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# 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.

## Introduction and background

Much of agricultural production in the United States (US) is attributed to larger, monoculture or commodity crop production. Mid-sized and large-scale family farms account for the majority of the revenues in the US (60%), but only 8% of all US farms (Hoppe, 2014). Larger operations are generally able to realize lower costs due to economies of scale associated with farming and ranching. These economies of scale are significantly influenced by technological and structural change in the industry and are positively associated with financial viability (MacDonald and McBride, 2009). Although small family farms<sup>1</sup> produce only 26% of the value of farm output, they represent 90% of US farms. Further, they are much less likely to be profitable compared with larger-sized operations, and thus attention to their economic viability is key to the resiliency of the sector (Hoppe, 2014). This study seeks to explore the financial efficiency of farms and ranches who participate in direct markets, a sector dominated by small operations.

Digging deeper into differences in the financial indicators of small farms compared with midsized<sup>2</sup> and large<sup>3</sup> family farms, we note some key discrepancies. Small family farms are much more likely to have tight financial margins making it much more difficult to weather market or production shocks. Hoppe (2014) shows that small farms are more likely to have a rate of return on assets (ROA)<sup>4</sup> of <1% and an operating profit margin of <10%; which he defines as the 'critical zone'. One mechanism that small farms have found to deal with scale diseconomies is through off-farm income. Small farm operators have a much larger

<sup>1</sup>Less than \$350,000 in gross cash farm income, based on the USDA definition.

<sup>2</sup>\$350,000 to \$999,999 in gross cash farm income, based on the USDA definition.

<sup>3</sup>\$1,000,000 or more in gross cash farm income, based on the USDA definition.

<sup>4</sup>Return on assets compares profits to resources used to produce them (Hoppe, 2014).

reliance on these non-farm sources of income and can thus be less reliant on the farm's returns for their household's economic well-being (Fernandez-Cornejo *et al.*, 2007; Hoppe, 2014).

Another opportunity for small producers may be adding value post-farmgate, through participating in consumer-focused, value-added and direct markets (Bauman *et al.*, 2017). These markets require producers to take on more supply chain functions, including marketing, processing and distribution; in return, they are able to retain a larger portion of the retail dollar (King *et al.*, 2010). In 2015, 167,000 operations sold through direct marketing channels, including direct-to-consumer sales (e.g., farmers' markets) and intermediated channels (e.g., farm-to-restaurant, farm-to-school), and accounted for \$8.7 billion in sales (USDA NASS, 2016). In recent years, the growth in local food marketing channels has been significant. For example, between 2006 and 2014, farmers' markets have grown 180% and food hubs by 288% (Low *et al.*, 2015).

Most of the economic research on local food systems has focused post-farmgate including supply chain analysis (e.g., King *et al.*, 2010; Hardesty *et al.*, 2014), economic impact studies (e.g., Hughes *et al.*, 2008; Brown *et al.*, 2014; Jablonski *et al.*, 2016; Schmit *et al.*, 2016) and consumer-oriented factors that have driven the demand for local food (e.g., Lusk and Briggeman, 2009; Onozaka and Thilmany, 2011; Costanigro *et al.*, 2014).

There is very little research that examines the farm financial outcomes associated with sales through these channels. Nor is there adequate 'peer' data that allow local food producers to compare themselves with similar farms or to provide a roadmap for strengthening financial viability or planning for market growth. Yet, farmers and ranchers, the US Department of Agriculture (USDA), lenders and private foundations that fund regional food systems have an interest in understanding how new markets influence the resiliency of farms. Particularly, understanding the financial well-being of beginning or smaller operations for whom more traditional commodity-oriented markets may have larger barriers to entry (e.g., Farm Credit Administration, 2016; Thilmany McFadden *et al.*, 2016a, b). Access to and consideration of this comparative information is one promising approach to better understand their competitive position, and if needed, consider factors influencing their 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) (USDA FSA, 2016). 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 (USDA RMA, 2017). In both cases, for financing and risk management programs to be structured effectively, a better understanding of the determinants of efficiency will be important.

