of debt than older producers (Mishra et al., 2002); we would expect financial efficiency to increase with age. This result might provide evidence that younger producers in the direct marketing sector are choosing to run lean operations, by leasing rather than owning land and other fixed assets, leading to higher financial efficiency. Operator education is only statistically significant (at the 10% level) in the model with marketing channel only (in column 6), where an increase in education leads to a decrease in financial efficiency. One possible explanation is that producers selling through local markets are more likely than other producers to be first generation farmers. Thus, they may have decided to enter farming after being educated in another field, and after having a career in an entirely different industry. In this case, many of these skills are not transferable and may not lead to an increase in management efficiency or profitability.

As the proportion of total acres farmed that are owned (rather than leased) increases, financial efficiency decreases. This is to be expected as an increase in any assets (the denominator of this ratio), ceteris paribus, will decrease ROA. Land is generally a significant capital investment. Leasing is becoming more common across all agricultural segments, and appears more common for producers who participate in local and regional food systems (particularly given the fact that they are more likely to be first generation farmers). Since an increase in ownership will lead to a decrease in ROA, at least in the short term; this finding may be counterintuitive to those who feel access to land ownership is a key determinant of success.

Gross cash farm income (our scale variable) is positive and statistically significant in both models in which it is included (columns 4 & 5). Other than the constant, gross cash farm income has the largest impact on financial efficiency, providing evidence that, all else constant, the most important factor in the efficiency of direct market producers is scale. This result was the same in the previous model specification with operating profit margin as the dependent variable.

In both models in which market channel is included (column 4 & 6), the market channel direct-to-consumer is significant but intermediated is not. If a producer markets only direct-to-consumer, they are less efficient than if they market to both direct-to-consumer and intermediated, corroborating previous findings (Low et al., 2015).[6] This suggest that farms and ranches that diversify beyond only selling through direct-to-consumer marketing channels are more profitable, ceteris paribus. Results from this SFA indicate there are economies of scale associated with farms and ranches that sell through local and regional markets, and that scale rather than marketing channel has the largest influence on financial efficiency.

When comparing farms and ranches that utilize local markets by commodity, we find that those with a primary commodity of livestock are more profitable and those that sell field crops and those who sell fruits and/or vegetables; as was the case in which operating profit margin is the dependent variable. These results show that livestock producers, all else constant, are more efficient than fruit and vegetable producers, an interesting results in a market segment often dominated by fruit and vegetable producers.

The average technical efficiency of producers participating in direct markets ranges from 0.40 to 0.44, indicating that the majority of producers are relatively far from the efficiency frontier. Both models (with operating profit and ROA as dependent variables) provide evidence that there are business models for producers participating in direct markets that can be very profitable, but the majority of participating producers have not yet found their niche.

[6]The same results hold if the omitted category is selling through intermediated marketing channels only.

Comparing model fit, based on the AIC/BIC statistic, the model containing both scale and marketing channel has the best fit (column 4). Additionally, we conduct two likelihood ratio tests to compare the goodness of fit between the restricted models (column 5 & 6) and the unrestricted model (column 4). In both cases, using the unrestricted model (including both scale and marketing channel) results in a statistically significant improvement in model fit, rejecting the null (with p-value of 0.00) that either restricted model is a better fit. Results indicates that although scale has the largest influence on efficiency, choice of market channel also influences efficiency, when financial efficiency is defined as ROA. This is counter to the previous model specification in which only scale influenced efficiency when efficiency is defined as operating profit. Comparing AIC/BIC across specifications with operating profit and ROA as the dependent variable, operating profit as the dependent variable has a better fit but has fewer statistically significant variables.

Conclusions

The goal of this paper is to identify the factors that have the greatest influence on the efficiency of farms and ranches that sell through local food markets, with a particular focus on the interaction between scale and market channel. Our estimation of the stochastic production frontier suggests that scale, production enterprise specialty, market outlet choices, land ownership, and management of expenses have the greatest influence on producer financial efficiency. Our model suggests that scale has the largest impact on financial efficiency, providing evidence that, all else constant, the most important factor in the efficiency of direct market producers is scale.

The influence of marketing channel on efficiency, however, depends on how profit is defined. When profit is defined as operating profit, results indicate that marketing channel is not an important indicator of efficiency. But when profit is defined as ROA, marketing channel is an important indicator of efficiency, albeit less in magnitude of influence than is scale. Results from this analysis indicate there are economies of scale associated with farms and ranches that sell through local and regional markets, and that scale rather than marketing channel has the largest influence on efficiency, but that marketing channel may play some mitigating role in offsetting some scale effects.

We found that participating in both direct-to-consumer and intermediated markets increases financial efficiency (defined as ROA) compared to participating in direct-to-consumer markets only, reinforcing previous work that found that scaling to some wholesale, high-volume markets may be key to viability (Low et al., 2015). This suggest that farms and ranches that diversify beyond only selling through direct-to-consumer marketing channels are more profitable, ceteris paribus. Results show that livestock producers, all else constant, are more efficient than fruit and vegetable producers, an interesting results in a market segment often dominated by fruit and vegetable producers.

The results for financial efficiency among direct and intermediated marketing producers will be useful for a wide array of audiences. For researchers, it allows us to consider how factors other than scale and product may influence efficiency, and what that means for how our methodological approaches and sampling designs may need vary if we are comparing new farm enterprise types to the traditional farm sector. For those who do outreach with producers, this information may shed light on best practices in newly emerging models of food production and marketing. Given the average technical efficiency ranges from 0.40 to 0.48, most direct market producers are not producing on the efficiency frontier. This is a market segment in which information on best practices could play a role in increasing efficiency. And, for those providing technical assistance, loans, grants or other support to producers operating in, or considering, alternative business models, this information may provide insights about expected financial performance to make more informed decisions.

Next steps for this project include using a translog production function and consideration of how the stochastic term of the model may be heterogeneously distributed depending on a few key factors (scale, type of production specialty and market orientation). Moreover, we will consider further refining the model specification to consider whether some interactions across variables (labor expenditures interacted with type of marketing strategy, as one example) may also be important to consider in understanding the financial efficiency of farms selling through local markets.

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