To our knowledge, there have been no studies that focus on the financial performance and efficiency of farming operations that participate in both the direct and intermediated marketing channels. This research explores: 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 the local food system? Is there

an optimal diversification strategy with respect to market orientation, or is that dependent on other factors (cost structure, scale, region, primary commodity)?

The goal of this paper is threefold: first, to ascertain the average (and comparative) efficiency levels of farm operations that participate in direct and intermediated markets; second, to identify the factors that have the greatest influence on the relative efficiency of farms and ranches that participate in local food systems; and finally, to estimate the relationship between marketing strategy and farm profitability and productivity, with a particular focus on the role of farm size. We build on Park (2015), utilizing more recent data (with larger sample sizes of local food producers) and different methods with a focus on efficiency impacts within the direct market sector only.

### Previous research on direct marketing farm financial outcomes

Given the well-documented evidence of consumer willingness to pay a premium for products sold through direct markets (e.g., Onozaka and Thilmany, 2011; Costanigro *et al.*, 2014), one must understand differential expenditure patterns associated with sales through these markets. There are only a handful of case studies that examine differential farm expenditures and sales by market channel (Hardesty and Leff, 2010; LeRoux *et al.*, 2010; Jablonski and Schmit, 2016). These three studies examine 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. Thus, past studies did not integrate methods that allow for rigorous comparison or analysis.

Jablonski and Schmit (2016) did compare their case studies to USDA, Agricultural Resource Management Survey (ARMS) data, however it was only for New York, for which the ARMS sample is relatively small. Literature examining farm financial outcomes for local food market participants is mixed. Low *et al.* (2015) use USDA ARMS data to conduct a preliminary exploration of the financial impacts of sales through direct markets. They find that, on one hand, farms who participate in direct markets, regardless of scale, are significantly more likely to survive (defined by the USDA as a farm business having positive sales in subsequent census, 2007 and 2012) than farms who market through more traditional, commodity market channels. However, farms with gross cash farm income (GCFI) >\$10,000 grew at a significantly slower pace during the same period than farms who used traditional markets.

Park (2015) uses national-level data and finds that, compared with traditional marketing channels, participating in direct markets has a negative impact on farm sales (which lessens as farm size increases). Detre *et al.* (2011) examines factors affecting the adoption of direct marketing strategies and its impact on gross sales using 2002 ARMS data. Results show that farms who adopt direct marketing strategies capture a larger proportion of the consumer dollar, thus increasing gross sales, compared to those using more traditional sales channels (such as large scale, commodity distributors).

Part of the reason for limited previous research on local foods markets is that national data were limited until very recently. Although national data on direct-to-consumer sales have been available since 1976 in the census, intermediated sales by farm operators have only been available since 2008, when the ARMS began collecting these data. As intermediated sales represent the

largest segment of local food sales, analysis before 2008 was incomplete. In a congressionally mandated report on Trends in Local and Regional Food Systems, Low *et al.* (2015) were only able to provide what they call ‘a synthetic estimate of local food sales values’ due to data deficiencies, illustrating the challenge. The ARMS now provides a sufficiently large sample of financial data for producers participating in local food systems at the national level, allowing for a more rigorous financial assessment of this subset of US farmers.

### Empirical approach

The most common approach to estimating production or financial efficiency across the farm sector is stochastic frontier analysis (SFA)<sup>5</sup>, whereby a production/cost/profit function is estimated with an error composed of both a productive inefficiency component and a random component. It is assumed that the production/cost/profit function is the theoretical ideal, mapped endogenously against those firms included in the data (peer direct market farms), so any deviation from this function is the result of an inefficiency (Green, 2012). Figure 1 describes a profit efficiency frontier. Input costs are on the  $x$ - and  $y$ -axes and a profit frontier is estimated, representing the combination of fixed and variable input costs that produce the highest profit. Producers that lie above or below the profit frontier could earn higher profits using a different combination of fixed and variable inputs, and are thus considered inefficient. Those producers who lie on the efficiency frontier are efficiently using inputs to create profit and would not increase profits if they were to shift their spending on fixed and variable inputs.

Although there have been no studies that evaluate the efficiency of local and regional food system participants, there have been numerous studies that use SFA to evaluate the efficiency of other types of US farming and ranching operations (e.g., Morrison and Nehring, 2005; Mayen *et al.*, 2010; Key and McBride, 2014), as well as international farming and ranching operations (e.g., Bokusheva *et al.*, 2012; Barath and Ferto, 2015). SFA allows us to estimate the maximum attainable output/profit for a given set of inputs and prices. By additionally including farm characteristics in our model beyond, we are able to determine the full set of factors that likely influence a producer’s ability to reach this ideal.

We estimate a profit frontier where profit is defined as ROA. Lack of data precludes estimation of an output function, so the remaining choices for this study were estimating either a profit or a cost function. The choice to use a profit function was based on a couple of factors given the context of this sector and study. The more commonly employed cost function<sup>6</sup>, focused on estimating cost inefficiency, does not enable us to capture the effects of the business strategy to focus on higher quality output one might expect farmers to market in highly differentiated markets. This is important as we assume such a quality-focused strategy would be more costly, but not necessarily inefficient if price premia offset additional costs of differentiation. By estimating a profit

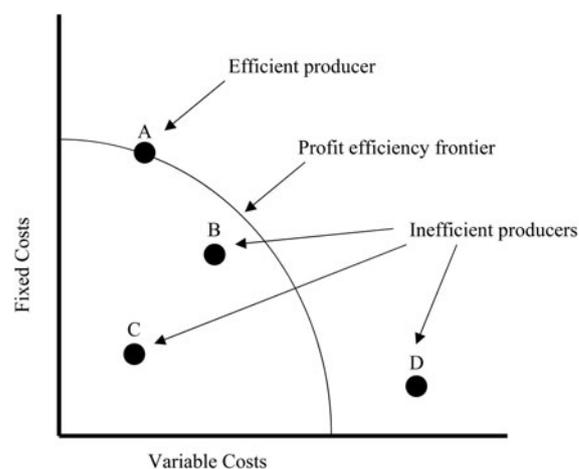


Fig. 1. Profit efficiency frontier.

frontier we can capture differentiation as the key specialization strategy, allowing the producers that produce higher quality outputs to compensate for the higher costs that they incur in the production process through increased revenue earnings (Maudos *et al.*, 2002). Another reason to focus on ROA rather than costs, or even operating profit<sup>7</sup>, is because it standardizes against one key metric: invested assets.

ROA is a commonly used metric to evaluate farm profitability and is calculated by dividing net income by total assets. It measures how efficiently a firm can create profit using their invested assets in a given year, accounting for the opportunity cost of money. Although not commonly used in profit frontier estimation, the use of a ‘standardized’ measure like ROA may allow some expected and interesting cases (such as lean management farms with few owned assets that compete through aggressively pursuing high end produce and product markets) to emerge more clearly (e.g., Ho *et al.*, 2013; Wolf *et al.*, 2016). In contrast, gross measures, such as operating profit, may mask some interesting aspects of farms participating in direct markets. In short, since ROA represents the profitability and returns relative to the dollar value of assets invested in the farm, it allows farms that may have adopted ‘lean’ management strategies (minimal overhead) to stand out as particularly strong performing. Given the local food sector’s inclusion of beginning, small or limited resource farms, such a metric where farms can rely on rented rather than owned assets may be of particular interest.

The main challenge associated with this approach is the existence of negative profits; one cannot take the natural log of a negative value. This challenge is not applicable in traditional SFA in which a production or a cost frontier is estimated as output and cost are always positive. Accordingly, results presented herein represent only the information provided by those farms with a positive value of ROA. Explanatory variables include variable and fixed expenses, operator age, education, market outlet, scale, primary commodity, year, off-farm income and per cent of farmland that is owned.

Using SFA allows us to disentangle the effect of scale on efficiency from the many other factors that influence efficiency, a particular focus here given the perceptions by policymakers and government agencies that local and regional food systems are

<sup>5</sup>Another common approach to estimate efficiency is data envelope analysis. Although data envelope analysis 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, particularly in a heterogeneous sector such as local foods.

<sup>6</sup>Please contact author to see results from cost frontier estimation.

<sup>7</sup>Calculated by subtracting operating expenses from gross profit.

particularly important business opportunities for smaller scale producers. In our study, we use GCFI as a proxy for 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. But, these differences are not necessarily clear and distinct. To disentangle the effects that scale and marketing channel may have on efficiency, the model is estimated with both included, and then again for comparative purposes, with only the marketing channel variables and only scale included. In addition to marketing channel, primary commodity may also have an influence on financial efficiency. While fruit and vegetable producers make up the majority of sales for producers in local food systems (Low and Vogel, 2011; Low *et al.*, 2015) 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 *et al.* (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 gaining access to traditional agricultural markets.

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 may be a greater reliance on aggressively managed marketing and operations compared with traditional market outlets because managers feel a need to gain the highest return possible on their more limited volume of production. If this is the case, 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. Indeed, Park *et al.* (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 US farm households have a 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 and Vogel, 2011). Given the reliance on off-farm income, it is likely to be an important factor in determining profitability, as found by Park *et al.* (2014). However, it may also compete with time spent focused on the agricultural enterprise, therein representing a challenge to managerial efficiency.

### Econometric model

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

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

where  $\pi_i$  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  $\beta$ . 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 second-order translog function such that  $f(x_i, \beta) = \beta_0 + \sum_{k=1}^K \beta_k \ln(x_{ik}) + \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \beta_{kj} \ln(x_{ik}) \ln(x_{ij})$ ,<sup>8</sup> where  $\beta_0$  is the constant and  $\beta_k$  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 profit of an individual producer to the maximum observed profit:

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

where  $0 \leq TE_i \leq 1$ . 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  $\text{var}[u] = \sigma_u^2 [(\pi - 2)/\pi]$ , where  $0 < u_i < \infty$ . The log-likelihood function is as follows:

$$\ln L(\pi|\beta, \lambda, \sigma^2) = \sum_{i=1}^N \left\{ \frac{1}{2} \ln\left(\frac{2}{\pi}\right) - \ln \sigma + \ln \Phi\left(\frac{-\varepsilon_i \lambda}{\sigma}\right) - \frac{\varepsilon_i^2}{2\sigma^2} \right\}$$

where  $\varepsilon_i = \pi_i - x_i' \beta$ ,  $\lambda = \sigma_u / \sigma_v$ ,  $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$  and  $\Phi$  is the standard normal cumulative distribution function (Aigner *et al.*, 1977).

The main parameter of interest,  $u_i$ , is the technical efficiency of each individual enterprise, which is a component of the estimated error,  $\varepsilon_i = v_i + u_i$ . As  $u_i$  is not directly estimable, to assess the technical efficiency for an individual enterprise, we estimate the expected value of  $u_i$  given  $\varepsilon_i$ :

$$E(u_i|\varepsilon_i) = \mu_{*i} + \sigma_* \left\{ \frac{\phi(-\mu_{*i}/\sigma_*)}{\Phi(\mu_{*i}/\sigma_*)} \right\}$$

where  $\mu_{*i} = \varepsilon_i \sigma_u^2 / \sigma^2$ ,  $\sigma_* = \sigma_u \sigma_v / \sigma$ , and  $\phi$  is the standard normal probability density function (StataCorp, 2013).

### Data

Data are taken from the 2013 and 2014 Phase III ARMS to estimate the parameters of the model. The data include GCFI, 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). It is the most comprehensive national source of farm financial data (Low and Vogel, 2011). 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

<sup>8</sup>A log-likelihood test was performed and Cobb-Douglas was rejected as an appropriate functional form.

producers, particularly in the non-core agricultural states. Although the ARMS is not designed to specifically collect data on agricultural sectors such as direct marketing, it does integrate questions on this sector and 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 as recommended by the USDA Economic Research Service). But, if the purpose is to describe variability within a sample (in our case 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). In other words, 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 the direct marketing farms' variance from being 'representative' that 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 or (3) institutions. Subsequently, they are asked to provide how much money was received 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, CSAs, (3) to a local retail outlet such as a restaurant or grocery store, (4) to a regional distributor such as a food hub or (5) to a local institutional outlet such as a school or hospital. We define local food system participants as 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, 41,912 (94%) reported no local food sales and 2624<sup>9</sup> (6%) responded that they had positive sales in any combination of local food marketing channels. For all those respondents who reported positive sales in local food marketing channels, 1690 (64%) had positive direct-to-consumer sales only, 380 (15%) had positive intermediated sales only and 554 (21%) had positive sales to both outlets. Table 1 provides summary statistics for the main variables used in the study, reported as an aggregate across all sales categories as well as broken out by sales category.

As a whole, farms participating in direct marketing channels show a broad range of profitability with farms over \$350,000 in sales reporting an average ROA of over 10%, a strong result for a

generally low margin industry such as agriculture. Fixed expenses as a portion of total expenses decrease with scale, ranging from 31% for producers with sales between \$1000 and \$74,999 to 15% for producers with sales over \$350,000. This is what we would expect and demonstrate one of the benefits of scaling up. Variable expenses as a percentage of total expense follow an opposite trend, increasing from 69 to 85% as scale increases from \$1000–\$74,999 to over \$350,000. Labor expense as a portion of total expense increases with scale, ranging from 7 to 32%. This greater reliance on labor could demonstrate a shift from operator and unpaid labor into paid labor and/or an increase in the reliance on more hours and skills within a labor force for specialized production and marketing activities as the size and complexity of a farming enterprises increases.

On average, producers are in the age range of 45–54 and have completed high school. The portion of acres owned to farm is 1.2 for the smallest scale producers; so on average, 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. This is one example we might expect to see if a farm was taking a 'lean' management approach. As was found to be the case with all small farms (Fernandez-Cornejo *et al.*, 2007), small direct market producers rely more heavily on off-farm income compared with mid-size and large farms.

On average, 64% of producers participate in direct-to-consumer marketing channels only, 15% in intermediated only and 21% in both types of channels. 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 participate in intermediated marketing channels. In terms of primary commodity, 34% of producers sell fruits and vegetables, 19% field crops and 41% livestock. The portion of fruit and vegetable production is relatively constant across scale categories, but small-scale producers are more likely to produce livestock, whereas larger producers are more likely to produce field crops.

## Results

Table 2 presents the results from the estimated model. All logged input expense variables are standardized to have means of zero, thus input expense coefficients can be interpreted as the partial elasticity at the sample mean. The first column of results (1) is from the model specification with ROA as the dependent variable<sup>10</sup> and includes both GCFI and market channel, the second column (2) includes only marketing channels and no GCFI, the last column (3) includes only GCFI and no marketing channels. These model specifications were chosen to disentangle the effects that market channel and scale have on profitability, thereby enabling us to gain insights that answer the question of whether it is scale or marketing channel that has the largest influence on efficiency. We first discuss overall model statistics and then parameter results for all three models.

We chose to use total variable expenses, with labor broken out, and total fixed expenses rather than individual expense categories as a data management choice that allows us to retain more of the sample. Some expense categories are only incurred by livestock producers and others only by crop producers, so the disaggregated categories would omit observations, thereby resulting in a

<sup>9</sup>Note that of those farms with direct sales, 141 reported their primary commodity as nursery and are not included in the SFA.

<sup>10</sup>The model was tested for heteroscedasticity and found not to be present.

**Table 1.** Summary statistics for local food farmers and ranchers

	All mean (s.d.)	\$1 K–\$75 K Mean (s.d.)	\$75 K–\$350 K Mean (s.d.)	\$350 K+ Mean (s.d.)
Return on assets (ROA) (\$)	−15.81 (267.82)	−32.83 (366.90)	0.30 (27.00)	10.45 (46.46)
Fixed expense as a per cent of total expense	0.25 (0.20)	0.31 (0.21)	0.19 (0.14)	0.15 (0.11)
Variable expense as a per cent of total expense	0.75 (0.20)	0.69 (0.21)	0.81 (0.14)	0.85 (0.11)
Labor expense as a per cent of total expense	0.15 (0.22)	0.07 (0.16)	0.19 (0.22)	0.32 (0.24)
Gross cash farm income	\$799,555 (4,229,506)	\$19,419 (18,802)	\$178,020 (74,708)	\$3,329,901 (8,423,248)
Direct-to-consumer sales only (0/1)	0.64 (0.48)	0.76 (0.43)	0.55 (0.50)	0.42 (0.49)
Intermediated sales only (0/1)	0.14 (0.35)	0.09 (0.29)	0.16 (0.36)	0.27 (0.45)
Direct-to-consumer and intermediated sales (0/1)	0.21 (0.41)	0.15 (0.35)	0.30 (0.46)	0.31 (0.46)
Primary commodity: fruit and/or vegetable (0/1)	0.34 (0.47)	0.33 (0.47)	0.32 (0.47)	0.39 (0.49)
Primary commodity: livestock and/or dairy (0/1)	0.41 (0.49)	0.47 (0.50)	0.37 (0.48)	0.28 (0.45)
Primary commodity: field crop (0/1)	0.19 (0.39)	0.16 (0.36)	0.23 (0.42)	0.26 (0.44)
Portion of total acres owned to farmed	0.99 (2.99)	1.2 (4.01)	0.86 (1.23)	0.64 (0.78)
Total household income divided by on-farm income	24.41 (214.88)	15.92 (105.48)	0.30 (0.54)	0.05 (0.13)
Age class <sup>1</sup>	3.74 (1.09)	3.80 (1.08)	3.61 (1.15)	3.67 (1.06)
Operator education <sup>2</sup>	2.98 (0.98)	3.01 (0.97)	2.87 (1.04)	3.02 (0.95)
2013 (0/1)	0.39 (0.49)	0.39 (0.49)	0.39 (0.49)	0.37 (0.48)
2014 (0/1)	0.61 (0.49)	0.61 (0.49)	0.61 (0.49)	0.63 (0.48)
Observations	2624	1375	543	593

<sup>1</sup>1: <34, 2:35–44, 3:45–54, 4:55–64, 5:65+.

<sup>2</sup>1: less than high school, 2: completed high school, 3: some college, 4: completed 4 yr of college or more.

relatively small sample. Labor is left as a disaggregated category as all producer types have labor expenses and there is evidence that labor is one of the largest variable expense categories for direct market producers (Schmit *et al.*, 2016; Bauman *et al.*, 2017).

As the dependent variable is logged in a stochastic frontier model, we lose all observations with negative ROA measures<sup>11</sup> (which accounts for 66% of the sample). This analysis only estimates efficiency for those producers with positive ROA. A generalized likelihood ratio test to determine if  $\sigma_u^2$  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.

In models 1 and 3, technical efficiency is 0.43 implying that, on average, a farm can increase profit by about 133% [(100 – 43) × 100/43] by improving efficiency. Technical efficiency decreases to 0.41 in model 2. Overall, most direct market producers are not producing on the efficiency frontier and could realize significant improvements in profitability with changes in their operations. Results provide evidence of the large degree of heterogeneity across the direct and intermediated marketing farm sector in which there are some producers that are very financially successful and efficient, while the majority are not, or at least are not meeting the potential profitability mapped out by the highest performing cohort of producers.

Comparing model fit, based on the Akaike information criterion/Bayesian information criterion statistic, the models containing

<sup>11</sup>In addition to observations with negative ROA, seven observations with ROA outside of two standard deviations from the mean were dropped.

both scale and marketing channel (1) as well as scale only (3) are very similar, with the model specification that includes scale only fairing slightly better in terms of fit. Moreover, both (1 and 3) have a better fit than the model specification with marketing channel only (2). We conduct two likelihood ratio tests to compare the goodness of fit between the restricted models (2 & 3) and the unrestricted model (1). When both scale and marketing channel are included, compared with including scale only, the resulting model fit is not a statistically different model, failing to reject the null (with a *P*-value of 0.17). The opposite is true when comparing the model that includes only marketing channel, as tests indicate that 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.

For models 1 and 3, input expense elasticities have the expected sign and are statistically significant with the exception of the coefficient on fixed costs. Results are similar in model 2, the model in which scale is not included, but labor expense is not the sign we would expect. As we saw from the summary statistics, larger operations use a larger share of labor; thus, the positive coefficient on labor expense is likely a result of the fact that labor is acting as a proxy for scale when it is not directly specified. This result provides evidence of the importance of scale in determining a producer's profit efficiency. In terms of magnitude, variable expenses (not including labor) has the largest impact on profit efficiency, ranging from −0.24 to −0.58, followed by labor expense. This finding suggests that managing variable expenses, not fixed expenses, are the key for direct market

**Table 2.** Stochastic frontier estimates for profit defined as return on assets

	(1)	(2)	(3)
<i>y</i> (Return on assets)			
Constant	1.15*** (0.38)	2.21*** (0.43)	1.05*** (0.37)
<i>x</i> 1 (Total fixed expense)	−0.10 (0.08)	−0.02 (0.09)	−0.10 (0.08)
<i>x</i> 2 (Total variable expense minus labor expense)	−0.58*** (0.10)	−0.24** (0.11)	−0.57*** (0.10)
<i>x</i> 3 (Labor expense)	−0.16** (0.03)	0.18** (0.08)	−0.16** (0.07)
<i>x</i> 1 × 1	−0.01 (0.08)	0.11 (0.09)	0.01 (0.08)
<i>x</i> 2 × 2	0.14 (0.09)	0.27*** (0.10)	0.16* (0.09)
<i>x</i> 3 × 3	−0.02 (0.03)	0.06 (0.04)	−0.01 (0.03)
<i>x</i> 1 × 2	−0.29 (0.15)	−0.37 (0.17)	−0.34** (0.15)
<i>x</i> 1 × 3	0.10 (0.08)	0.05 (0.09)	0.10 (0.08)
<i>x</i> 2 × 3	0.05 (0.10)	−0.09 (0.11)	0.04 (0.10)
$\ln\sigma_v^2$ (Random error)			
Constant	−1.01*** (0.24)	−0.50*** (0.22)	−0.99*** (0.23)
$\ln\sigma_u^2$ (Technical inefficiency)			
Constant	0.66*** (0.18)	0.81** (0.21)	0.67*** (0.17)
Gross cash farm income	1.19*** (0.11)		1.20*** (0.11)
Direct-to-consumer sales only (0/1)	−0.15 (0.14)	−0.16 (0.16)	
Intermediated sales only (0/1)	0.12 (0.16)	0.16 (0.19)	
Primary commodity: fruit and/or vegetable (0/1)	0.21 (0.14)	0.33** (0.16)	0.24* (0.14)
Primary commodity: livestock and/or dairy (0/1)	0.16 (0.11)	0.19 (0.17)	0.14 (0.14)
Portion of total acres farmed that are owned	−0.27*** (0.05)	−0.26*** (0.06)	−0.28*** (0.05)
Total household income divided by on-farm income	−0.03 (0.04)	−0.29*** (0.05)	−0.02 (0.04)
Age class <sup>1</sup>	−0.02 (0.05)	−0.06 (0.06)	−0.03 (0.05)
Operator education <sup>2</sup>	−0.02 (0.06)	−0.05 (0.07)	0.02 (0.06)
Year (0/1)	0.19* (0.11)	0.22* (0.13)	0.19* (0.11)
Average technical efficiency	0.43	0.41	0.43
Log likelihood	−477	−528	−478
Observations	334	334	334

<sup>1</sup>: ≤34, 2: 35–44, 3:45–54, 4:55–34, 5:65+.

<sup>2</sup>: less than high school, 2: completed high school, 3: some college, 4: completed 4 yr of college or more.

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.

producers to achieve profit efficiency. The only statistically significant cross effect is fixed and variable expense (not including labor), ranging from −0.29 to −0.37, indicating that managers may see them as substitutes for one another. One obvious example is a yearly rental payment for land and/or delivery vehicle compared to the fixed expenses of owning those same assets.

GCFI (our scale variable) is positive and statistically significant in both models in which it is included (1 and 3). GCFI 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. Marketing channel is not significant in either of the models in which it is included (1 and 2). This result demonstrates that scale, and not market channel, is the biggest determinant of financial efficiency.

When comparing farms and ranches that utilize local markets by commodity, the fruit and vegetable dummy is the only variable that is statistically significant. We find that those reporting a

primary commodity of fruit and vegetables are more profitable than both those who sell field crops and livestock. Field crop producers represent a relatively small market share of the direct market segment and it may be expected that they are the least profitable given the relatively lower margins and fewer consumption-ready and value-added extension lines created from grains that have appeared in local and regional markets when compared to livestock products, fruits and vegetables. These results show that fruit and vegetable producers, all else constant, are more efficient than livestock and field crop producers.

As the proportion of total acres farmed that are owned (rather than leased) increases, financial efficiency decreases, with parameter values ranging from −0.26 to −0.28. This is to be expected as an increase in any asset (the denominator of this ratio), *ceteris paribus*, will decrease ROA. Land is generally a significant capital investment, so there has been higher demand for leasing in recent years (Oppendahl, 2013). Our data show that leasing is a more

common option for producers who participate in local and regional food systems (particularly given the fact that they are more likely to be first-generation farmers).

Off-farm income is only statistically significant in the model in which scale is not included (2). The negative coefficient tells us that as total income divided by on-farm income increases, efficiency decreases. This finding is in line with Park *et al.* (2014), but in contrast to Fernandez-Cornejo *et al.* (2007). The fact that off-farm income is only statistically significant in the model specification that does not include scale provides evidence that the negative and significant coefficient on off-farm income in model 2 is likely a proxy for scale. The remaining variables in the model are not significant, except the dummy variable for year 2013, which is significant at the 10% for all years. This result is as to be expected as 2013 was a good year for many farming operations based on production and market conditions.

## Conclusions

The goal of this paper is to identify the factors that have the greatest influence on the financial 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 profit frontier suggests that scale, management of variable expenses, production enterprise specialty and land ownership have the greatest influence on producer financial efficiency. Our model provides evidence that, all else constant, the most important factor driving the variability in efficiency levels among direct market producers is scale.

Market channel participation, on the other hand, was not statistically significant in any of our model specifications. This result tells us that there are many different choices a producer can make in terms of where they choose to sell their product and remain efficient; it is likely that many of the effects of market outlet on efficiency are captured in the differences in business models and strategies, which would be accounted for in the differences in variable expenses across outlets. Again, results demonstrate that scale, rather than market outlet is the driver of efficiency. That being said, other literature provides evidence that intermediated markets are the best marketing strategy to achieve that scale while still maintaining local or regional differentiation (e.g., Hardesty *et al.*, 2014).

Fixed expenses were found to be insignificant; managing variable expenses, not fixed expenses, is the key managerial focus for direct market producers to achieve profit efficiency. Results show that fruit and vegetable producers, all else constant, are more efficient than livestock and field crop producers. Overall, choice of commodity category has a relatively small impact on efficiency. Additionally, results provide evidence that ownership is not a determinant of efficiency in the direct marketing sector, which may be counterintuitive to those who feel access to land ownership is a key determinant of success. In fact, these results suggest that wealth building strategies (land ownership and growth through value appreciation) may run counter to attaining short-term profitability and cash returns.

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 commodity may influence efficiency, and what that means for how our methodological approaches and sampling designs may need to 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 average technical efficiency ranges from 0.41 to 0.43, most direct market producers are not producing along 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. The good news is that other, related research provides preliminary evidence that at all scales there are local food market participants who are profitable (Bauman *et al.*, 2017). Additional technical assistance based on findings from this research may provide needed support and managerial guidance for farms selling through diversified, local markets.

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